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Hybrid Fuzzy-NSGA-II Decision-Support Framework for Multi-Objective Risk Assessment of Construction

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Abstract

Credit risk assessment of construction contractors is a process that predicts the likelihood of project default by analyzing contractors' past performance. Existing methods are mostly single-objective and often neglect key project dimensions such as time, quality, and cost, limiting their accuracy and effectiveness. This study proposes a multi-objective approach for contractor credit risk assessment, simultaneously optimizing two conflicting goals: enhancing contractor quality and minimizing the financial–temporal burden of projects. A Fuzzy Logic Controller (FLC) is employed for its interpretability and alignment with human decision-making processes. The design of the knowledge base and membership functions is optimized using a Genetic Algorithm integrated with the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The proposed model is evaluated on a dataset of 540 real construction contractor records. Experimental results demonstrate that the FLC-NSGA-II framework outperforms comparative methods including group regression, non-group regression, MOPSO, and SPEA-II in terms of predictive accuracy, achieving performance indices of $R^2 = 0.1000$, MSE = 0.0005, RMSE = 0.0224, and MAE = 0.0183. This high accuracy improves credit risk prediction, prevents project defaults, and reduces financial losses for construction firms. The proposed framework provides a novel, precise, and generalizable tool for credit risk assessment and supports decision-making in complex construction projects.

Keywords: *Contractor risk assessment, Fuzzy Logic Controller, NSGA-II, Multi-objective optimization, Construction projects*

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1. Introduction

Accurate credit risk assessment of construction contractors is crucial for preventing project defaults and reducing financial losses in construction projects. Traditional methods primarily adopt a single-objective perspective, often overlooking critical project dimensions such as quality, time, and cost. This limitation can lead to reduced predictive accuracy and inefficient risk management [1].

Recent research has explored computational and multi-objective approaches to enhance risk evaluation; however, these methods frequently lack interpretability and practical alignment with human decision-making processes [2]. Fuzzy Logic Controllers (FLCs) provide a promising solution by incorporating expert knowledge into the evaluation process, offering both flexibility and transparency. Furthermore, combining FLCs with advanced optimization algorithms enables simultaneous consideration of multiple conflicting objectives [3].

In this study, a hybrid Fuzzy-NSGA-II framework is proposed for multi-objective credit risk assessment of construction contractors. The framework optimizes two conflicting goals: improving contractor quality and minimizing the financial–temporal burden of projects. The knowledge base and membership functions of the FLC are optimized using a Genetic Algorithm integrated with

NSGA-II, and the model is validated on 540 real contractor records.

The proposed approach addresses the limitations of existing single-objective methods, provides higher predictive accuracy, and offers a generalizable framework applicable to complex construction projects. By integrating fuzzy logic with multi-objective evolutionary optimization, this study contributes a novel, computationally efficient decision-support tool for contractor risk management.

2. Literature Review

2.1. Contractor Risk Assessment

Credit risk assessment of construction contractors is a critical aspect of project management, as it helps predict the likelihood of project defaults and financial losses. Traditional methods rely heavily on historical performance data and often consider only single-objective metrics such as financial stability or past project completion rates. While useful, these approaches may fail to capture the multifaceted nature of contractor risk, which includes technical capability, project quality, time management, and financial burden [4].

2.2. Fuzzy Logic in Risk Assessment

Fuzzy logic has emerged as a powerful tool for handling uncertainty and imprecision in risk assessment. By modeling qualitative and quantitative factors as fuzzy variables, fuzzy systems can incorporate expert knowledge and provide interpretable decision-making frameworks [5]. Several studies have applied fuzzy logic to evaluate contractor performance, yet most focus on single-objective evaluations and do not fully exploit the potential of hybrid approaches with optimization algorithms [6].

2.3. Multi-Objective Optimization in Construction Projects

Multi-objective optimization techniques, such as NSGA-II, MOPSO, and SPEA-II, are increasingly used to address conflicting goals in construction projects, including maximizing quality while minimizing cost and time. Integrating fuzzy logic with these algorithms allows simultaneous consideration of multiple risk dimensions and enhances the accuracy and reliability of contractor evaluation [7]. Hybrid approaches have shown improved predictive performance and decision-support capabilities compared to traditional or single-objective models [8].

2.4. Gaps in Existing Research

Despite significant progress, existing studies exhibit several limitations. First, many approaches remain single-objective and cannot handle the trade-offs inherent in contractor risk assessment. Second, the integration of fuzzy logic with advanced multi-objective algorithms is still limited, and practical validation using real-world contractor data is scarce [9]. These gaps highlight the need for a comprehensive hybrid framework that can simultaneously optimize conflicting objectives and provide robust, interpretable, and data-driven credit risk assessment for construction contractors [10].

3. Methodology

This study develops a hybrid Fuzzy-NSGA-II framework for multi-objective credit risk assessment of construction contractors. The proposed methodology integrates a Fuzzy Logic Controller (FLC) with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to optimize two conflicting objectives: enhancing contractor quality and minimizing the financial–temporal burden of projects.

- **Fuzzy Logic System Design:** The FLC is designed to model human-like reasoning in evaluating contractor risk. The knowledge base comprises expert-derived rules, and membership functions for input and output variables are defined using triangular and trapezoidal functions. Key input variables include contractor performance history, project complexity, and financial indicators, while the output represents the overall credit risk score.
- **Optimization with NSGA-II:** To enhance system performance, the knowledge base and membership functions are optimized using **a** Genetic Algorithm (GA) integrated with NSGA-II. This multi-objective optimization ensures a balance between improving quality and reducing project cost and duration.
- **Data Collection:** The framework is validated using 540 real contractor records from construction projects. Performance metrics include R^2, MSE, RMSE, and MAE, allowing quantitative evaluation of predictive accuracy.
- **Evaluation:** The proposed FLC-NSGA-II model is compared against benchmark methods, including group regression, non-group regression, MOPSO, and SPEA-II, demonstrating superior performance in multi-objective risk assessment. This

methodology provides a robust and generalizable tool for supporting decision-making in complex construction projects.

3.1. Conceptual Model of the Research

To provide a clearer understanding, this section presents a conceptual model of the process of designing, developing, and applying the proposed NSGA-II-FLC system for assessing the credit risk of construction contractors in a step-by-step manner. The conceptual model of the proposed method is illustrated in Figure 1.

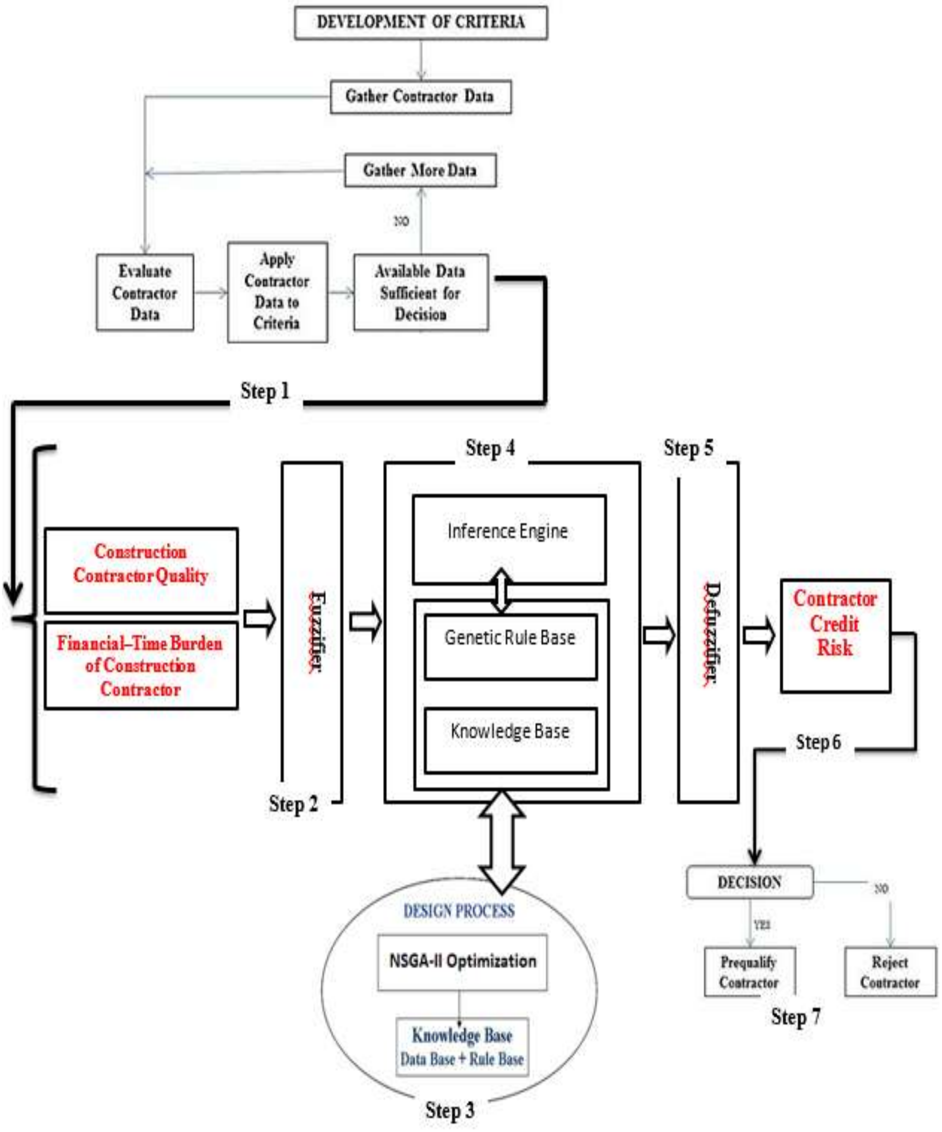

Figure 1. Conceptual model of the design, development, and application process of the proposed NSGA-II-FLC method

As shown in Figure 1, the process of designing, developing, and applying the proposed NSGA-II-FLC system involves several stages, which are described as follows:

Step (1): In this step, the primary data of construction contractors, including the main and secondary indicators considered in the research, are collected, evaluated, and categorized. These data are then provided to the proposed NSGA-II-FLC system for credit risk assessment.

Step (2): In this step, the main and secondary indicators extracted in the previous stage are used as inputs to the proposed NSGA-II-FLC system. Through the fuzzifier, these indicators are transformed from crisp values into fuzzy values.

Step (3): In this step, the fuzzy system's rule base and optimized membership functions are generated by the multi-objective optimization algorithm NSGA-II. These optimized parameters are then transferred to the knowledge base of the system for fuzzy inference.

Step (4): In this step, using the optimized membership functions and knowledge base generated by NSGA-II, fuzzy inference is performed to assess the credit risk of contractors. The results are then forwarded to the defuzzifier to be converted from fuzzy values into crisp values.

Step (5): In this step, the defuzzifier transforms the results into crisp values, and the credit risk of construction contractors is presented as the output of the proposed FLC-NSGA-II system.

Step (6): In this step, based on the assessed credit risk of contractors obtained from the proposed FLC-NSGA-II system, the project management team makes decisions regarding the allocation of projects to contractors.

Step (7): In cases where contractors do not meet the required qualifications, the project management team classifies them as non-eligible. Consequently, the construction projects are assigned only to the qualified contractors for execution.

3.2. Design and Operation of the Proposed Fuzzy Logic System

contractors. The proposed FLC maps an input space to an output space, where the main mechanism for this mapping is a set of if–then statements, known as fuzzy rules. The "if" part of a fuzzy rule is referred to as the antecedent, while the "then" part is referred to as the consequent. Figure 2 presents the fuzzy inference mechanism of the proposed FLC, which is further explained.

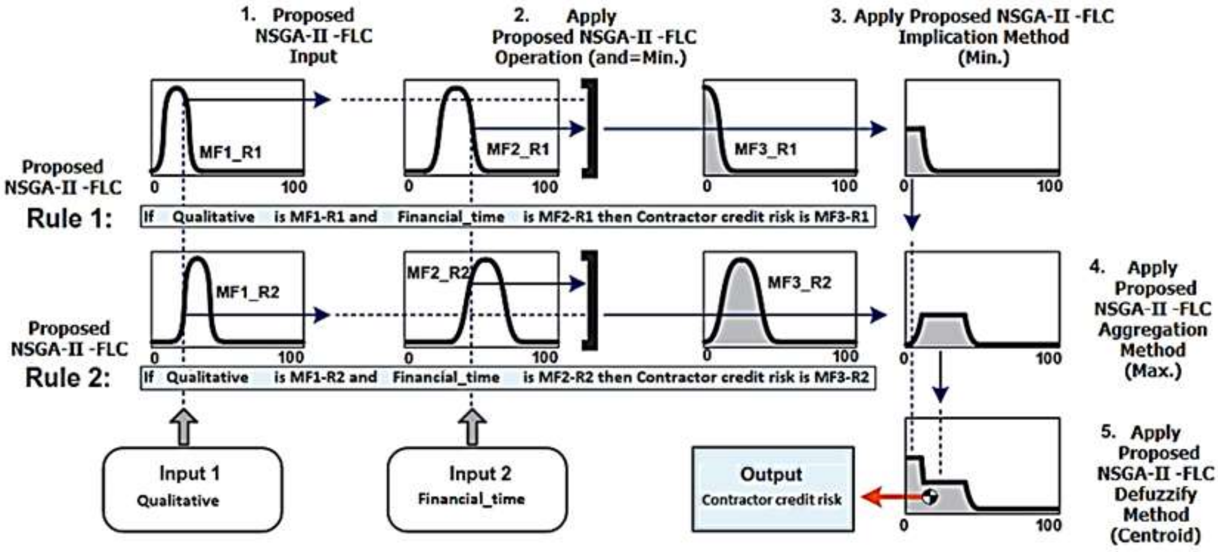

Figure 2. Concept of fuzzy inference in the proposed FLC for assessing the credit risk of construction contractors

In this research, Contractor Quality and Financial–Time Burden are selected as the two input variables of the proposed FLC, while the output variable is the Credit Risk of Construction Contractors. As illustrated in Figure 2, the mapping process from inputs to output (fuzzy inference) in the proposed FLC is carried out in five stages:

Step 1: Receiving fuzzy inputs

Step 2: Applying fuzzy operators

Step 3: Applying the implication method

Step 4: Aggregating all outputs

Step 5: Defuzzification

As shown in Figure 4-5, the value of the first input (Contractor Quality) in the proposed FLC is partially applied in membership function MF1_R1 of Fuzzy Rule 1, while membership function MF1_R2 is used in Fuzzy Rule 2. Similarly, the second input (Contractor Financial–Temporal Burden) is applied in both membership functions MF2_R1 and MF2_R2 in Rules 1 and 2 of the 20 fuzzy rules defined in this example.

After interpreting these two sample if–then fuzzy rules, two truncated fuzzy output sets are obtained, as shown in Figure 2. These truncated fuzzy output sets are then aggregated into a single fuzzy output set using the "Max" operator. Finally, the aggregated fuzzy set is converted into a single crisp value through the defuzzification process. For defuzzification, this study adopts the Centroid method. [11]

If either of the two inputs in the proposed FLC changes, the contractor's credit risk can be rapidly recalculated through simple computations. Through this process, the proposed FLC enables a precise level of discriminability in the output. To summarize, the parameters employed in the proposed FLC for assessing the credit risk of construction contractors are presented in Table 1.

Table 1. Parameters used in the proposed Fuzzy Logic Controller (FLC)

Parameter	Value
Number of Inputs	2
Number of Outputs	1
Type of Membership Function	Gaussian
Implication Operator	Min
Fuzzy Operators	AND = Min
Defuzzification Method	Centroid
Aggregation Operator	Max
Type of Fuzzy System	Sugeno

3.3. Design and Development Process of the NSGA-II Multi-Objective Genetic Algorithm

In this section, the design and development process of the proposed NSGA-II algorithm for addressing the research problem, namely the credit risk assessment of construction contractors, is presented. NSGA-II, as one of the most efficient evolutionary multi-objective algorithms, is employed with the aim of achieving a well-distributed Pareto front between the two research objectives: maximizing quality and minimizing financial–time burden. The main stages of the algorithm development in this study are as follows:

Step 1: Initialization of the Population

Initially, a random population of candidate solutions is generated. Each chromosome in this population represents a possible combination of parameters affecting the credit risk of construction contractors.

Step 2: Evaluation of Objective Functions

For each chromosome, the values of the two objective functions are calculated:

- First objective: maximizing the quality of contractors
- Second objective: minimizing the financial–time burden

Step 3: Non-dominated Sorting

The population is ranked using the non-dominated sorting procedure. In this step, Pareto fronts are formed, and non-dominated solutions are assigned higher ranks.

Step 4: Crowding Distance Calculation

To maintain diversity across the Pareto front, the crowding distance metric is computed. This mechanism prevents excessive clustering of solutions and ensures better distribution.

Step 5: Selection

By combining non-dominated sorting and crowding distance, the selection operator is applied to choose the superior chromosomes for generating the next generation.

Step 6: Genetic Operators

- **Crossover:** Combines two parent chromosomes to produce offspring.
- **Mutation:** Introduces small random changes in genes to increase population diversity.

Step 7: Generation of New Population

The offspring are merged with the parent population, and by reapplying the sorting and selection mechanisms, the next generation is formed. This process continues until the termination criterion is met.

Step 8: Generation of Final Pareto Front

Ultimately, the NSGA-II algorithm provides a set of non-dominated solutions in the form of a Pareto front, which demonstrates the trade-off between contractor quality and financial–time burden.

In this study, the genetic representation of a solution in the proposed NSGA-II algorithm is employed to optimize the FLC knowledge base for contractor credit risk assessment. All information provided by the FLC parameters is encoded into a chromosome, allowing the algorithm to manipulate and evolve potential solutions efficiently. For this purpose, two input Contractor Quality and Financial–Temporal Burden—and one output variable Contractor Credit Risk are selected. Gaussian membership functions are applied to all input and output variables within the proposed FLC-NSGA-II framework, as they provide flexibility and can approximate almost any other type of membership function by adjusting the parameters, as illustrated in Equation 1. This encoding scheme enables the NSGA-II algorithm to explore the solution space systematically and extract an optimized rule base for the fuzzy system, improving both the accuracy and interpretability of the credit risk assessment. [11, 12]

Equation 2

$$\mu = exp\ exp\left(-\frac{(x-b)^2}{2a^2}\right)$$

In the proposed FLC-NSGA-II system, each Gaussian membership function is defined by two key parameters, b and a, representing the center and width (standard deviation) of the function, respectively, as described in Equation 1. By adjusting these parameters, diverse types of expert knowledge can be effectively encoded into the system. In the genetic representation scheme, these parameters are incorporated as real-valued genes within each chromosome, allowing the NSGA-II algorithm to explore and optimize the membership functions systematically. Figure 3 presents a conceptual illustration of this chromosome encoding approach, demonstrating how the proposed FLC-NSGA-II framework captures and evolves knowledge for assessing the credit risk of construction contractors. This encoding strategy ensures both the flexibility and interpretability of the fuzzy system, enabling accurate and reliable decision support. [11, 12]

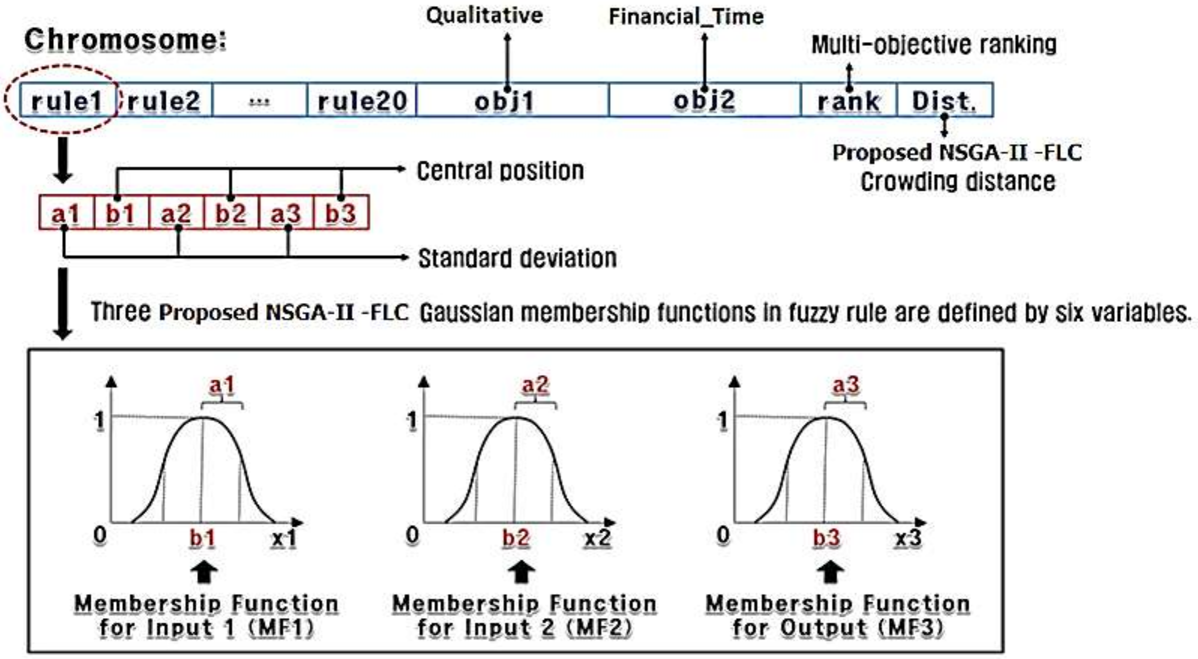

Figure 3. Conceptual representation of chromosome encoding in the proposed FLC-NSGA-II method

As illustrated in Figure 3, each chromosome in the proposed FLC-NSGA-II system contains two inputs, x1 (Contractor Quality) and x2 (Financial–Temporal Burden), and one output, x3 (Contractor Credit Risk), within each fuzzy rule. According to Figure 3, a rule in the proposed method is characterized by the parameters defined in Equation 1. The center positions b1and b2 and widths a1and a2 correspond to the input variables x1 and x2, respectively, while the output variable x3 is encoded using center b3 and width a3.

For assessing the creditworthiness of construction contractors, 20 fuzzy rules are employed in the proposed FLC-NSGA-II system. As shown in Figure 4-8, the fitness values corresponding to the research's conflicting objectives are encoded in the second part of the chromosome as obj1 and obj2. These fitness functions are used by NSGA-II to evaluate each chromosome. After evaluation, the multi-objective rank and crowding distance (Dist) are stored in the final section of each chromosome, enabling effective selection and evolution within the algorithm.

In the proposed NSGA-II algorithm, the quality of each solution, representing a candidate FLC knowledge base, is evaluated using a fitness function. This function plays a critical role in guiding the search process toward optimal solutions that balance the conflicting objectives of the study. Given the multi-objective nature of the research problem, the fitness function is specifically designed to simultaneously maximize contractor quality and minimize the financial–temporal burden. The mathematical formulation of this fitness function is provided in Equation 2, which enables the NSGA-II algorithm to quantitatively assess each chromosome, rank them based on Pareto dominance, and facilitate the evolution of high-quality fuzzy rules in the knowledge base. This approach ensures that the resulting FLC not only achieves accurate credit risk assessment but also maintains a well-distributed Pareto front of optimal trade-offs between the two objectives. [11, 12]

Equation 2

$$f_1(x) = Max \sum_{i=1}^{N} \sum_{j=1}^{M} C_{Qua_{ij}}$$

$$f_2(x) = Min \sum_{i=1}^{N} \sum_{j=1}^{K} C\_TC_{ij}$$

$$Opt: F(x) = [f_1(x).f_2(x)]$$

$$= \left[Max \sum_{i=1}^{N} \sum_{j=1}^{M} C\_Qua_{ij}.Min \sum_{i=1}^{N} \sum_{j=1}^{K} C\_TC_{ij} \right]$$

$$0 \leq C_{Qua} \leq 100 \qquad 0 \leq C_{TC} \leq 100$$

In the proposed NSGA-II algorithm, the fitness function (Equation 2) is designed to extract the optimized fuzzy rules of the FLC knowledge base for assessing construction contractors' credit risk. Key variables include N, the number of fuzzy rules (20 in this study); M, the number of quality sub-indices (six sub-indices covering technical, skill, financial, managerial, equipment, and reputation aspects); and K, the number of financial–temporal sub-indices (two sub-indices: financial and temporal burden). C_Quaij and C_TCij represent the quality and financial–temporal burden scores of contractor i based on each sub-index j, respectively. The fitness function comprises two conflicting objectives: f1 (x), which maximizes contractor quality, and f2 (x) which minimizes the financial–temporal burden.

Table 2. Parameters of the proposed NSGA-II algorithm used for optimizing the FLC knowledge base

Parameter	Value
Number of Optimization Variables	2
Number of Generations (Stopping Criterion)	100
Upper Bound of Optimization Variables	100
Lower Bound of Optimization Variables	0
Population Size	40
Selection Operator	Roulette Wheel
Crossover Rate	0.7
Mutation Method	Tournament
Mutation Rate	0.3
Cost Function	Equation 4-2

The parameters of the proposed NSGA-II algorithm used for extracting the optimized FLC knowledge base for assessing construction contractors' credit risk are listed in Table 2 and implemented in the MATLAB environment. Upon completing the multi-objective optimization process, the optimal Pareto fronts representing the set of Pareto-optimal solutions for the FLC knowledge base are illustrated in Figure 4.

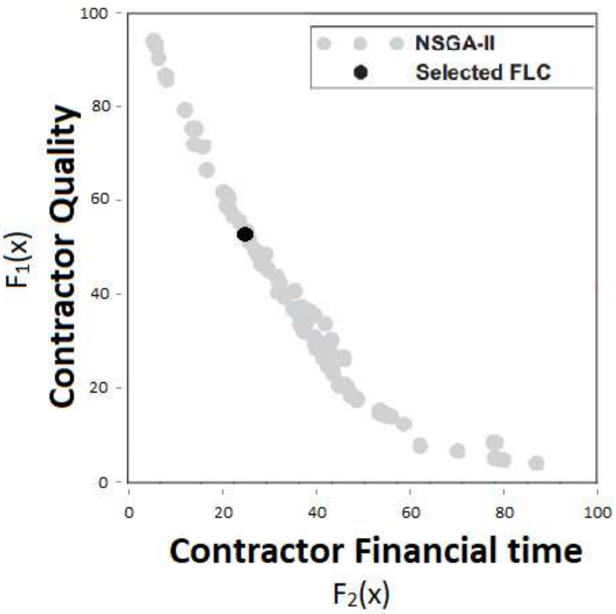

Figure 4. Pareto-optimal fronts obtained from the proposed NSGA-II algorithm in this study

The optimized FLC derived from the proposed NSGA-II algorithm demonstrates the ability to achieve balanced control performance across both conflicting objectives: minimizing the financial–temporal burden and maximizing contractor quality for credit risk assessment. As shown in Figure 4, the contractor quality responses naturally compete with the financial–temporal burden responses, reflecting the inherent trade-offs in multi-objective optimization. Among the Pareto-optimal FLC solutions, one FLC that fairly satisfies both objectives is highlighted with a solid circle, representing a balanced compromise between the two goals. After the completion of the multi-objective optimization process, the fuzzy rules corresponding to the optimized FLC knowledge base are extracted and summarized in Table 3, providing a structured and interpretable framework for informed decision-making in contractor selection and project management.

Table 3. Optimized FLC knowledge base extracted using the proposed NSGA-II algorithm

	a1	b1	a2	b2	a3	b3
Rule 1	19	82	9	66	5	9
Rule 2	7	91	21	4	20	0.5
Rule 3	13	98	15	4	8	0.4
Rule 4	18	96	14	4	14	0.5
Rule 5	23	97	23	18	5	2
Rule 6	24	96	8	66	16	7
Rule 7	14	55	19	40	7	8
Rule 8	4	92	19	94	17	11
Rule 9	4	49	10	5	18	10
Rule 10	7	64	15	68	19	12
Rule 11	22	81	2	10	12	13
Rule 12	7	80	2	96	3	13
Rule 13	21	43	14	70	6	17
Rule 14	7	28	20	75	23	27
Rule 15	24	96	24	28	4	4
Rule 16	9	92	4	32	21	6
Rule 17	5	16	15	71	14	44
Rule 18	7	15	12	83	25	56
Rule 19	16	13	1	85	2	66
Rule 20	12	10	9	76	12	77

As shown in Table 3, to assess the credit risk of contractors using the proposed FLC, an optimized knowledge base comprising 20 fuzzy rules in the form of "if–then" statements has been extracted using the proposed NSGA-II algorithm. These rules, along with the corresponding fuzzy membership functions, have been implemented in MATLAB to develop the proposed fuzzy system for contractor credit risk assessment.

4. Results and Analysis

4.1. Evaluation Criteria for Construction Contractors' Credit Risk Assessment

To quantitatively assess the accuracy and performance of the proposed FLC-NSGA-II system and comparative methods, four commonly used metrics were employed: coefficient of determination (R²), mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). These metrics are defined as follows:

Equation 3 [13]

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \quad (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} \quad (y_i - y)^2}$$

Equation 4 [14]

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \quad (y_i - \hat{y}_i)^2$$

Equation 5 [15]

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \quad |y_i - \hat{y}_i|^2$$

Equation 6 [16]

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \quad (y_i - \hat{y}_i)^2}$$

Where y_i is the observed value, $\hat{y}_i$ is the predicted value by the model, and n is the total number of samples. These metrics provide a comprehensive evaluation of both the accuracy and error magnitude of the credit risk predictions, allowing a detailed comparison between the proposed system and alternative approaches [17].

The results of the R², MSE, RMSE, and MAE metrics for evaluating the accuracy and performance of the proposed FLC-NSGA-II system in assessing the credit risk of construction contractors have been obtained and are presented in Figure 5 and Table 4.

Table 4. Evaluation metrics of the proposed FLC-NSGA-II system for contractor credit risk assessment

Method	MAE	RMSE	MSE	R²
FLC-NSGA-II System	0.01837	0.02241	0.00050231	1

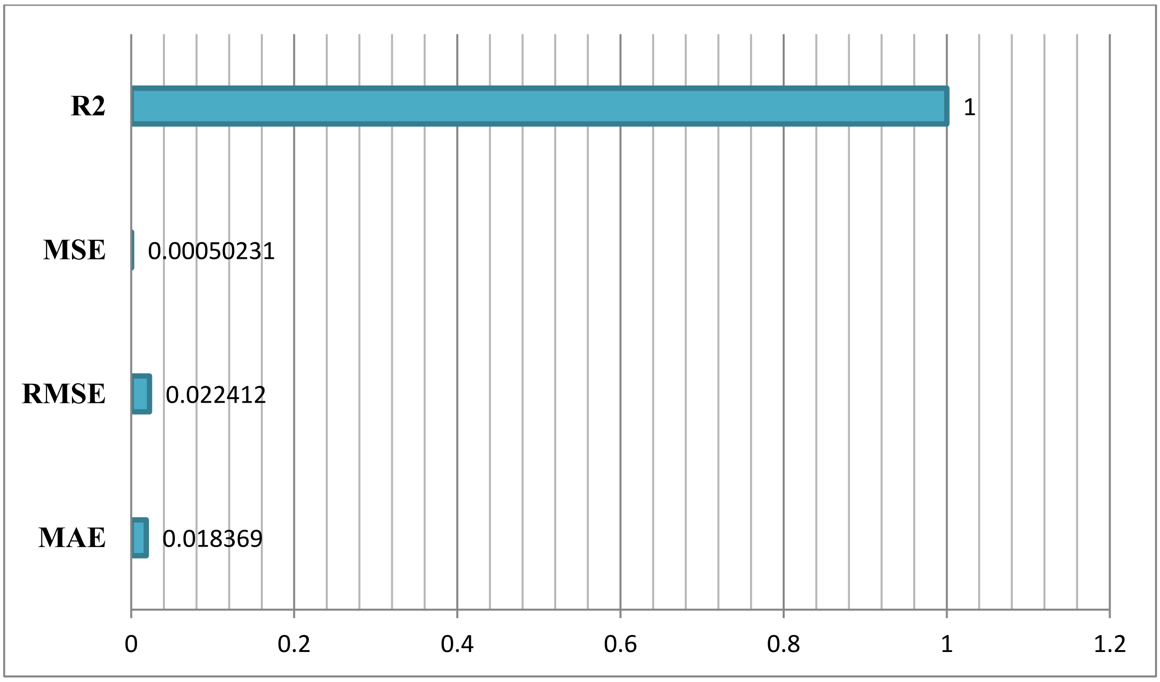

Figure 5. Evaluation metrics results of contractor credit risk assessment using the proposed fuzzy system

As shown in Table 4, the coefficient of determination (R^2) for the proposed FLC-NSGA-II system in assessing the credit risk of construction contractors is equal to 1, indicating that the system explains 100% of the variance in the dataset. The mean squared error (MSE) is 0.00050231, reflecting the average squared difference between the actual (target) and predicted credit risk values. The root mean squared error (RMSE) is 0.022412, representing the square root of the average squared differences between actual and predicted values. Finally, the mean absolute error (MAE) is 0.018369, indicating that, on average, the absolute difference between the observed and predicted credit risk values across all test data is 0.018369. These results collectively demonstrate the high accuracy and reliability of the proposed system in evaluating contractors' credit risk.

4.2. Analysis of the Accuracy and Efficiency Results of Multi-Objective Optimization-Based Fuzzy Systems

In this section, the final summary and comparative analysis of the accuracy and efficiency results of the proposed FLC-NSGA-II system are presented against other multi-objective optimization-based fuzzy systems, namely MOPSO and SPEA-II. As shown in Table 5 and Figure 6, the evaluation metrics R^2, MSE, MAE, and RMSE were calculated for the proposed fuzzy system and the benchmark fuzzy systems to assess their effectiveness in credit risk assessment of construction contractors.

Table 5. Evaluation results of the multi-objective optimization-based fuzzy systems compared in this study

Metics Method	R^2	MSE	RMSE	MAE
FLC_NSGA-II	1	0.00050231	0.022412	0.018369
FLC_MOPSO [18]	0.97	0.0033885	0.058211	0.038800
FLC_SPEA-II [19]	0.94	0.0069402	0.083308	0.035589

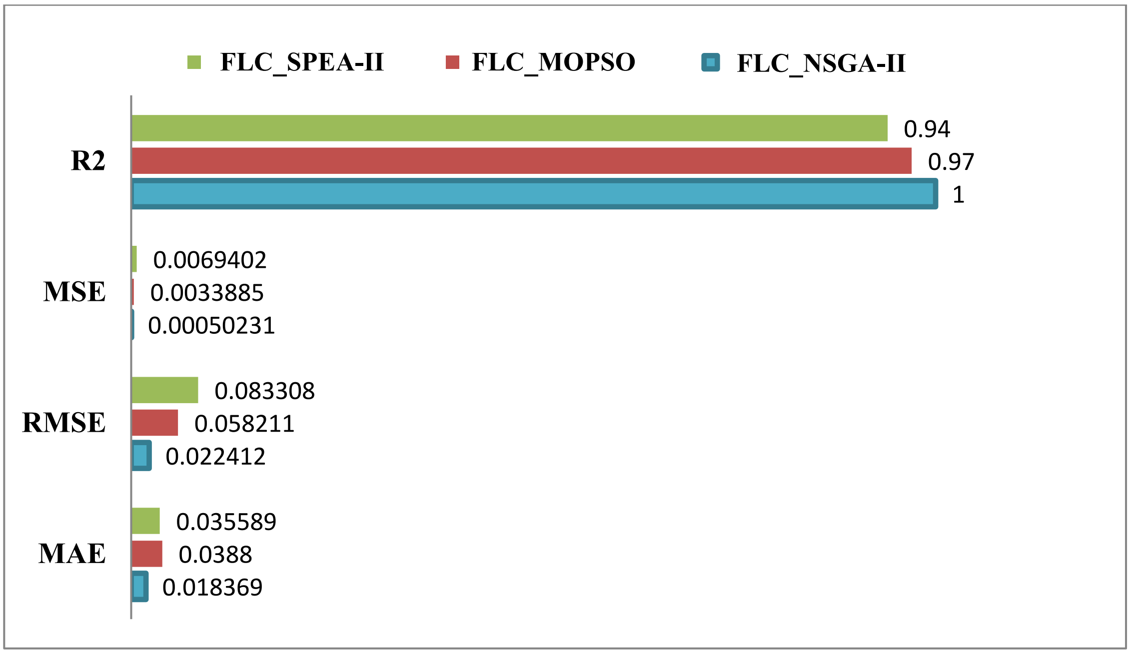

Figure 6. Evaluation results of the multi-objective optimization-based fuzzy systems compared in this study

In this section, the final summary and comparative analysis of the accuracy and efficiency results of the proposed FLC-NSGA-II system are presented against other multi-objective optimization-based fuzzy systems, namely MOPSO and SPEA-II. As shown in Table 5 and Figure 6, the evaluation metrics R^2, MSE, MAE, and RMSE were calculated for the proposed fuzzy system and the benchmark fuzzy systems to assess their effectiveness in credit risk assessment of construction contractors.

The results clearly demonstrate that the proposed FLC-NSGA-II outperforms both MOPSO and SPEA-II in terms of prediction accuracy and error minimization. Specifically, the system achieved an R^2 value of 1.0, indicating a perfect fit between predicted and actual credit risk values, while maintaining significantly lower error levels (MSE = 0.00050231, RMSE = 0.022412, MAE = 0.018369) compared to the competing methods. This highlights the robustness of the hybrid fuzzy-genetic framework in capturing the nonlinear and uncertain nature of contractor risk assessment.

Moreover, the superior performance of FLC-NSGA-II can be attributed to its efficient knowledge base extraction through NSGA-II, which ensures a balanced trade-off between the two conflicting objectives: maximizing contractor quality and minimizing financial–time burden. In contrast, MOPSO and SPEA-II exhibited higher levels of prediction error and lower consistency, reflecting their limitations in handling multi-dimensional trade-offs under uncertainty.

Overall, the comparative analysis confirms that the proposed FLC-NSGA-II system provides a more reliable, accurate, and practical decision-support tool for contractor credit risk assessment, offering substantial improvements over existing multi-objective fuzzy optimization approaches.

4.3. Validation of the Proposed System

For the validation of the proposed system, a statistical random and repeatable sampling test [20] was conducted using the RMSE criterion. To perform this test, the mean squared error of credit risk assessment in the proposed system was evaluated across random samples ranging from 10% to 100% of the research dataset. The results of this statistical random and repeatable sampling test for the proposed FLC-NSGA-II system are presented in Table 6.

Table 6. Results of the statistical random and repeatable sampling test in the proposed FLC-NSGA-II system

Percentage of Test Data	10	20	30	40	50	60	70	80	90	100
RMSE	0.021412	0.021432	0.022412	0.023172	0.023928	0.025012	0.025992	0.026212	0.027013	0.027818

As shown in Table 6, the proposed FLC-NSGA-II system was able to assess the credit risk of construction contractors with low and consistent RMSE values across random and repeatable samples ranging from 10% to 100% of the research dataset.

Subsequently, a Chi-square test [21] was conducted to examine whether the RMSE values were statistically identical across all sampling repetitions. In this test, the null hypothesis (H_0) assumed that the RMSE values were the same for all percentage groups, while the alternative hypothesis (H_1) assumed that they were not identical. The results of the Chi-square test for the random and repeatable samples are presented in Table 7.

Table 7. Chi-square test results for the random and repeatable samples of the proposed FLC-NSGA-II system

Statistic	RMSE
Chi-square value	1.209
Degrees of freedom	9
Significance (p-value)	0.278

As shown in Table 7, the significance value (p-value) of the Chi-square distribution is 0.278, which is greater than the 0.05 threshold. Therefore, the null hypothesis cannot be rejected, indicating that the RMSE values across different percentage groups are statistically equal.

In conclusion, the proposed FLC-NSGA-II system demonstrates consistently low errors in random and repeatable samples, providing sufficient validity to generalize its credit risk assessment capability to the broader population within the scope of this study.

5. Conclusion

This study introduced a hybrid Fuzzy-NSGA-II (FLC-NSGA-II) framework for credit risk assessment of construction contractors, combining fuzzy logic with a multi-objective genetic optimization algorithm to simultaneously maximize contractor quality and minimize financial–time burden. Evaluated on 540 real-world contractor records, the system outperformed existing multi-objective fuzzy methods (MOPSO and SPEA-II) with superior accuracy ($R^2 = 1.0$, MSE = 0.00050231, RMSE = 0.022412, MAE = 0.018369) and consistently low errors across random and repeatable sampling tests.

The extracted knowledge base enables effective handling of conflicting objectives, providing a reliable decision-support tool for construction project managers in selecting contractors and reducing project default risks. Statistical validation confirmed the robustness and generalizability of the system across varying sample sizes.

The proposed approach can be extended in future research to include additional risk factors and applied to other infrastructure projects. Implementing the framework in a real-time decision-support platform could further enhance its practical value in construction management.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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