

Intelligent Modeling of the Circular Economy Sustainability Index in Construction Projects Using an Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract

The circular economy, as a contemporary approach to sustainable development, plays a significant role in improving resource efficiency, reducing waste, and enhancing the environmental performance of construction projects. However, the complex relationships among its influencing indicators necessitate the application of intelligent modeling techniques. Accordingly, this study aimed to model and predict the Circular Economy Sustainability Index in construction projects using an Adaptive Neuro-Fuzzy Inference System (ANFIS) integrated with the Fuzzy Analytic Hierarchy Process (FAHP). This applied research adopted a descriptive-analytical methodology with a mixed-methods approach. Data were collected through questionnaires completed by academic and industry experts. After identifying the key indicators, their relative importance was determined using the FAHP method, while the questionnaire-based indicator data were used to construct the ANFIS model for capturing nonlinear relationships and predicting the sustainability index. A total of 80 questionnaires were distributed, of which 68 valid responses were included in the final analysis. The 68 expert-response observations were randomly divided into 48 training, 10 validation, and 10 testing cases, corresponding to approximately 70%/15%/15% (70.6%/14.7%/14.7%). The findings identified Resource Efficiency (0.2659), Design for Disassembly (0.2304), and Construction Waste Management (0.1744) as the three highest-weighted circular economy criteria after normalization of the six FAHP weights to a total of 1.0000. Within the 10-observation test subset, the ANFIS model demonstrated satisfactory predictive performance, achieving $RMSE = 0.039$, $MAPE = 4.2\%$, and $R^2 = 0.89$. These results support the internal predictive performance of the expert-assessed model but do not establish project-level generalizability. The integrated FAHP-ANFIS framework can therefore support evaluation of an expert-assessed Circular Economy Sustainability Index and may inform construction-related decision-making, subject to validation using independent project-level data.

Keywords: (Circular economy, construction projects, adaptive neuro-fuzzy Inference system (ANFIS), sustainability, artificial intelligence)

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1 Introduction

The construction industry is one of the major drivers of economic and social development, playing a vital role in infrastructure provision, urban development, and the improvement of quality of life. However, it is also among the largest consumers of natural resources, energy, and raw materials, while contributing substantially to construction and demolition waste generation, greenhouse gas emissions, and environmental degradation. Rapid urbanization, increasing demand for infrastructure development, and the growing scarcity of natural resources have exposed the limitations of the traditional linear model of “take make use dispose”, highlighting the urgent need to adopt more sustainable development approaches. In this context, the circular economy has emerged as a promising strategy that emphasizes reducing virgin resource consumption, promoting material reuse, recycling, refurbishment, and extending product life cycles. By closing resource loops within construction projects, this approach seeks to minimize environmental impacts while simultaneously improving economic efficiency and project sustainability [21].

Despite the well-recognized benefits of circular economy practices in the construction sector, their effective implementation in construction projects remains challenging. Decision-making in such projects is influenced by a wide range of economic, technical, managerial, and environmental factors whose interactions are often nonlinear, complex, and subject to considerable uncertainty. Furthermore, a substantial portion of project evaluation relies on expert judgments and qualitative information, limiting the applicability of conventional analytical methods that assume deterministic and linear relationships. Consequently, there is an increasing demand for intelligent decision-support tools capable of simultaneously handling quantitative data, qualitative knowledge, and inherent uncertainties in construction project management [10, 17].

In recent years, advances in artificial intelligence (AI) and machine learning have opened new opportunities for modeling complex engineering systems. Among these techniques, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has attracted considerable attention because it combines the learning capability of artificial neural networks with the reasoning power of fuzzy logic. This hybrid approach effectively models nonlinear relationships, manages uncertainty and ambiguity within data, and identifies hidden patterns among variables, providing a flexible approach for modeling nonlinear relationships and handling uncertainty in complex engineering problems. As a result, ANFIS has been widely applied in diverse engineering fields, including structural performance prediction, project management, risk assessment, and optimization of decision-making processes [17, 5].

A review of the existing literature indicates that although numerous studies have investigated circular economy practices in the construction industry, sustainability indicators, construction waste management, and intelligent modeling approaches, most have addressed only specific aspects of the problem. The majority of previous research has focused on ranking sustainability indicators, evaluating circular economy policies, or employing conventional decision-making techniques. Comparatively few studies have developed intelligent predictive models for estimating the Circular Economy Sustainability Index in construction projects. Moreover, the nonlinear interactions among sustainability-related indicators have rarely been modeled in an integrated framework, and the generalization capability of predictive models has seldom been rigorously evaluated through independent training, validation, and testing phases. These limitations reveal a significant research gap in the development of intelligent predictive models for assessing the sustainability performance of construction projects based on circular economy principles [5, 1].

To address this gap, the present study develops an intelligent prediction framework based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) for modeling and forecasting the Circular Economy Sustainability Index in construction-project contexts. The proposed framework focuses on a consistent set of circular economy indicators used across the analytical stages of the study. The selected indicators represent key dimensions of resource efficiency, design for disassembly, construction waste management, carbon emission reduction, material reuse, and material recycling and remanufacturing. Their relative importance was first assessed using the Fuzzy Analytic Hierarchy Process (FAHP), while the subsequent ANFIS analysis was used to model the relationships between the normalized indicator data and the expert-assessed Circular Economy Sustainability Index. Model performance was evaluated during the training, validation, and testing stages using the standard performance metrics RMSE, MAPE, and the coefficient of determination (R^2). The framework is intended as a decision-support approach for modeling an expert-assessed Circular Economy Sustainability Index, while further validation using independent project-level data is required before broader application to actual construction projects.

2 Theoretical Background and Literature Review

As one of the largest consumers of natural resources and generators of waste, the construction industry plays a vital role in achieving sustainable development goals. In recent years, the circular economy has gained increasing

attention among researchers and policymakers as an effective approach to reducing resource consumption, improving resource efficiency, promoting the reuse of construction materials, and optimizing construction waste management. At the same time, the complexity of decision-making in construction projects, together with the nonlinear relationships among sustainability indicators, has made the application of intelligent models, particularly the Adaptive Neuro-Fuzzy Inference System (ANFIS), an important focus of contemporary research. Accordingly, this section first reviews the fundamental concepts related to the study, then examines previous research, and finally identifies the existing research gap.

2.1 Circular Economy

The circular economy has emerged as a modern resource management approach aimed at replacing the traditional linear economic model. Rather than relying on the continuous extraction of resources followed by production, consumption, and final disposal, this approach seeks to retain the value of materials, energy, and products within production and consumption cycles for as long as possible. Accordingly, strategies such as reducing virgin material consumption, reuse, repair, refurbishment, remanufacturing, and recycling are recognized as the fundamental principles of the circular economy [14, 13].

The circular economy is not merely an environmental strategy; rather, it represents a comprehensive framework for improving economic efficiency, enhancing supply chain resilience, and reducing dependence on limited natural resources. Implementing this approach can lower production costs, preserve the economic value of materials, and mitigate the negative impacts associated with excessive resource consumption and waste generation. Consequently, the circular economy has become one of the key pillars of sustainable development and resource management policies [6, 8].

Within the construction industry, the significance of the circular economy is even greater than in many other sectors, as construction accounts for a substantial proportion of raw material consumption, energy use, and solid waste generation. The adoption of recyclable construction materials, design for disassembly, enhancement of structural durability, effective construction waste management, and the implementation of low-carbon technologies are among the most important measures that can facilitate the realization of circular economy principles in construction projects [12, 2].

Recent studies indicate that the successful implementation of the circular economy in construction projects requires the simultaneous consideration of economic, environmental, technical, and managerial dimensions. Therefore, evaluating project performance based on a comprehensive set of multidimensional indicators provides a more realistic assessment of the extent to which circular economy objectives have been achieved than relying on individual criteria. Such an integrated perspective has paved the way for the development of intelligent models for evaluating and predicting project performance [4].

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is an artificial intelligence-based intelligent modeling technique that combines the learning capability of artificial neural networks with the reasoning ability of fuzzy logic to model complex and nonlinear relationships. By integrating fuzzy inference rules with a data-driven learning process, this system is capable of identifying hidden patterns between input and output variables and developing predictive models with high levels of accuracy [3, 19].

The architecture of ANFIS is generally based on the Sugeno fuzzy inference system and consists of several computational layers, each responsible for a specific function, including fuzzification, calculation of rule firing strengths, normalization, generation of rule outputs, and computation of the final output. The parameters of the membership functions and the consequent rule coefficients are optimized during the training process using learning algorithms to minimize the discrepancy between observed and predicted values [20, 11].

One of the most significant advantages of ANFIS is its ability to handle uncertainty and ambiguity in data effectively. Unlike many statistical models that rely on assumptions of linearity and predefined probability distributions, ANFIS can capture complex relationships among variables without requiring explicit mathematical formulations. This capability has led to its widespread application across various engineering fields, including structural performance prediction, risk assessment, project management, energy systems analysis, and sustainability indicator modeling [24, 23].

Previous studies have demonstrated the applicability of ANFIS to problems involving nonlinear relationships among economic, environmental, and technical indicators. Its ability to combine fuzzy inference with data-driven learning makes it a suitable candidate for modeling complex sustainability-related relationships. Accordingly, ANFIS can be

considered a suitable modeling approach for investigating the nonlinear relationships associated with the Circular Economy Sustainability Index [18, 15].

2.3 Literature Review

In recent years, alongside the growing adoption of the circular economy concept, numerous studies have investigated various aspects of its implementation within the construction industry. Chammout and El-Adaway [4] examined the factors influencing decision-making in the implementation of circular economy practices in construction projects and demonstrated that the successful adoption of this approach depends on the interaction among managerial, economic, technical, and environmental factors. Their findings further indicated that the use of integrated decision-making frameworks can significantly enhance implementation effectiveness [4]. Similarly, Ortiz-de-Montellano et al. [6] reported that the circular economy plays a crucial role in achieving sustainable development goals by reducing resource consumption, improving waste management, and enhancing resource efficiency, thereby generating substantial economic and environmental benefits [6].

With regard to the application of circular economy principles in the construction sector, Joensuu et al. [12] identified material reuse, life cycle-based design, and construction waste management as the principal implementation strategies and emphasized their contributions to reducing virgin resource consumption and improving the environmental performance of construction projects [12]. Likewise, Antwi-Afari et al. [2] analyzed the evolution of research in this field and concluded that, although studies on the circular economy in the construction industry have expanded considerably, the development of quantitative and intelligent models for evaluating project performance remains limited [2]. Furthermore, Hart et al. [8] identified inadequate infrastructure, insufficient policy support, and limited collaboration among stakeholders as the major barriers to implementing circular economy practices [8].

Alongside the rapid advancement of artificial intelligence technologies, intelligent modeling techniques have increasingly been employed to address problems related to the circular economy. Akinade and Oyedele [1] developed an ANFIS-based system for construction waste analysis and demonstrated that this model is highly effective in predicting and managing construction and demolition waste [1]. Similarly, Petković et al. [6] applied an Adaptive Neuro-Fuzzy Inference System (ANFIS) to evaluate the effects of energy and material efficiency on sustainable development and concluded that ANFIS provides high predictive accuracy in modeling the nonlinear relationships among circular economy indicators [6].

Several studies have also been conducted in Iran on various aspects of the circular economy. Shahdkar et al. [22] identified and prioritized the factors affecting the implementation of the circular economy and highlighted the critical role of managerial and organizational factors in facilitating its adoption [22]. Likewise, Hosseinpour and Ghorbanpour [9] proposed a framework integrating circular economy principles with cleaner production and emphasized the importance of adopting advanced technologies to enhance sustainable productivity [9]. In addition, Hosseinpour et al. [10] evaluated the circular economy performance of the Persian Gulf countries and identified the development of waste management infrastructure as one of the key determinants of improving circular economy performance [10]. Furthermore, Ghaem-Maghamsi Hazaweh et al. [7] demonstrated that implementing circular economy principles in the cement industry can reduce environmental impacts while optimizing resource utilization [7].

Despite the valuable contributions of previous studies, the existing literature indicates that most research has primarily focused on identifying influential factors, ranking sustainability indicators, analyzing circular economy policies, or applying intelligent models to relatively narrow problems. In contrast, studies that have comprehensively modeled and predicted the Circular Economy Sustainability Index in construction projects using the Adaptive Neuro-Fuzzy Inference System (ANFIS) remain very limited. Moreover, in most existing studies, the combined effects of key circular economy indicators on project sustainability have not been evaluated within a unified intelligent modeling framework, nor has model performance been systematically validated through independent training, validation, and testing datasets. Therefore, the present study aims to develop an ANFIS-based framework for modeling and predicting the Circular Economy Sustainability Index using expert-assessed indicator data, thereby addressing the identified research gap. The proposed framework is intended to support the analysis of sustainability relationships in construction contexts, while further validation using independent project-level data would be necessary before generalizing the model to actual construction projects [4].

3 Materials and Methods

The present study is applied in terms of its objective and adopts a descriptive-analytical research design using a mixed-methods (qualitative-quantitative) approach. In the first stage, the indicators influencing the sustainability of

the circular economy in construction projects were identified through an extensive literature review and a systematic review of relevant scientific publications. Based on these findings, the conceptual framework of the study was developed. Subsequently, to refine the identified indicators and ensure their relevance to construction projects, expert opinions were obtained from specialists in project management, civil engineering, and sustainable development.

During the empirical phase, the research data were collected using a specialized questionnaire designed on the basis of fuzzy linguistic scales. The target population consisted of academic experts and industry professionals with expertise in project management, construction, and the circular economy, who were selected through purposive sampling. Following a thorough review of the completed questionnaires, only valid responses were included in the final analysis. To ensure the quality of the research instrument, its content validity was assessed using the Content Validity Index (CVI), which was 0.83, exceeding the acceptable threshold of 0.79. Construct validity was further supported by a Kaiser–Meyer–Olkin (KMO) value of 0.81 and a significant Bartlett’s test of sphericity ($p < 0.001$). The internal reliability of the questionnaire was assessed using Cronbach’s alpha, which yielded a value of 0.91 for the overall questionnaire and 0.88 across its dimensions, indicating a high level of internal consistency. The general characteristics of the participating experts are presented in Table 1.

A total of 80 questionnaires were distributed, 72 were returned, and 4 incomplete questionnaires were excluded, resulting in 68 valid questionnaires for the final analysis. The final sample consisted of 24 academic experts (35.3%) and 44 industry experts, including employers, consultants, and contractors (64.7%). Each of the 68 valid questionnaire responses was treated as one observation in the subsequent ANFIS analysis; therefore, the model was developed from expert-assessed indicator data rather than from 68 independently measured construction projects. As shown, the study sample comprised both academic and industry professionals with diverse educational backgrounds and professional experience.

Table 1: Characteristics of the expert panel

Characteristic	Frequency	Percentage (%)
Distributed questionnaires	80	100.0
Valid questionnaires	68	85.0
Academic experts	24	35.3
Industry experts	44	64.7
Master’s degree	41	60.3
Doctoral degree (Ph.D.)	27	39.7
Professional experience > 15 years	30	44.1

Following the completion of data collection, the proposed FAHP–ANFIS framework was implemented in two sequential and complementary stages. First, the relative importance of six main circular-economy criteria was determined using the Fuzzy Analytic Hierarchy Process (FAHP). The six FAHP values were normalized across the reported criteria by dividing each value by their total (0.929), yielding weights that sum to 1.0000 without changing their ranking. The normalized criteria were Resource Efficiency (0.2659), Design for Disassembly (0.2304), Construction Waste Management (0.1744), Carbon Emission Reduction (0.1485), Material Reuse (0.1055), and Material Recycling and Remanufacturing (0.0753). The FAHP stage therefore provided the expert-based prioritization of the main circular-economy criteria. Second, the questionnaire-based indicator data were used to construct the ANFIS dataset, comprising 68 expert-response observations and 7 input variables with 1 output variable representing the expert-assessed sustainability index. Thus, the FAHP weights were used to establish the relative importance of the six main criteria, whereas the ANFIS model used the seven observed indicator variables to learn nonlinear relationships and estimate the sustainability index. This sequential structure avoids treating the six FAHP weights as direct substitutes for the seven ANFIS input variables and clarifies the methodological relationship between the two stages. The initial fuzzy rule structure was identified using subtractive clustering with a cluster radius of 0.5. The three Gaussian membership functions (Low, Medium, and High) reported in Tables 7 and 8 were specified as the initial linguistic partitions of the normalized variables before ANFIS training; subtractive clustering was used to initialize the rule structure rather than to determine the number of membership functions. During ANFIS learning, the premise parameters of the Gaussian membership functions and the consequent parameters were subsequently optimized. The training configuration allowed a maximum of 200 epochs. The reported model run executed 100 epochs, while the error curve became approximately stable after 40–50 epochs; these values therefore refer, respectively, to the maximum allowed epochs, the executed epochs, and the approximate convergence region. The error goal was set to 0. The resulting fuzzy inference structure was optimized using the ANFIS learning procedure to minimize the prediction error between the observed and predicted sustainability index values. The overall methodological framework of the study

is illustrated in Figure 1.

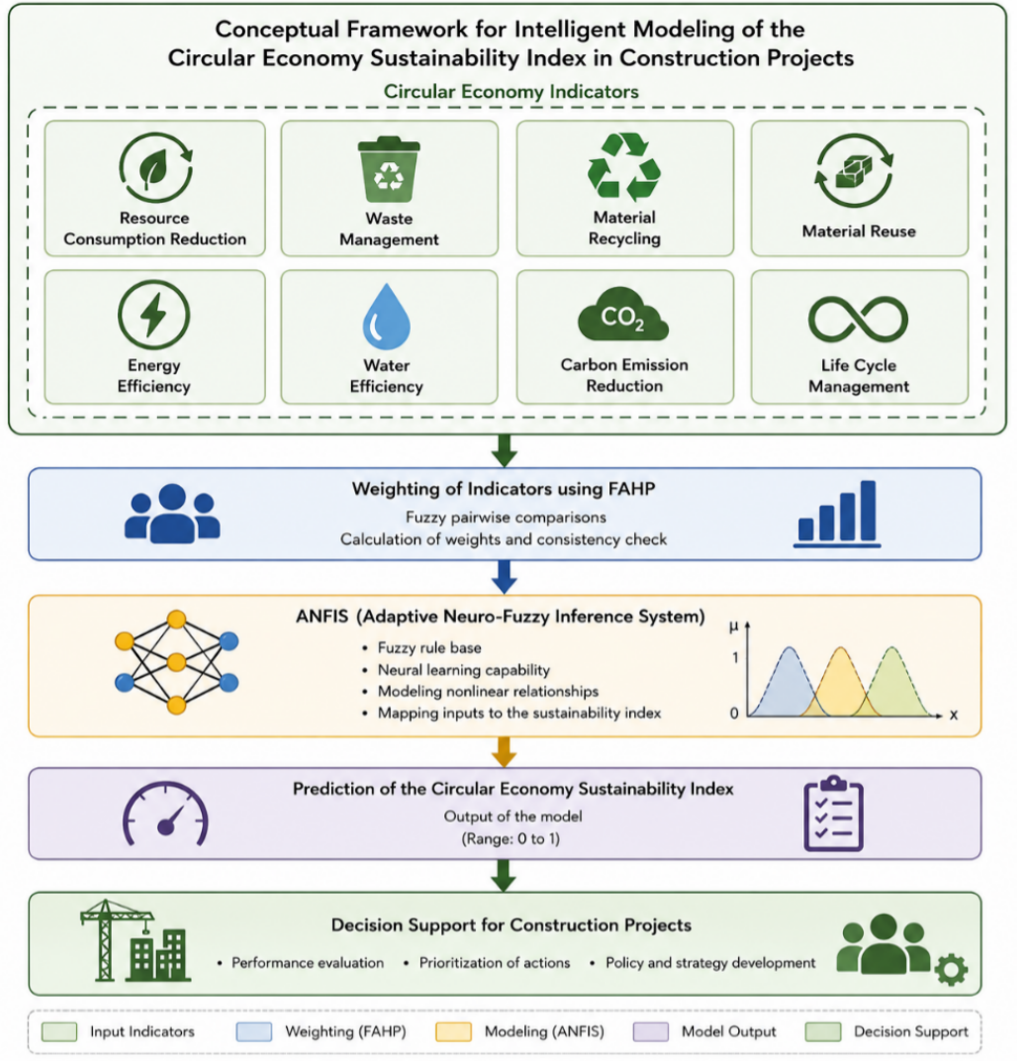


Figure 1: Conceptual framework of the proposed research model

As illustrated in Figure 1, the research process begins with the identification of the key circular economy indicators. These indicators are subsequently evaluated using the Fuzzy Analytic Hierarchy Process (FAHP) to determine the relative importance of the six main criteria, while the seven observed indicator variables are used independently as inputs to the Adaptive Neuro-Fuzzy Inference System (ANFIS) to model nonlinear relationships and predict the expert-assessed Circular Economy Sustainability Index. By integrating the learning capability of artificial neural networks with the reasoning mechanism of fuzzy logic, the ANFIS model captures the complex nonlinear relationships among the selected indicators. The model output is intended as a potential decision-support input for construction-project contexts; independent project-level validation is required before direct operational use.

During the data analysis stage, the relative importance of the circular economy indicators was first determined using the Fuzzy Analytic Hierarchy Process (FAHP). The application of fuzzy logic enabled the transformation of experts' linguistic judgments into quantitative values, thereby reducing the uncertainty and ambiguity associated with human evaluations. The ANFIS model was formulated with seven normalized input variables and one output variable. The seven inputs were Life Cycle-Based Design (X_1), Reduction in Raw Material Consumption (X_2), Component Disassembly Capability (X_3), Waste Generation Reduction (X_4), Water Consumption Optimization (X_5), Use of Low-Carbon Technologies (X_6), and Energy Consumption Optimization (X_7), each defined on a 0–1 scale. The output variable (Y) was the expert-assessed Circular Economy Sustainability Index. In the questionnaire, Y was measured through the first item of Section ??, which asked experts to assess the overall success of circular-economy implementation using a five-point scale ranging from very low to very high; the resulting values were normalized to the

0–1 interval for ANFIS modeling. According to the operational classification used in the dissertation, values below 0.40 indicate weak performance, values from 0.40 to 0.70 indicate moderate performance, and values above 0.70 indicate a desirable level of circular-economy performance. The seven ANFIS inputs were obtained from the questionnaire-based assessment of circular-economy performance, whereas the FAHP stage was used to determine the relative importance of the six main criteria. The ANFIS dataset therefore consisted of 68 expert-response observations, with seven input variables and one output variable, all expressed on a normalized 0–1 scale.

The dataset consisted of 68 valid expert-response observations. To evaluate the performance of the ANFIS model, the observations were randomly divided using an approximately 70%/15%/15% allocation, resulting in 48 training observations (70.6%), 10 validation observations (14.7%), and 10 testing observations (14.7%). A fixed random seed of 7 was used to ensure reproducibility of the random partitioning. After the training phase, the model's predictive accuracy was assessed using the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These performance metrics measure agreement between predicted and observed expert-assessed index values. The developed model is therefore interpreted as a framework for modeling and predicting an expert-assessed Circular Economy Sustainability Index in construction-project contexts rather than as direct project-level empirical validation.

4 Results

4.1 Preliminary Data Analysis

Before performing the criteria weighting using the Fuzzy Analytic Hierarchy Process (FAHP) and developing the Adaptive Neuro-Fuzzy Inference System (ANFIS) model, it was necessary to examine the statistical characteristics of the research data. Preliminary data analysis provides an overview of the investigated indicators while enabling the assessment of data dispersion, variability, and conformity with the underlying statistical assumptions. Accordingly, descriptive statistics, including the minimum, maximum, mean, standard deviation, and coefficient of variation, were first calculated for the principal research indicators. Subsequently, the normality of the data distribution was evaluated using the Shapiro–Wilk test. The descriptive statistics of the main research indicators are presented in Table 2. This table reports the minimum and maximum values, mean, standard deviation, and coefficient of variation for each indicator, thereby facilitating a comparative assessment of their relative characteristics.

Table 2: Descriptive Statistics of the Main Research Indicators

Indicator	Maximum	Minimum	Mean	Standard Deviation	Coefficient of Variation (%)
Resource Efficiency	5.00	2.70	4.12	0.61	14.81
Material Reuse	5.00	2.20	3.98	0.74	18.59
Material Recycling	5.00	2.10	3.86	0.77	19.95
Design for Disassembly	5.00	2.90	4.21	0.58	13.78
Construction Waste Management	5.00	2.60	4.09	0.66	16.14
Carbon Emission Reduction	5.00	2.30	3.91	0.71	18.16
Energy Efficiency	5.00	2.80	4.18	0.63	15.07
Project Sustainability Index	5.00	2.70	4.06	0.60	14.78

According to the results presented in Table 2, the mean values of all indicators range from 3.86 to 4.21, indicating a relatively favorable evaluation by experts regarding the status of circular economy components in construction projects. Among the examined indicators, Design for Disassembly, with a mean value of 4.21, and Energy Efficiency, with a mean value of 4.18, obtained the highest scores, highlighting the significant role and importance of these two components in enhancing the sustainability of construction projects. In contrast, the Material Recycling indicator showed the lowest mean value (3.86), which may reflect the existence of operational and managerial constraints in developing recycling processes within construction projects.

Furthermore, the standard deviation values ranged from 0.58 to 0.77, while the coefficients of variation were between 13.78% and 19.95%. These findings indicate relatively low data dispersion and a high degree of consensus among experts' opinions. The relatively low coefficients of variation also demonstrate the stability of responses and confirm the reliability of the collected data for conducting subsequent analyses.

Following the descriptive assessment of the data, the normality of variable distributions was evaluated using the Shapiro–Wilk test. The results of this test are presented in Table 3.

Table 3: Results of the Shapiro–Wilk Test for Assessing Data Normality

Variable (Indicator)	Shapiro–Wilk Statistic	Significance Level (Sig.)
Resource Efficiency	0.962	0.081
Material Reuse	0.955	0.067
Material Recycling	0.947	0.053
Design for Disassembly	0.969	0.114
Construction Waste Management	0.958	0.072
Carbon Emission Reduction	0.952	0.061
Energy Efficiency	0.964	0.089
Project Sustainability Index	0.971	0.128

The results presented in Table 3 indicate that the significance level (Sig.) for all variables is greater than 0.05. Therefore, the null hypothesis of normality was not rejected at the 0.05 significance level ($p > 0.05$), indicating no statistically significant evidence of departure from normality in the examined variables. Although normality is not a strict prerequisite for either FAHP or ANFIS, the Shapiro–Wilk test was conducted as a preliminary diagnostic to characterize the statistical properties of the collected questionnaire data and to provide additional information about their distribution. To provide a graphical representation of the normality test results, the significance levels of the variables are illustrated in Figure 2.

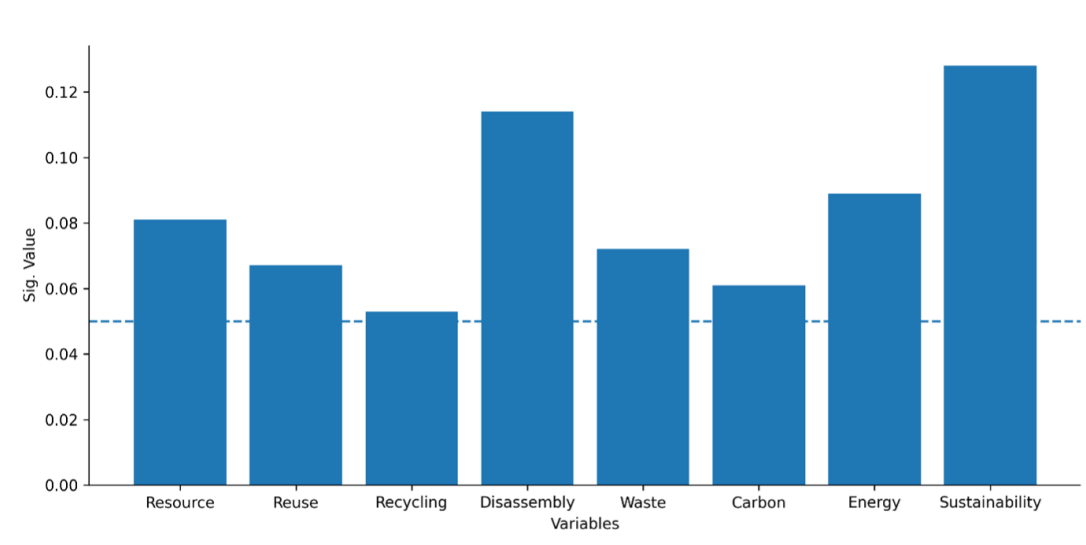


Figure 2: Significance Levels of the Normality Test

As illustrated in Figure 2, the significance levels of all indicators are above the threshold value of 0.05, confirming the results presented in Table 3. Accordingly, the Shapiro–Wilk results provide no statistical evidence of substantial deviation from normality in the examined variables. The normality analysis was reported as supplementary descriptive information and was not treated as a prerequisite for applying FAHP or ANFIS.

4.2 Extraction of Indicator Weights Using FAHP

Following the statistical assessment of the data characteristics and ensuring their quality and suitability for further analysis, the process of determining the relative importance of the main circular economy indicators was conducted using the Fuzzy Analytic Hierarchy Process (FAHP) method. In this approach, experts' judgments were initially aggregated in the form of fuzzy pairwise comparison matrices. The individual fuzzy pairwise comparison judgments provided by the experts were aggregated using the geometric mean method to obtain a collective fuzzy pairwise comparison matrix. The resulting aggregated matrix was then used to calculate the final fuzzy weights of the six main circular-economy criteria. Subsequently, the final weights of each criterion were calculated through the fuzzy analytic hierarchy process.

Prior to extracting the weights, evaluating the consistency level of experts' judgments is essential, as the validity and reliability of the weighting results depend on the consistency of the pairwise comparisons. The calculated values

of the Consistency Index (CI) and Consistency Ratio (CR) for the pairwise comparison matrix of the main criteria are presented in Table 4.

Table 4: Results of the Consistency Index and Consistency Ratio Calculation for the Pairwise Comparison Matrix of the Main Criteria

Evaluation Indicator	Symbol	Value
Number of Criteria	n	6
Maximum Eigenvalue	$\lambda_{\max}$	6.452
Consistency Index	CI	0.090
Random Index	RI	1.24
Consistency Ratio	CR	0.078
Acceptable CR Threshold	–	0.10
Matrix Status	–	Acceptable

The calculated Consistency Ratio ($CR = 0.078$) was below the acceptable threshold of 0.10, indicating an acceptable level of consistency in the pairwise comparison matrix and supporting its use in the subsequent FAHP weighting analysis.

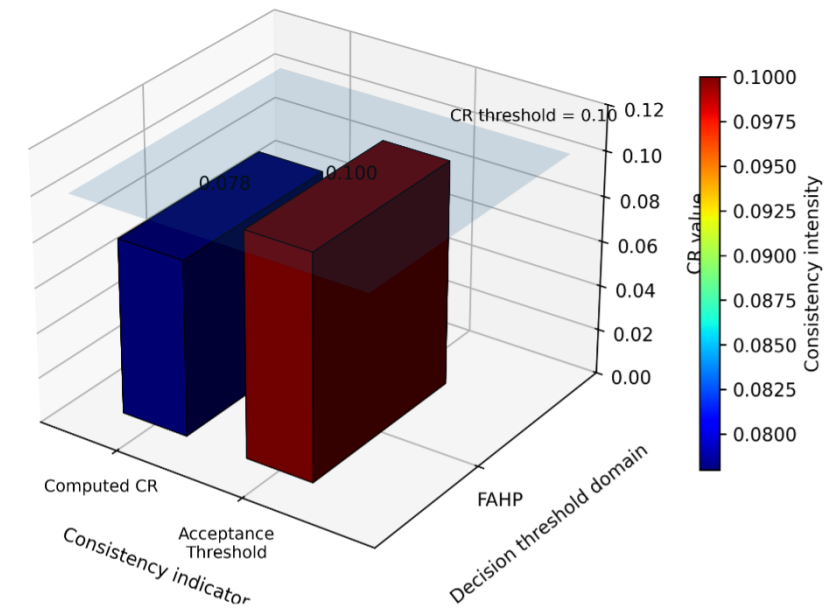


Figure 3: Comparison of the Calculated Consistency Ratio ($CR = 0.078$) with the Acceptable Threshold ($CR = 0.10$) in the FAHP Process

Figure 3 visually confirms that $CR = 0.078$ is below the 0.10 acceptance threshold. The associated values were $CI = 0.090$, $\lambda_{\max} = 6.452$, and $RI = 1.24$. The normalized FAHP weights are reported in Table 5.

Table 5: Normalized Final Weights and Ranking of the Main Circular Economy Criteria in Construction Projects Based on the FAHP Method

No.	Criterion	Final Weight	Importance Percentage (%)	Rank
1	Resource Efficiency	0.2659	26.59	1
2	Design for Disassembly	0.2304	23.04	2
3	Construction Waste Management	0.1744	17.44	3
4	Carbon Emission Reduction	0.1485	14.85	4
5	Material Reuse	0.1055	10.55	5
6	Material Recycling and Remanufacturing	0.0753	7.53	6
–	Total	1.0000	100.00	–

The results presented in Table 5 indicate that Resource Efficiency, with a normalized weight of 0.2659 and an importance share of 26.59%, was identified as the most important criterion for evaluating circular economy sustainability in construction-project contexts. Design for Disassembly, with a weight of 0.2304, ranked second, while Construction Waste Management, with a weight of 0.1744, obtained the third rank.

In contrast, Carbon Emission Reduction, Material Reuse, and Material Recycling and Remanufacturing were ranked fourth to sixth, respectively. Although the weights of these criteria are lower compared with the first three criteria, the overall distribution of the obtained weights demonstrates that all selected indicators have a meaningful contribution to evaluating circular economy sustainability, and excluding any of them would not be scientifically justified.

To provide a visual comparison of the relative importance of the criteria, the results are presented graphically in Figure 4.

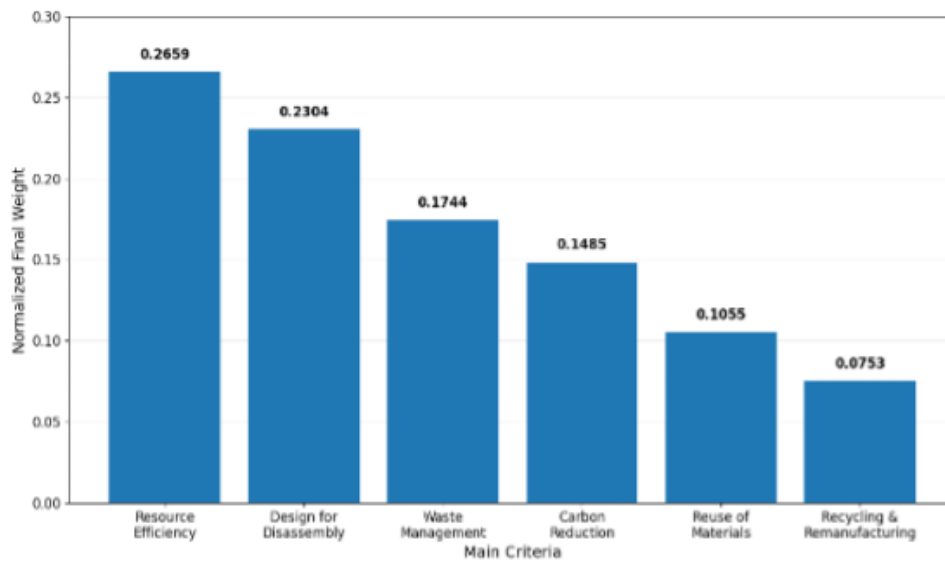


Figure 4: Comparison of the Final Weights of the Main Circular Economy Criteria Extracted from the FAHP Model

As illustrated in Figure 4, the normalized weights indicate differences in the relative importance of the criteria. Resource Efficiency, Design for Disassembly, and Construction Waste Management remain the three highest-ranked components. The normalized FAHP weights were used to establish the relative importance of the six main criteria, while the questionnaire-based data for the seven observed indicator variables were used independently to develop the ANFIS model in the subsequent stage.

4.3 Intelligent Modeling of the Sustainability Index Using ANFIS

After determining the relative importance of the six main circular economy criteria using the Fuzzy Analytic Hierarchy Process (FAHP) method, the intelligent modeling stage was conducted independently using the Adaptive Neuro-Fuzzy Inference System (ANFIS) with seven observed indicator variables as inputs. By integrating the reasoning capability of fuzzy systems with the learning ability of artificial neural networks, this model enables the representation and modeling of nonlinear relationships among the factors affecting circular economy sustainability.

In the present study, the ANFIS structure was designed to predict the expert-assessed Circular Economy Sustainability Index for construction-project contexts based on the selected indicators. The characteristics of the input and output variables used in the model design are presented in Table 6.

Table 6: Input and Output Variables Used in the Design of the ANFIS Model

Variable Type	Symbol	Variable	Range of Variation
Input	X1	Life Cycle-Based Design	0–1
Input	X2	Reduction in Raw Material Consumption	0–1
Input	X3	Component Disassembly Capability	0–1
Input	X4	Waste Generation Reduction	0–1
Input	X5	Water Consumption Optimization	0–1
Input	X6	Use of Low-Carbon Technologies	0–1
Input	X7	Energy Consumption Optimization	0–1
Output	Y	Circular Economy Sustainability Index	0–1

According to Table 6, the ANFIS model consists of seven input variables, including Life Cycle-Based Design, Reduction in Raw Material Consumption, Component Disassembly Capability, Waste Generation Reduction, Water Consumption Optimization, Use of Low-Carbon Technologies, and Energy Consumption Optimization. All input variables were defined within the normalized range of zero to one to ensure data scale consistency and improve the stability and accuracy of the network training process.

The output variable of the model is the expert-assessed Circular Economy Sustainability Index, which represents respondents' overall assessment of circular-economy implementation rather than an independently measured project-level outcome. To illustrate the overall structure of the model, the input–output architecture of the ANFIS model is presented in Figure 5.

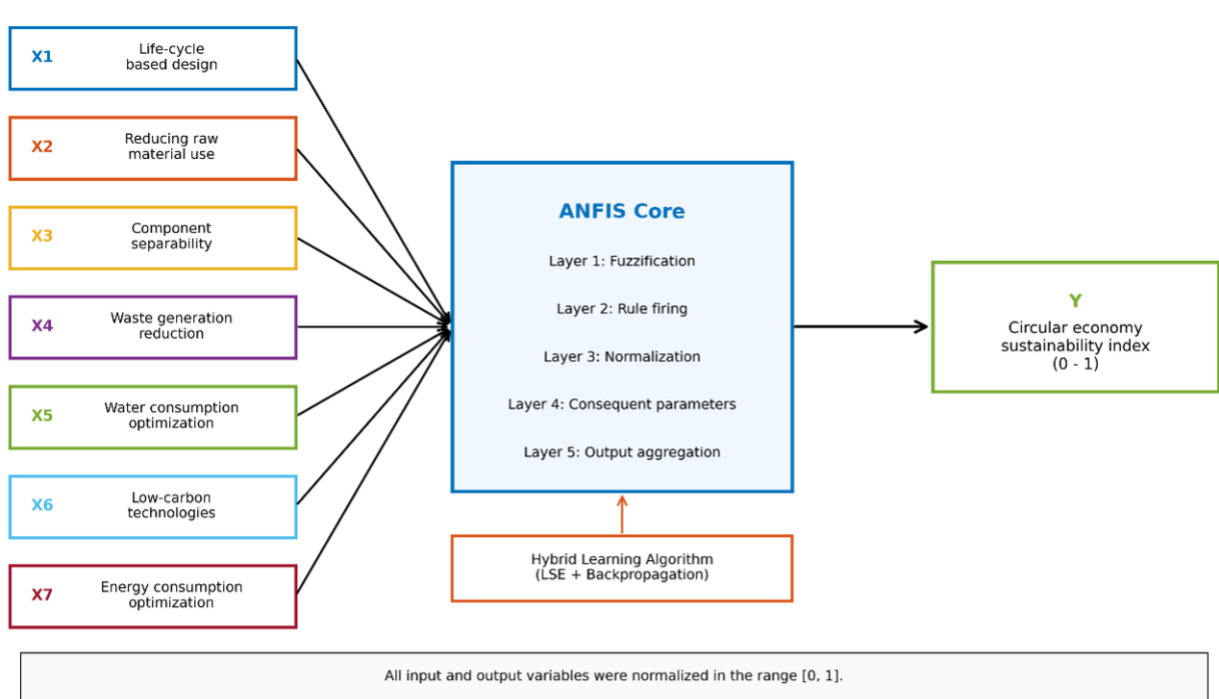


Figure 5: Input–Output Structure of the ANFIS Model for Predicting the Circular Economy Sustainability Index

As shown in Figure 5, the developed model utilizes a Multi-Input Single-Output (MISO) structure, in which each selected indicator participates as an independent input in the inference process. This structure enables the simultaneous modeling of interactions among the indicators and provides an appropriate framework for extracting nonlinear relationships between the variables affecting the sustainability of construction projects.

Subsequently, to define the fuzzy space of the model, the type and characteristics of the membership functions for the input and output variables were determined. The results of this stage are presented in Tables 7 and 8.

Table 7: Characteristics of the Defined Membership Functions for the Input Variables of the ANFIS Model

Variable	Membership Function Type	Number of Membership Functions	Linguistic Levels
Life Cycle-Based Design	Gaussian	3	Low, Medium, High
Life Cycle-Based Design	Gaussian	3	Low, Medium, High
Reduction in Raw Material Consumption	Gaussian	3	Low, Medium, High
Component Disassembly Capability	Gaussian	3	Low, Medium, High
Waste Generation Reduction	Gaussian	3	Low, Medium, High
Water Consumption Optimization	Gaussian	3	Low, Medium, High
Use of Low-Carbon Technologies	Gaussian	3	Low, Medium, High
Energy Consumption Optimization	Gaussian	3	Low, Medium, High
Circular Economy Sustainability Index	Gaussian	3	Low, Medium, High

Table 8: Initial Parameters of Gaussian Membership Functions Used in the ANFIS Model

Linguistic Level	Membership Function Center	Membership Function Width	Numerical Interpretation
Low	0.20	0.18	Poor indicator status
Medium	0.50	0.18	Moderate indicator status
High	0.80	0.18	High indicator status

According to the results presented in Tables 7 and 8, three Gaussian membership functions—Low, Medium, and High—were specified as the initial linguistic partitions for each input and output variable. These initial functions were defined on the normalized 0–1 scale before ANFIS training, while subtractive clustering was used to initialize the fuzzy rule structure. During ANFIS learning, the premise parameters of the Gaussian functions and the consequent parameters were subsequently optimized. Gaussian functions were selected because of their continuity and smoothness in approximating nonlinear relationships.

Furthermore, applying an identical number of membership functions to all variables contributed to maintaining the structural consistency of the model and facilitated the network training process. The graphical representation of the initial membership functions is presented in Figure 6.

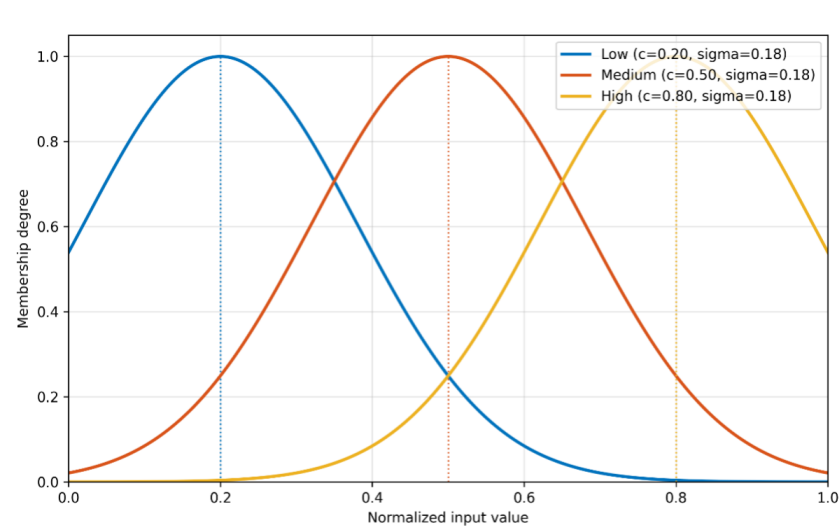


Figure 6: Initial Gaussian Membership Functions for the Input Variables of the ANFIS Model

As illustrated in Figure 6, the membership functions exhibit appropriate overlap and provide a gradual transition between different linguistic levels. This characteristic enables gradual variations in input values to be represented within the fuzzy inference process without creating rigid boundaries, thereby improving the prediction accuracy of the model.

Evaluation of the ANFIS Model Performance

After designing the model structure and defining the membership functions, the performance of the Adaptive Neuro-Fuzzy Inference System was evaluated during three stages: training, validation, and testing. The 68 expert-response observations were divided using an approximately 70%/15%/15% allocation: 48 observations for training (70.6%), 10 for validation (14.7%), and 10 for testing (14.7%). Model performance was assessed using the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). The evaluation results are presented in Tables 9, 10, and 11.

Table 9: Performance Indicators of the ANFIS Model During the Training Stage

Evaluation Indicator	Value
Training n (%)	48 (70.6%)
Epochs executed (max)	100 (200)
RMSE	0.032
MAPE	3.4%
R^2	0.94
Training Status	Converged

Table 10: Performance Indicators of the ANFIS Model During the Validation Stage

Evaluation Indicator	Value
Validation n (%)	10 (14.7%)
RMSE	0.036
MAPE	3.9%
R^2	0.91
Model Status	No substantial evidence of overfitting was observed

Table 11: Performance Indicators of the ANFIS Model During the Final Testing Stage

Evaluation Indicator	Value
Testing n (%)	10 (14.7%)
RMSE	0.039
MAPE	4.2%
R^2	0.89
Testing Status	Acceptable

The results presented in Table 9 indicate that the ANFIS model achieved an RMSE value of 0.032, a MAPE value of 3.4%, and a coefficient of determination (R^2) of 0.94 during the training stage, demonstrating the high accuracy of the model in learning the relationships between input and output variables. Furthermore, during the validation stage, the model obtained an RMSE value of 0.036 and an R^2 value of 0.91, indicating that it maintained suitable prediction accuracy while achieving an acceptable level of generalization capability.

In the final testing stage, the model achieved $RMSE = 0.039$, $MAPE = 4.2\%$, and $R^2 = 0.89$, demonstrating satisfactory predictive performance within the present 10-observation test subset. The relatively close performance across the training, validation, and testing stages provides no substantial evidence of overfitting in the evaluated dataset. The training error became approximately stable after about 40–50 iterations within the 100 executed epochs, consistent with the observed convergence pattern.

To compare the actual values with the values predicted by the model, the results are presented in Figure 7.

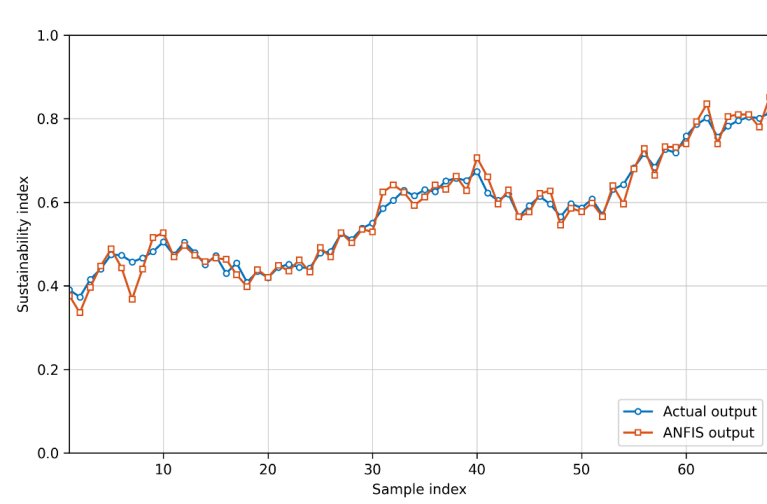


Figure 7: Comparison of Actual and Predicted Values During the Training Stage of the ANFIS Model

As shown in Figure 7, the values predicted by the model appropriately follow the trend of changes in the actual values, and the differences between the two curves are very limited in most cases. This overlap indicates that the developed model has a satisfactory capability in learning the patterns embedded in the data and is able to predict variations in the circular economy sustainability index with an appropriate level of accuracy. To evaluate the correlation between the actual and predicted values, the scatter plot is presented in Figure 8.

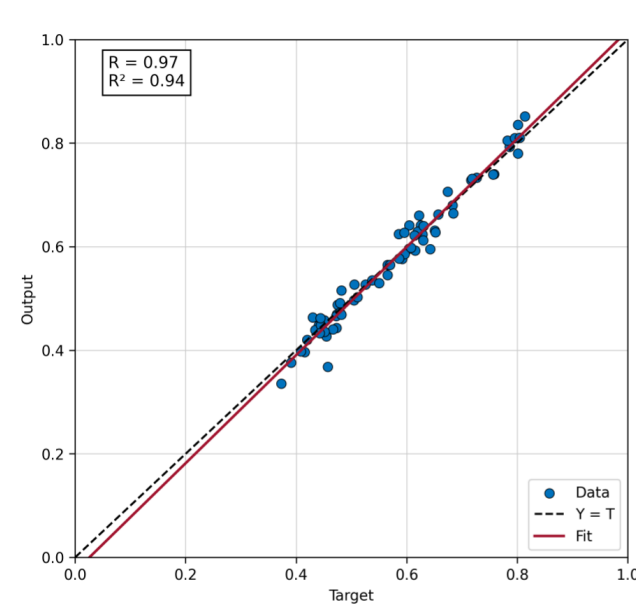


Figure 8: Scatter Plot of Actual and Predicted Values for the ANFIS Training Dataset

The examination of Figure 8 shows that the majority of data points are located close to the equality line ($Y = X$), indicating a strong correlation between the actual and predicted values. For the training dataset, the coefficient of determination was $R^2 = 0.94$, indicating a strong agreement between the observed and predicted values and demonstrating that the model explains a substantial proportion of the variation in the sustainability index. The concentration of points around the reference line indicates that the prediction error is limited and that the model possesses an acceptable level of accuracy and reliability. Furthermore, the trends of training and validation errors during the learning process are illustrated in Figure 9.

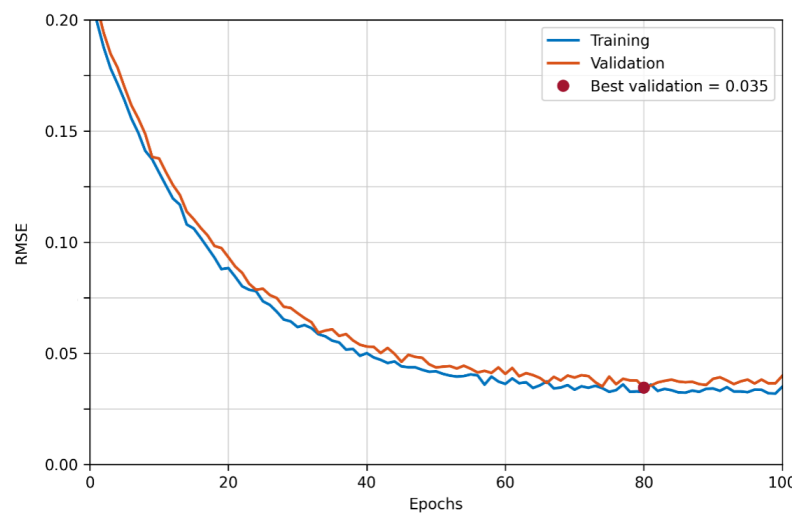


Figure 9: Comparison of Training and Validation Error Trends During the ANFIS Network Training Process

According to Figure 9, the training and validation errors gradually decreased as the number of learning iterations increased and eventually converged to approximately stable values. The close similarity between the trends of the two curves and the absence of a significant gap between them indicate satisfactory convergence and stable model behavior. These results provide no substantial evidence of overfitting in the evaluated model.

These findings indicate that the developed ANFIS structure modeled nonlinear relationships between the circular-economy indicators and the expert-assessed Circular Economy Sustainability Index with satisfactory performance within the present dataset. The framework therefore has potential as a decision-support approach for construction-project contexts, but independent project-level validation is required before broader operational application.

5 Discussion

The FAHP results identified Resource Efficiency, Design for Disassembly, and Construction Waste Management as the three highest-weighted circular-economy criteria, with normalized weights of 0.2659, 0.2304, and 0.1744, respectively. This finding indicates that the success of circular economy implementation depends not only on end-of-life practices such as recycling, but also on decisions made during the design phase, material selection, and resource management at the early stages of the project life cycle.

This result is consistent with the findings of Chammout and El-Adaway [4], who demonstrated that successful implementation of circular economy principles in construction projects requires the simultaneous interaction of managerial, economic, technical, and environmental factors. They further emphasized that the adoption of integrated decision-making frameworks can significantly enhance the effectiveness of circular economy strategies. In addition, the results of this study are in agreement with Ortiz-de-Montellano et al. [6], who stated that circular economy approaches play a critical role in achieving sustainable development goals by improving resource efficiency, reducing waste generation, and optimizing material consumption.

Furthermore, Joensuu et al. [12], emphasized that life cycle-based design, material reuse, and systematic construction waste management are among the most important strategies for improving the environmental performance of construction projects. The consistency between the findings of the present study and these previous studies indicates that focusing on resource management and design-stage decisions represents a fundamental prerequisite for achieving circular economy objectives in construction projects.

In contrast, Hart et al. [8] highlighted that inadequate implementation infrastructures, the absence of supportive policies, and insufficient collaboration among stakeholders are among the major barriers to circular economy adoption. This issue may explain why certain indicators, such as material recycling, obtained lower weights compared with resource efficiency in the present study. In situations where operational and managerial infrastructures are not sufficiently developed, preventive strategies implemented during the early stages of design and project management may provide greater effectiveness than end-of-life approaches.

The intelligent-model evaluation showed favorable predictive performance for the ANFIS model within the present expert-response dataset. This finding is consistent with the use of ANFIS in related nonlinear engineering applications, including the construction-waste study of Akinade and Oyedele [1]. However, because the present study did not include an external project-level validation sample or a benchmark predictive model, these results should not be interpreted as evidence of general superiority over alternative approaches.

Similarly, Petković et al. [16] reported that the ANFIS system can accurately model the simultaneous effects of indicators related to energy efficiency, material consumption, and sustainable development, while maintaining appropriate generalization capability under real-world conditions. The agreement between the findings of the present study and these previous studies demonstrates that artificial intelligence-based models combined with fuzzy logic can overcome the limitations of conventional decision-making methods when dealing with nonlinear and uncertain data.

Moreover, the findings of this research are consistent with previous domestic studies. Shahdkar et al. [22] emphasized the role of managerial and organizational factors in the implementation of circular economy practices, while Hosseinpour and Ghorbanpour [9] highlighted the importance of applying advanced technologies to enhance sustainable efficiency. This aspect was achieved in the present study through the development of an integrated FAHP–ANFIS-based model.

Furthermore, the results reported by Hosseinpour et al. [10] and Ghaem-Maghani Hazaveh et al. [7] indicated that the development of waste management infrastructures, optimization of resource consumption, and adoption of emerging technologies play decisive roles in the successful implementation of circular economy principles. Therefore, the findings of the present study not only confirm previous research outcomes but also contribute to addressing an existing gap in the literature by proposing an integrated intelligent framework for weighting, modeling, and predicting the circular economy sustainability index.

The proposed model may provide a structured decision-support basis for managers, consultants, and policymakers in construction-related contexts by organizing expert-assessed sustainability information. Its use as a direct project-level prediction tool should be considered provisional until independent project data are used for external validation.

A further limitation is that the predictive performance of the ANFIS model was not compared with benchmark models such as multiple regression, support vector machines, or random forests. Therefore, the reported performance metrics should not be interpreted as evidence that ANFIS is superior to these alternative predictive approaches.

6 Conclusions and Recommendations

The present study aimed to develop an intelligent model for an expert-assessed Circular Economy Sustainability Index in construction-project contexts based on the Adaptive Neuro-Fuzzy Inference System (ANFIS). The key circular-economy criteria were first identified and weighted using the Fuzzy Analytic Hierarchy Process (FAHP), after which the ANFIS model was developed and evaluated using questionnaire-based expert-response observations.

The findings demonstrated that Resource Efficiency, Design for Disassembly, and Construction Waste Management were the three highest-weighted criteria in the normalized FAHP analysis, with weights of 0.2659, 0.2304, and 0.1744, respectively. Their ranking emphasizes the importance of early-stage design, resource management, and waste-management decisions in circular-economy planning.

The ANFIS model achieved $RMSE = 0.039$, $MAPE = 4.2\%$, and $R^2 = 0.89$ in the 10-observation test subset, indicating satisfactory predictive performance within the present dataset. Given the limited test-sample size and the expert-response nature of the observations, these results should be interpreted as internal model-performance evidence rather than as confirmation of project-level generalizability.

A principal contribution of the study is the integration of FAHP-based prioritization with ANFIS-based nonlinear modeling of an expert-assessed Circular Economy Sustainability Index. The framework extends beyond indicator ranking by providing a structured predictive layer, but direct application to construction-project performance requires validation with independently measured project-level data.

From a practical perspective, the findings may inform project managers, consultants, designers, and policymakers about the relative importance of resource efficiency, life cycle-based design, and construction waste management. The proposed framework should currently be viewed as a potential decision-support approach based on expert assessments rather than as a fully validated project-level prediction system.

Despite the valuable findings, this study has several limitations. The observations were derived from a specific expert population rather than from independently measured construction projects, and the testing subset contained only 10 observations; consequently, broader generalization requires external project-level validation. In addition, no

benchmark predictive model was evaluated. Therefore, the reported ANFIS performance should not be interpreted as evidence of superiority over alternatives such as multiple regression, support vector machines, or random forests. Some economic, social, and institutional factors influencing circular-economy implementation were also not included because of data limitations.

Future studies should validate the proposed framework using independent construction-project datasets with different scales and operational conditions and should compare ANFIS with benchmark statistical and machine-learning approaches, including multiple regression, support vector machines, random forests, and neural-network models. Further research may also integrate the framework with Building Information Modeling (BIM), the Internet of Things (IoT), big-data analytics, and digital twins, and investigate governmental policies, economic incentives, regulatory requirements, and multi-objective decision-support formulations.

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