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Research Article

Application of a fuzzy logic model for quality indexing in reinforced cement concrete construction

Gaurav Singh[1*], Laxmi Kant Mishra[1] and Virendra Kumar Paul[2]
Department of Civil Engineering, Motilal Nehru National Institute of Technology Allahabad, Prayagraj-211004, Uttar Pradesh, India[1]
Building Engineering and Management, School of Planning and Architecture New Delhi, Delhi-110002, India[2]

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Abstract
It is essential to quantify construction quality rather than rely solely on subjective evaluations to effectively control and assess the standard of any construction work. This study employs a fuzzy mathematical model as an effective methodology to reduce subjectivity and establish a uniform quantification scale for assessing the overall quality index of reinforced cement concrete (RCC) construction. The model evaluates various quality attributes related to materials, construction processes, and the hardened state of concrete. A case study was conducted to validate the proposed model by assessing the quality indices of three RCC buildings constructed by different agencies. The findings revealed that Building 1 achieved the highest overall quality index of 76.847 (on a scale of 100), indicating superior construction quality. Building 2 followed with a score of 73.883, while Building 3 had the lowest quality index of 72.221. Based on the numerical ratings, Building 1 was classified as "excellent," whereas Buildings 2 and 3 were rated as "good." This framework replaces subjective assessments with objective numerical values, enabling consistent quality evaluation. It offers construction companies a competitive advantage by enhancing construction quality, aiding in facility ranking, project prioritization, and serving as a critical criterion in contractor selection.

Keywords
Fuzzy logic, Quality indexing, Reinforced cement concrete (RCC), Construction quality assessment, Quality attributes, Subjective evaluation elimination.

1.Introduction
Reinforced cement concrete (RCC) is a vital structural component in modern construction due to its ability to reduce voids and enhance structural performance, adaptability, and overall integrity [1, 2]. It combines the compressive strength of concrete with the tensile strength of steel reinforcement, making it indispensable in contemporary infrastructure. The quality of RCC construction can be broadly classified into three main aspects: material quality, construction quality, and hardened state quality. Material quality focuses on the properties of constituent materials such as setting time, cement fineness, aggregate size, and texture [3], which significantly influence mechanical and physical characteristics, including workability and strength [4].

Construction quality refers to the proactive implementation of procedures and best practices throughout the project lifecycle, with emphasis on mixing, formwork, placement, compaction, and curing [5].

Hardened state quality addresses strength, durability, and other physical characteristics influenced by workmanship, batching processes, equipment [6], site supervision [7], and sampling. In response to the rising demand for affordable and sustainable infrastructure, particularly in developing countries, research has increasingly focused on improving the resource efficiency and longevity of RCC through optimized quality management practices [8]. This has led to the use of quality control measures such as testing, supervision, and resource optimization to ensure both economic viability and the responsible use of natural resources [9]. Despite RCC's widespread adoption, the development of a reliable quality index remains a significant challenge. Quality management in RCC construction is critical not only

*Author for correspondence

for ensuring structural robustness and durability but also for optimizing material utilization and minimizing waste.

However, the assessment of RCC quality often relies on a limited set of criteria, typically involving non-destructive testing (NDT), partial testing, and destructive testing methods [10]. Given the complexity of RCC performance under varied site conditions, these approaches are often inadequate for a holistic evaluation of structural quality. A comprehensive quality assessment must consider all influencing factors to avoid overlooking aspects that may compromise structural integrity [11]. Key challenges include variability in material properties and inconsistency in workmanship, which must be addressed to achieve reliable and durable RCC construction [12].

It is essential for researchers to develop a clear and comprehensible construction quality analysis index that can be effectively utilized by supervisors, project managers, and engineers [13]. Advanced decision-making methods like fuzzy modelling and the analytical hierarchy process (AHP) have surfaced to address these issues, providing organised frameworks to handle the subjectivity and complexity inherent in RCC quality assessment [14]. These methods produce more dependable and helpful framework for evaluating quality, allowing for a methodical dissection of RCC quality attributes, prioritising essential elements, and accounting for uncertainties in material properties, workmanship, and environmental conditions.

Quality evaluation in construction is a complex task that often relies on the heuristic knowledge of professionals due to the diverse range of quality issues and their underlying causes [15]. To support practical decision-making, expert systems for quality evaluation [16] and preliminary assessment criteria [17] are being developed. This study introduces a novel RCC quality assessment approach that integrates fuzzy modelling with the AHP, enabling a comprehensive evaluation of RCC construction by accounting for the relative importance of quality attributes and incorporating expert knowledge. The proposed framework bridges the gap between theoretical models and real-world construction challenges, offering professionals a robust and adaptable tool for proactive quality control. It aims to mitigate adverse outcomes arising from factors such as material variability, inconsistent workmanship, and site-specific conditions.

This work builds upon a prior framework that focused on generating the relative weightage of various quality attributes using AHP analysis [18]. In the current study, the framework is further refined by applying fuzzy mathematical modelling to integrate these weightages with in-situ and laboratory test results. This enables a more detailed and quantitative evaluation of RCC construction quality and associated facilities. The framework specifically targets the identification and resolution of substandard quality issues arising from human error, material defects, equipment limitations, and site-related factors [19].

The rest of the paper is organized as follows. Section 2 provides a comprehensive review of the existing literature. Section 3 details the methodology adopted in this study. The results and experimental validation are presented in Section 4, followed by a discussion of the key findings in Section 5. Finally, Section 6 outlines the conclusions and suggests directions for future research.

2.Literature review

This section outlines numerous studies that have been conducted on the subject of assessing the quality of RCC construction and the related construction facilities. These studies have used a variety of methodologies, such as analytical, experimental, post-construction performance techniques and soft computing techniques in addition to the conventional evaluation method.

Faghfouri et al. (2024) [20] integrated lean construction principles, mechanical properties, seismic analysis, and the fuzzy AHP to optimize the design of concrete gravity dams. Their approach demonstrated a potential 20% reduction in concrete usage compared to traditional design methods. Future research could explore the adaptability of this framework across various dam structures and expand the range of sub-criteria to enhance structural safety and reliability.

Ghorbani et al. (2024) [21] developed an artificial neural network (ANN) model to predict the compressive strength of self-compacting concrete, considering input parameters such as fly ash, cement, and limestone powder. The model effectively identified fine aggregate, water-to-cement ratio, and limestone powder as the most influential factors. However, the model’s focus solely on compressive strength restricts its applicability for holistic quality modelling, as other critical attributes influencing concrete quality are not accounted for.

Ling et al. (2024) [22] investigated the splitting tensile and compressive strengths of secondary steel fiber-reinforced concrete using a fuzzy neural network approach. The study evaluated the impact of varying steel fiber types, lengths, and dosages using standardized testing procedures. The findings indicated that optimal fiber combinations could significantly enhance strength. Nonetheless, the study's applicability is limited due to a lack of extensive testing across diverse engineering conditions.

Raza et al. (2024) [23] investigated the structural performance of glass-fibre reinforced rubberized concrete compression members through testing and theoretical analysis. With a smaller stirrup spacing, rubberized concrete demonstrated improved ductility and a greater capacity to support loads. The study was limited, though, in that it assumed immaculate connections between rubberized concrete and reinforcement, ignored early geometric flaws and manufacturing problems, and might not have applied to all kinds of reinforced rubberized concrete compression elements.

Mandal et al. (2024) [24] examined machine learning (ML) methods for forecasting concrete slump and compressive strength using 200 mix designs and 15 trial mixes. The most accurate model was determined to be an adaptive neuro-fuzzy inference system (ANFIS), which produced strong forecasts with slight inaccuracy. Additionally, gene expression programming provided useful optimization formulas. Data reliance and lack of a more comprehensive mix of designs are among the barriers. Future research should optimize ML techniques and increase datasets for more applications.

Wang et al. (2024) [25] predicted the compressive strength of geopolymer concrete generated from fly ash and blast furnace slag using artificial intelligence models (ANN, ANFIS, and Gene expression programming). The Gene expression programming model fared better with reliable statistical validation and precise predictions with low error rates than ANN and ANFIS. Nevertheless, there are disadvantages, like the absence of larger dataset limits and parameter modifications.

Rane et al. (2023) [26] identified five key factors influencing the selection of formwork systems for residential buildings: initial cost, durability, labour cost, material waste, and repetition. The study found that aluminium formwork systems offered faster construction, reduced long-term costs, and generated less material waste compared to traditional methods, which remained prevalent due to their lower initial investment. The authors recommended that future research should encompass a broader range of project types and be conducted at a national scale to ensure wider applicability of the findings.

Rubin et al. (2023) [27] employed hydration-accelerating admixtures to investigate the effects of structuration rate on the characteristics of three-dimensional (3D)-printed concrete. The results demonstrated enhanced structural stability and resistance to deformation, particularly with the 4% admixture containing concrete mix, which profited from early ettringite precipitation. However, because excessive admixture consumption inhibited the synthesis of calcium silicate hydrate, it decreased long-term strength. One of the limitations is the isolation of interdependent phenomena such as interlayer adhesion and hydration.

Jiao et al. (2023) [28] modelled compressive strength using a fuzzy inference technique. The study's concentration on particular types of recycled aggregate and its lack of investigation into the long-term performance and the impact of varying fibre lengths and distributions are constraints.

Ali et al. (2023) [29] incorporated ML models to predict the tensile and flexural strengths of 3D-printed concrete. The dataset included 77 mixed designs for flexural strength and 49 for tensile strength. The study highlights the potential of ML for optimizing 3D concrete printing, but the limited dataset and diversity limit generalization.

Kulasooriya et al. (2023) [30] estimated basalt fibre-reinforced concrete's compressive, flexural, and tensile strengths using tree-based ML models. Explainable artificial intelligence techniques were employed to interpret the predictions. Explainable artificial intelligence offered transparency and emphasized the significance of algorithm-dependent features. Characteristics should be expanded in future research, and domain experts should be consulted for validation.

Abbas and Khan (2023) [31] proposed a fuzzy-logic numerical model to forecast the compressive stress-strain behaviour of hybrid fibre-reinforced concrete.

The model successfully represented post-cracking stages at a cheap computational cost and demonstrated excellent prediction accuracy for strain at peak stress, elasticity modulus, and stress-strain behaviour. Subsequent research examines the efficacy of the suggested fuzzy-logic methodology utilising diverse membership function (MF) sizes and types.

Agor et al. (2023) [32] employed an ANFIS to forecast the mechanical characteristics of concrete with sisal fibre and aluminium waste. Tests in the lab verified the improved qualities, with a high prediction accuracy of 99.57%. However, there are drawbacks, such as a limited range of datasets and dependence on particular materials. More testing settings and material kinds should be used in future studies to improve model dependability.

Gutiérrez-garcía et al. (2023) [33] developed a predictive model based on fuzzy logic to use electrical resistivity measurements to determine the 28-day compressive strength of mortar. The model demonstrated a strong relationship between resistivity and strength based on variables like cement dosage and curing times. However, the study was limited by the small dataset size and restricted experimental settings. More extensive datasets and a range of mortar compositions should be used in future studies.

Han et al. (2023) [34] employed an ANFIS to develop a sustainable self-consolidating green concrete incorporating partial cement replacement. The study identified micro silica and volcanic powder as the most effective additives for enhancing durability and compressive strength. However, the absence of site-specific variables and long-term performance evaluations were noted as key limitations of the research.

Liu et al. (2023) [35] predicted the bond strength between fibre-reinforced cement mortar and concrete using an ANFIS. With its high accuracy and minimal prediction errors, the model may help reduce testing costs and material waste. However, including a short dataset size and restricted testing settings indicates that larger datasets and a wider range of scenarios should be the main focus of future research.

Limited research has been done to estimate the quality rating of RCC construction using the fuzzy model based on the condition evaluation of RCC structures. An effective way to estimate the quality rating of any RCC construction may be to combine a fuzzy rule base and the quality attributes of RCC construction.

This research investigation attempts to develop a systematic methodology to incorporate the fuzzy mathematical model and the relative weightages of various quality attributes of the RCC structure. This methodology focuses on determining the quality of RCC structures using fuzzy mathematical models. It incorporates all identified attributes along with their relative weightages to generate a quality index rated on a 100-point scale.

2.1Introduction of fuzzy model approach

Fuzzy set theory allows the organized calculation of linguistically comparable data (facts). Fuzzy models are well-executed and describe human knowledge and experiences in the optimum model; these particular models are very interpretable. Zadeh [36] first proposed fuzzy set theory to overcome the limitation of traditional Boolean logic, which has only two possibilities of statements, either true or false. However, fuzzy logic provides a value between true and false, giving a degree of truthfulness to any statement. The fuzzy model had to be developed to address the ambiguity in any statement or decision. Fuzzy sets are useful for translating language features into a more logical algorithmic description [37]. These fuzzy sets can be represented by a variable of the universe, which necessitates the division of the cosmos into segments, for which sets must overlap and be extremely exact [38]. The fuzzy model's set theory provides a systematic approach to handling such data linguistically, which does the numerical computation using language labels defined by an MF. The numerical computation uses the linguistic labels obtained from the MF. The fuzzy inference system (FIS) is built on fuzzy rules and reasoning and the key components of fuzzy modelling based on fuzzy set theory. A fuzzy variable defines the phrase used to describe a fuzzy idea, like height, age, or temperature. The fuzzy MF displays the degree of similarity between the data value and the class's origin or archetypal data value.

The MF represents the degree of truthiness and fuzziness of any fuzzy collection. These MFs, which are presented graphically, are helpful in solving problems based on experience rather than knowledge. The statements/problems and the quantity of data sets/mappings with a suitable degree of MF determine the form of MFs, and the best-fitting MF shape is determined by experience. Other crucial factors that guarantee the efficacy of fuzzy sets are the interval and range of MFs. The number and form of MFs significantly impact how long it takes to compute the fuzzy set. Therefore, the most appropriate kind and quantity of MFs should be included to maximize the fuzzy model's performance [39]. *Figures 1, 2,* and *3* illustrated the triangular, trapezoidal, and Gaussian MF, respectively.

- Triangular MF: Characterized by a value peak, upper limit, and lower limit.
- Trapezoidal MF: Having a flat top, this function resembles a triangle.
- Gaussian MF: A curve with a bell shape that depicts seamless transitions.

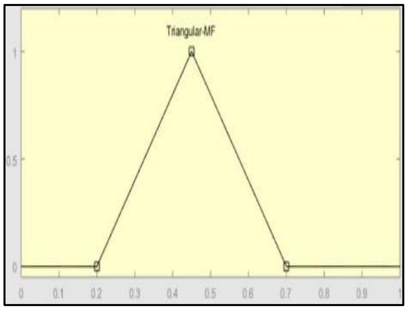

Figure 1 Triangular MF

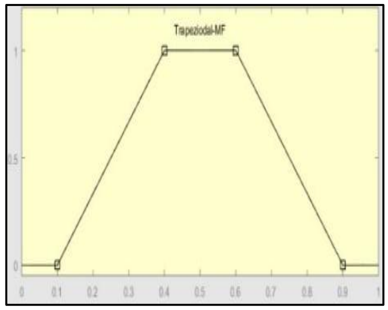

Figure 2 Trapezoidal MF

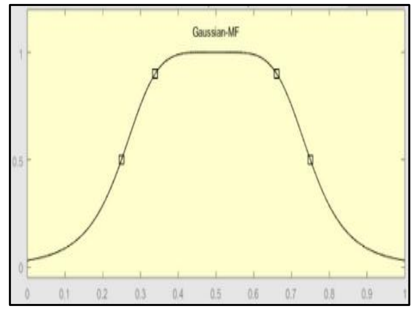

Figure 3 Gaussian MF

In fuzzy systems, membership values are frequently arbitrary and determined by past data or expert views [40]. Different outputs resulting from varying membership levels may impact quality ratings. "High Strength" and "Moderate Workability" are ambiguous linguistic variables that could not have widely accepted definitions. Inconsistent inputs may result from expert interpretations. Fuzzification, inference, and defuzzification spread uncertainty, affecting the end outcome. Different numerical quality ratings for the same input parameters may arise from fuzzy rules, linguistic terminology, or MF design variations.

Probabilistic methods using fuzzy sets in the fuzzy logic model were considered to reduce uncertainty in quality assessments. This approach was performed with expert knowledge to reduce biases and provide consensus-based designs for MFs and linguistic variables [41]. A sensitivity analysis was employed to determine how membership value changes or linguistic variable definitions affected ratings [42]. Reduce biasedness and subjectivity by utilizing ML techniques data-driven functions of MFs derived from empirical data [43].

After determining the MF, FIS converts the crisp data/value into fuzzy sets, which serve as input [44]. The fuzzy model calculation using a rule-base, in this calculation, develops a relationship between input and output. A rule base is a set of rules utilized in a fuzzy system. It can be analyzed under conditions known as rule bases. There are two rule bases, i.e., Mamdani and Takagi-Sugeno type FIS, which formulate rule bases in the fuzzy model [45]. However, the rule base has some limitations. An increase in input quantity leads to an increase in the rule base exponentially [46]. Rule-base establish the relationships between the linguistic variables in the input and output. To create a rule base, the antecedents (IF conditions) and consequents (THEN results) must be specified [47].

Defuzzification is the process of extracting a single numerical value from the output of the combined fuzzy set. It is employed to produce a crisp output from the conclusions of an FIS. Defuzzification converts it to a crisp value in the desired format. All conversions using the MF were developed based on professional judgment, transforming a crisp set into a fuzzy set and back into a crisp set. Defuzzification is essential for determining the most appropriate responses or set of values from the FIS model. The defuzzification process can be performed using various methods, including the center average method, center of gravity, and mean of maximum, among others [48]. *Figure 4* illustrates the fuzzy process. The crisp values of input variables are transformed using fuzzy composition and mapped to output variables in nine ways, referred to as a rule base. Using the center average method, the fuzzified value is converted back into a crisp value through defuzzification.

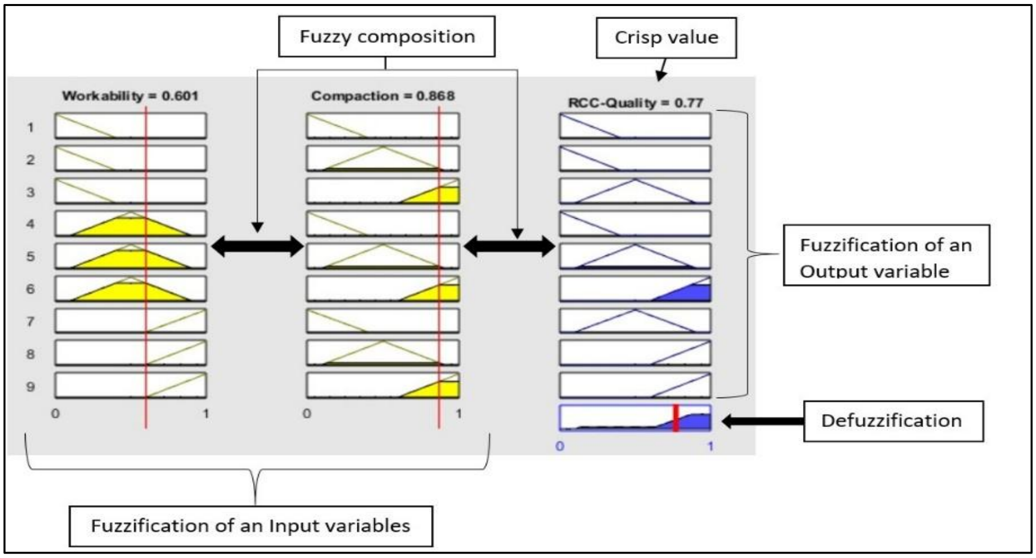

Figure 4 Visualization of the fuzzy composition and defuzzification process

2.2 Advantages of the fuzzy mathematical model over other methods

The fuzzy mathematical model is a reliable and adaptable method for evaluating quality in RCC construction with benefits over statistical and ML models. Due to subjective assessments, changing material properties, and environmental influences, the fuzzy mathematical model helps manage ambiguity and uncertainty in construction processes. It enables the direct integration of expert knowledge and can function well with sparse, inaccurate, or missing data. Its rule-based structure allows for the direct incorporation of expert knowledge, ensuring that judgments align with practical realities and domain expertise. Due to its inherent interpretability, it avoids the black-box complexity of ML algorithms and remains transparent for stakeholders [49]. The fuzzy mathematical model enables accurate, transparent, and real-time decision-making in quality control, effectively integrating statistical and ML approaches.

2.3 Fuzzy mathematical model for quality indexing of various RCC construction projects

In this study, fuzzy mathematical modelling was utilized to rate the quality attributes of three different RCC construction projects, determine their quality, and evaluate the construction quality or performance of different construction agencies. This model helped to quantify the workmanship and other construction practices employed by various construction agencies.
The primary objective of this study was to remove subjective judgment during the overall quality assessment of RCC construction through identified RCC construction attributes, which the fuzzy mathematical model could appropriately manage to quantify and rate the RCC construction facilities. To evaluate RCC construction, the selected attributes were grouped into three aspects: material quality, construction quality, and hardened state quality. The research aimed to establish a fuzzy mathematical model for assessing RCC construction quality. The quality rating of the RCC structure was the output of the fuzzy set. A case study was developed using a triangular MF to rate various concrete constructions and validate the fuzzy mathematical model. The evaluation criteria were derived from multiple sources, including relevant literature, the American Concrete Institute (ACI) guidelines, and Indian Standard (IS) codes.

3.Materials and methods

3.1Experimental setup

The quality indexing model used three quality considerations: material, construction, and hardened state quality. Material quality consideration includes identified attributes such as the physical and mechanical properties of cement, fine and coarse aggregates, reinforcement, water, and admixture used in RCC structures. In construction, quality considerations such as workmanship, dimension tolerance of formwork, etc., and hardened state of concrete quality considerations include depth of cover, curing time, permeability, etc.

As per the investigation done by Singh et al.[18], there were 380 experts, including industrial experts, contractors, academicians, and consultants with 1 to

30 years of experience. Additionally, the Cronbach Alpha test was incorporated in the previous study to assess the biasedness of the questionnaire responses. The associated attributes of material quality consideration were identified through a questionnaire administered to an expert panel, along with their relative weightage (Wi) and individual weightage (wi), determined using AHP analysis, as shown in *Table 1*. The W_i was referred to as the weighted average of w_i of attributes, i.e., $W_i = (w_i)/\sum w_i$. Similarly, *Table 2* and *Table 3* presented the associated attributes and their relative weightage for the construction and hardened state quality considerations, respectively. The framework defines the selection criteria for each particular attribute. In a study by Singh et al. [18], the AHP calculation was used to establish the score related to the relative weightage of each characteristic in a specific instance. The attributes with the highest relative weightages were chosen for additional quality quantification calculations. The effectiveness of the suggested AHP model was evaluated using a consistency ratio of relative weightage, which should always be less than 10%, and as well as sensitivity analysis was done in a previous study [18].

Table 1 Attributes of material quality consideration with relative weightage

S. No.	Material quality consideration	w_i	W_i
1.	Crushing value	0.330	0.165
2.	Impact value	0.330	0.165
3.	Abrasion Value	0.330	0.165
4.	Particle shape [elongated &flakiness]	0.231	0.116
5.	Fine Aggregate Grading	0.227	0.114
6.	Water absorption	0.337	0.169
7.	Elongation of reinforcement	0.210	0.105
Summation		**1.995**	**1.000**

Table 2 Attributes of construction quality consideration with relative weightage

S. No.	Construction quality consideration	w_i	W_i
1.	Attainment of compliance strength at the site	0.265	0.404
2.	Deviation from specified dimensions of the cross-section of columns and beams	0.391	0.596
Summation		**0.656**	**1**

Table 3 Attributes of hardened state quality consideration with relative weightage

S. No.	Hardened state quality consideration	w_i	W_i
1.	Cover depth	0.215	0.292
2.	Minimum curing times	0.196	0.265
3.	Water permeability of concrete	0.327	0.443
Summation		**1.079**	**1**

The proposed methodology, based on the fuzzy mathematical model [50], was employed to analyze RCC construction quality. The flowchart illustrating this methodology is presented in *Figure 5*, which categorizes the model into three main stages. The first stage, fuzzification, involves integrating both experimental and in-situ attribute results with the appropriate MFs, including their corresponding linguistic labels and defined ranges. In the second stage, these fuzzified values (Ri) are combined with the relative weightages of each attribute to form a fuzzy composition—commonly referred to as the rule base. In the final stage, the model performs defuzzification, wherein a crisp quality index is derived from the output MF using the center average method. This systematic approach enables the conversion of subjective and imprecise data into a quantifiable measure of construction quality.

The present study assessed the qualities of RCC construction in three buildings to validate the suggested fuzzy mathematical model. Additionally, visual comparisons and NDT results of these RCC constructions have been used to validate the overall quality indexing framework and benchmarking criteria to validate the construction quality indexing model [51]. Quality indexing framework combined various laboratories' test results and sound construction practices, workmanship such as formwork, compaction techniques, curing type, etc. The main aim was to club each factor involved in construction to quantify the overall quality of RCC Construction.

These buildings were situated in Prayagraj, with G+10 to G+12 RCC framed structures, and constructed by different construction agencies. The height of each floor of these buildings was approximately 3 m. Buildings 1 and 3 were designed for student accommodation, whereas building 2 was intended for residential purposes. These three RCC buildings are situated in nearby localities, and all environmental factors are approximately the same. The selection criteria were the environmental condition of Prayagraj, which has mild exposure; these buildings are in residential categories and newly constructed by well-established companies.

Various material quality attributes per the expert opinion for each of the three buildings, along with their lab and in-situ test results provided by certified laboratories, as shown in *Table 4.* The National Accreditation Board for Testing and Calibration Laboratories India accredited these laboratories testing facilities, adhering to IS codes of practice.

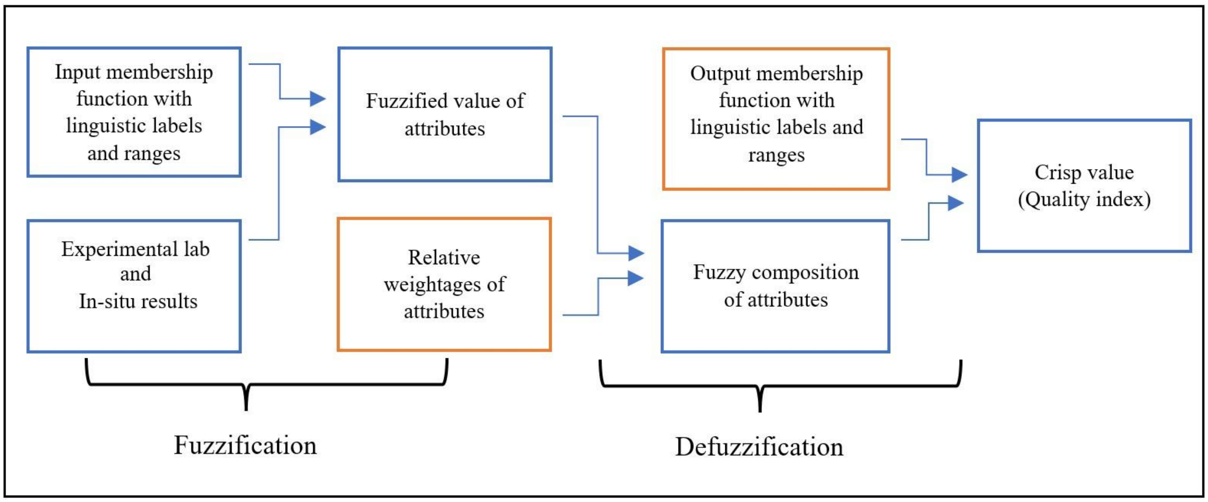

Figure 5 Flowchart of the fuzzy mathematical model for RCC construction quality evaluation

Table 4 Properties of material as per laboratory investigation

S. No.	Material quality consideration	Building 1	Building 2	Building 3
1	Crushing Value (%)	8.50	11.40	9.00
2	Impact Value (%)	10.00	15.50	14.00
3	Abrasion Value (%)	11.00	14.40	15.00
4	Particle shape [elongated & flakiness] (%)	17.00	24.00	20.00
5	Fine Aggregate Grading (fineness modulus)	2.10	2.50	2.20
6	Water absorption of fine aggregate (%)	0.50	1.00	1.10
7	Elongation of reinforcement (%)	13.50	13.60	13.20

The experimental and in-situ data related to construction quality considerations were collected for three different RCC buildings. These include deviations in compliance strength observed at the site and dimensional deviations in beams and columns, as presented in *Table 5* and *Table 6*, under hardened state quality considerations. Additionally, deviations in parameters such as concrete cover, minimum curing duration, and water permeability of concrete were also assessed to provide a comprehensive evaluation of construction quality.

Table 5 In-situ data of construction quality considerations

S. No.	Construction quality considerations	Building 1	Building 2	Building 3
1	Attainment of compliance strength at the site (deviation) (MPa)	5.10	5.20	5.10
2	Deviation from specified dimensions of the cross-section of beams and columns (mm)	5.00	5.00	6.00

Table 6 In-situ data of hardened state quality considerations

S. No.	Hardened state quality considerations	Building 1	Building 2	Building 3
1	Deviation in Concrete cover (mm)	5.00	5.00	4.00
2	Minimum curing times (days)	28	28	21
3	Water permeability of concrete (m/s)	2 *10^ (-12)	4*10^ (-12)	5*10^ (-12)

4.Results

4.1Result analysis of Fuzzy mathematical model

The proposed fuzzy mathematical model uses the triangular MF, as shown in Equation 1, of various RCC building attributes with linguistic variables and varying ranges. The linguistic variables were grouped according to literature and expert opinions, as shown in *Tables 7(a)* and *7(b)*, *Table 8*, and *Table 9*. Labels of linguistic variables were Excellent, Good, Fair, and Poor.

$$\text{Triangular MF} = \max\left[min\left\{\frac{(x-a)}{(b-a)}, \frac{(c-x)}{(c-b)}, 0\right\}\right] \quad (1)$$

where a is the min, c is the max, and b is the midpoint.

Table 7 (a) Labels and ranges of triangular MF for material quality consideration

Label	Crushing value (%)	Impact value (%)	Abrasion value (%)	Combined flakiness-elongation index (%)
Excellent	[0, 8, 15]	[0, 5, 10]	[0, 5, 10]	[5, 10, 15]
Good	[5, 10, 30]	[5, 10, 30]	[5, 10, 30]	[10, 15, 25]
Fair	[10, 30, 45]	[10, 30, 45]	[10, 30, 50]	[15, 25, 40]
Poor	[30, 45, 50]	[30, 45, 50]	[30, 50, 60]	[25, 40, 45]

Table 7 (b) Labels and ranges of triangular MF for material quality consideration

Label	Fine Aggregate Grading (Fineness modulus)	Water absorption of Fine aggregate (%)	Elongation of reinforcement (%)
Excellent	[2, 2.8, 3.2]	[0, 0.5, 1]	[13, 13.5, 18]
Good	[1.8, 2, 2.8]	[0.5, 1, 2]	[12.5, 13, 13.5]
Fair	[2.8, 3.2, 3.5]	[1, 2, 3]	[12, 12.5, 13]
Poor	[0, 1.8, 2]	[2, 3, 3.5]	[0, 12, 12.5]

Table 8 Labels and ranges of triangular MF for construction quality considerations

Label	Attainment of compliance strength at the site (deviation) (MPa)	Deviation in specified dimensions of the cross-section of columns and beams (mm)
Excellent	[0, 4, 5]	[0, 3, 6]
Good	[4, 5, 6]	[3, 6, 9]
Fair	[5, 6, 7]	[6, 9, 12]
Poor	[6, 7, 10]	[9, 12, 15]

Table 9 Labels and ranges of triangular MF for hardened state quality considerations

Label	Cover depth (deviation) (mm)	Minimum curing times (days)	Water permeability of concrete (m/sec)	
Excellent	[0, 3, 5]	[10, 28, 35]	[0 0.5 1]	$<10^{(-12)}$
Good	[3, 5, 7]	[7, 10, 28]	[0.5, 1, 10]	$10^{(-12)}$ to $10^{(-11)}$
Fair	[5, 7, 10]	[3, 7, 10]	[1, 10, 100]	$10^{(-11)}$ to $10^{(-10)}$
Poor	[7, 10, 15]	[0, 3, 7]	[10, 100, 120]	$>10^{(-10)}$

The quality of the RCC building was determined through the output average value of the fuzzy set (O_i). The MF of output has four linguistic parameters, which were Excellent, Good, Fair, and Poor, with defined ranges as shown in *Figure 6* and *Table 10*. The center average defuzzification method was applied to convert the fuzzified value into a crisp value.

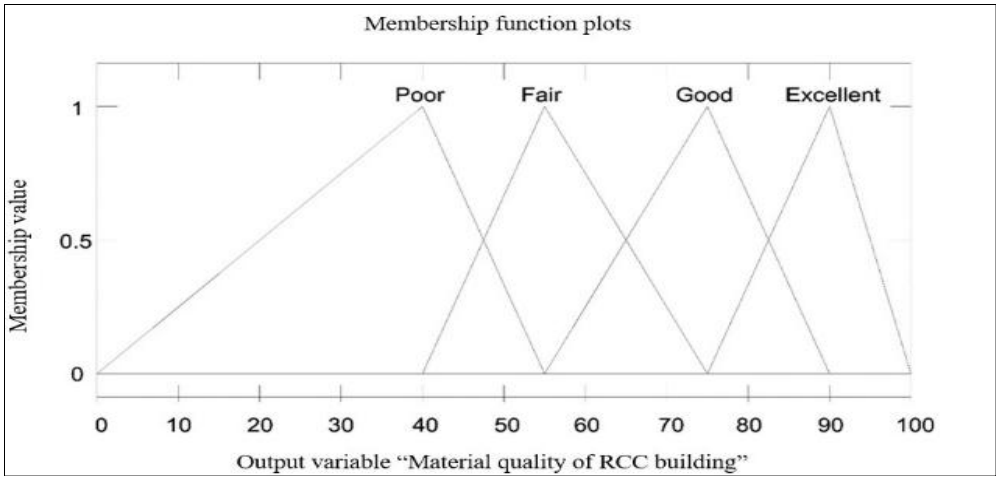

Figure 6 Triangular MF of fuzzy output

Table 10 Triangular MF of output (Quality of RCC building)

Label	Membership	Fuzzy center average value (O_i)
Excellent	[75, 90, 100]	90
Good	[55, 75, 90]	75
Fair	[40, 55, 75]	55
Poor	[0, 40, 50]	40

Now, crisp values of various attributes were converted into fuzzy values through matrix methods of material quality consideration for three different RCC buildings, as shown in *Figure 7*, *Figure 8*, and *Figure 9*. The Ri of material quality consideration were the resultant fuzzy function of experimental and in-situ values with the triangular MF of the proposed attributes. The Ri of material quality consideration were the resultant fuzzy function of experimental and in-situ values with the triangular MF of the proposed attributes. The Ri of the attributes were represented by the four linguistic values—Excellent, Good, Fair, and Poor—of each attribute displayed in *Figure 7*. For instance, the crushing value had the following linguistic values: Excellent with a membership value of 0.929; Fair and Poor have a membership value of 0; Good has a membership value of 0.071.

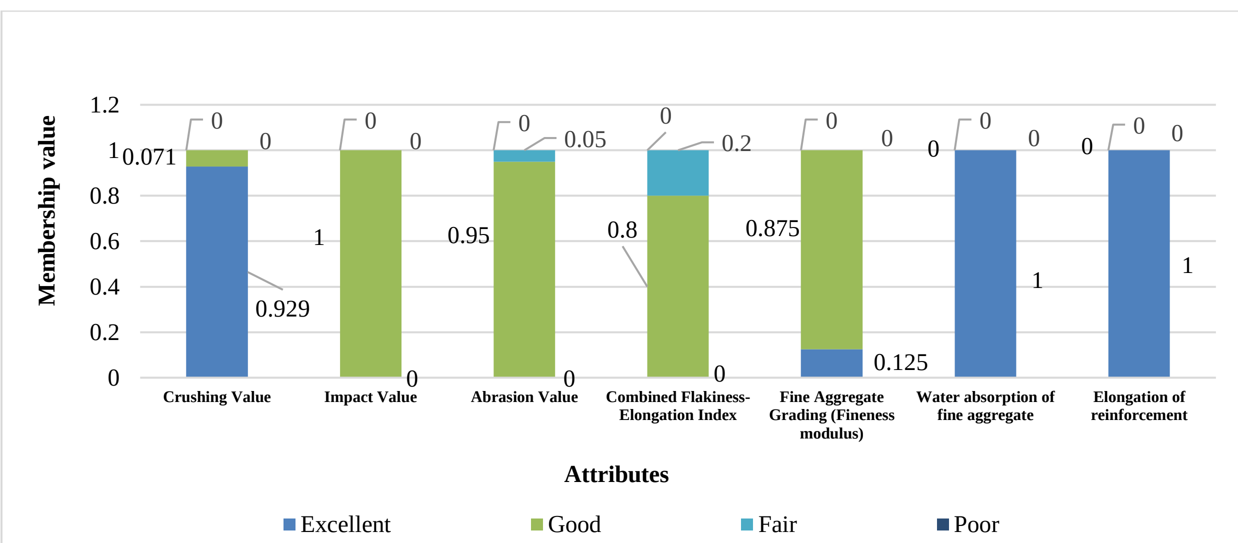

Figure 7 Fuzzified value of material quality consideration using matrix method for building 1

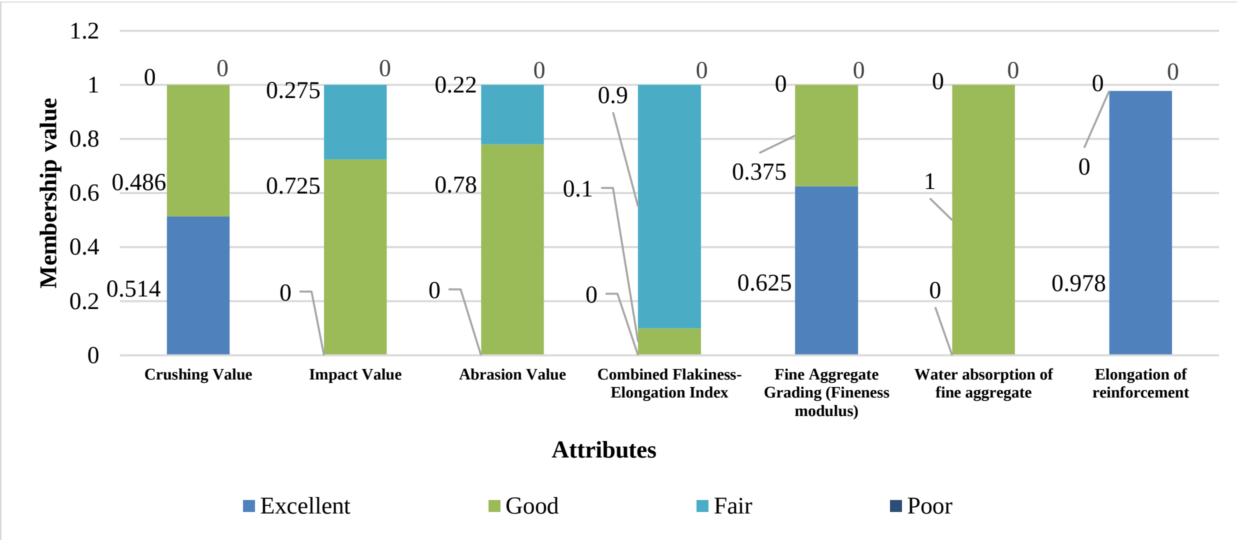

Figure 8 Fuzzified value of material quality consideration using matrix method for building 2

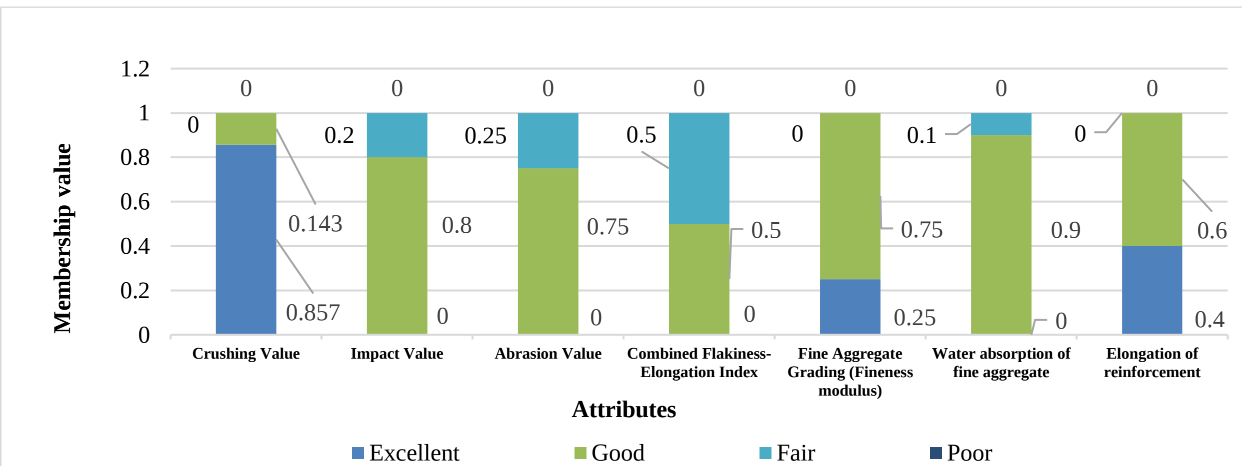

Figure 9 Fuzzified value of material quality consideration using matrix method for building 3

The fuzzy composition matrix of Wi and Ri of material quality consideration for RCC buildings determines the summation of linguistic variables known as labels, i.e., Excellent, Good, Fair, and Poor. As per Ross (2009) [52], the fuzzy composition was the summation of the maxima of individual minima of Wi and Ri for each attribute and its relative weightage, as shown in Equation 2. The fuzzy composition values for three different RCC buildings were building 1: 0.450, building 2: 0.500, and building 3: 0.500, as shown in *Table 11*, *Table 12*, and *Table 13* respectively.

$$W \circ R = max\,\{min\,(W_i, R_i)\} \qquad (2)$$

Table 11 Fuzzy composition of relative weightage and Ri of material quality consideration for building 1

Crushing value	**Impact value**	**Abrasion value**	**Combined flakiness-elongation index**	**Fine aggregate grading (fineness modulus)**	**Water absorption of fine aggregate**	**Elongation of reinforcement**	**Building 1** ($\boldsymbol{W \circ R}$) **[Lvi]**
			$min\,(W_i, R_i)$				$max\,\{min\,(W_i, R_i)\}$
0.165	0.000	0.000	0.000	0.114	0.169	0.105	0.169
0.071	0.165	0.165	0.116	0.114	0.000	0.000	0.165

Crushing value	Impact value	Abrasion value	Combined flakiness-elongation index	Fine aggregate grading (fineness modulus)	Water absorption of fine aggregate	Elongation of reinforcement	Building 1 $(\boldsymbol{W} \circ \boldsymbol{R})$ [Lv_i]
0.000	0.000	0.050	0.116	0.000	0.000	0.000	0.116
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Summation of Fuzzy composition $\sum(\boldsymbol{W} \circ \boldsymbol{R})$ =							**0.450**

Table 12 Fuzzy composition of relative weightage and Ri of material quality consideration for building 2

Crushing Value	Impact Value	Abrasion Value	Combined Flakiness-Elongation Index	Fine Aggregate Grading (Fineness modulus)	Water absorption of fine aggregate	Elongation of reinforcement	Building 2 $(\boldsymbol{W} \circ \boldsymbol{R})$ [Lv_i]
			$min\,(W_i, R_i)$				$max\,\{min\,(W_i, R_i)\}$
0.165	0.000	0.000	0.000	0.114	0.000	0.105	0.165
0.165	0.165	0.165	0.100	0.114	0.169	0.000	0.169
0.000	0.165	0.165	0.116	0.000	0.000	0.000	0.165
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Summation of Fuzzy composition $\sum(\boldsymbol{W} \circ \boldsymbol{R})$ =							**0.500**

Table 13 Fuzzy composition of relative weightage and Ri of material quality consideration for building 3

Crushing Value	Impact Value	Abrasion Value	Combined Flakiness-Elongation Index	Fine Aggregate Grading (Fineness modulus)	Water absorption of fine aggregate	Elongation of reinforcement	Building 3 $(\boldsymbol{W} \circ \boldsymbol{R})$ [Lv_i]
			$min\,(W_i, R_i)$				$max\,\{min\,(W_i, R_i)\}$
0.165	0.000	0.000	0.000	0.114	0.000	0.105	0.165
0.143	0.165	0.165	0.116	0.114	0.169	0.105	0.169
0.000	0.165	0.165	0.116	0.000	0.100	0.000	0.165
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Summation of Fuzzy composition $\sum(\boldsymbol{W} \circ \boldsymbol{R})$ =							**0.500**

Table 11, *Table 12*, and *Table 13* illustrated the fuzzy composition values, also referred to as Ri, which were defuzzified using the weighted average method of defuzzification [53] as indicated in Equation 3. The defuzzification method was incorporated in the fuzzified value of material quality consideration, construction quality considerations, and hardened state quality considerations.

$$Quality\ of\ RCC\ structure\ (Individual\ aspect) = \frac{\sum(O_i * Lv_i)}{\sum Lv_i} \quad (3)$$

Where Oi = Fuzzy membership average value of output, Lvi= Individual linguistic value (i.e., Excellent, Good, Fair, Poor), ∑Lvi= Summation of all linguistic values. The quality index of RCC buildings on a scale of 100 for material quality consideration was building 1: 75.484 (Excellent), building 2: 73.345 (Good), and building 3: 73.345 (Good), as shown in *Table 14*.

Similar to the material quality consideration, the fuzzy mathematical model has also been incorporated into construction quality consideration and hardened state quality consideration. The quality index of RCC buildings on a scale of 100 for the construction quality consideration of building 1: 77.914 (Excellent), building 2: 75.885 (Excellent), and building 3: 72.127 (Good), as shown in *Table 15*. Similarly, the quality index of RCC buildings on a scale of 100 for the hardened state quality consideration of building 1: 77.142 (Excellent), building 2: 72.418 (Good), and building 3: 71.191 (Good), as shown in *Table 16*.

Table 14 Defuzzification of rating of RCC buildings for material quality consideration

Label	Building 1	Building 2	Building 3
Excellent (Lv_1)	0.169	0.165	0.165
Good (Lv_2)	0.165	0.169	0.169
Fair (Lv_3)	0.116	0.165	0.165
Poor (Lv_4)	0.000	0.000	0.000
$\sum Lv_i$	0.450	0.500	0.500
$\sum (O_i \times Lv_i)$	33.977	36.654	36.654
Quality index of RCC buildings	**75.484**	**73.345**	**73.345**

Table 15 Defuzzification of rating of RCC buildings for construction quality consideration

Label	Building 1	Building 2	Building 3
Excellent (Lv_1)	0.333	0.333	0.000
Good (Lv_2)	0.596	0.596	0.596
Fair (Lv_3)	0.100	0.200	0.100
Poor (Lv_4)	0.000	0.000	0.000
$\sum Lv_i$	1.029	1.129	0.696
$\sum (O_i \times Lv_i)$	80.203	85.703	50.203
Quality index of RCC buildings	**77.914**	**75.885**	**72.127**

Table 16 Defuzzification of rating of RCC buildings for hardened state quality consideration

Label	Building 1	Building 2	Building 3
Excellent (Lv_1)	0.265	0.265	0.292
Good (Lv_2)	0.443	0.443	0.443
Fair (Lv_3)	0.111	0.333	0.443
Poor (Lv_4)	0.000	0.000	0.000
$\sum Lv_i$	0.819	1.042	1.178
$\sum (O_i \times Lv_i)$	63.211	75.433	83.859
Quality index of RCC buildings	**77.142**	**72.418**	**71.191**

4.2 Sensitivity analysis on the proposed fuzzy mathematical model

Using the Pearson correlation coefficient for multiple variables in a sensitivity analysis typically involves determining how the changes in each independent variable influence the dependent variable [54]. Here, the linear relationship between each independent and dependent variable was evaluated. Perform for each pair of variables to create a correlation matrix using the Pearson correlation coefficient formula, as shown in Equation 4.

$$Pearson \text{ correlation coefficient } (r) = \frac{\sum_{i=1}^{n} x_i y_i - \frac{1}{n}\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{\left[\sum_{i=1}^{n} x_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)^2\right]}\sqrt{\left[\sum_{i=1}^{n} y_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} y_i\right)^2\right]}} \quad (4)$$

Here, n = number of observations; x_i and y_i are dependent and independent values.

The closed interval [−1, +1] contains the coefficient values. A value of '+1' indicates a perfect positive correlation, a value of '-1' indicates a perfect negative correlation and a value of '0' indicates no correlation. When $r_{xy} > 0.70$, the correlation coefficient is deemed satisfactory; when $r_{xy} > 0.85$, it is considered very satisfactory [55]. The sensitivity analysis evaluated the performance of the proposed framework and assessed the correlation between the multiple variables. The quality indexes of the proposed model were determined by using five sets of proposed data with different values of quality attributes, as shown in *Table 17*.

The correlation matrix gives a pairwise overview of the Pearson correlation coefficients for each attribute in the dataset. Every attribute has a perfect correlation with itself, resulting in a symmetric matrix with diagonal entries that always comprise 1. The Correlation matrix, as shown in *Table 18*, indicates the values of independent variables (quality attributes) and dependent variables (quality index). Identify quality attributes with strong correlations with the target attributes, such as quality index. A highly satisfying relationship between the quality attributes and the quality indices is indicated by correlation coefficient values ranging between 0.8 and 1.0.

Table 17 Proposed data of quality attributes to perform sensitivity analysis

Descriptions	Set 1	Set 2	Set 3	Set 4	Set 5
Crushing Value (%)	17	22	30	28	30
Impact Value (%)	17	21	23	22	27
Abrasion Value (%)	22	25	27	25	28
Particle shape [elongated & flakiness] (%)	15	17	18	21	22
Fine Aggregate Grading (fineness modulus)	2.1	2.2	2.4	2.3	2.5
Water absorption [Fine aggregate] (%)	0.8	0.7	2.1	2.1	2.8
Elongation of reinforcement (%)	12	12.1	12.4	12.3	12.7
Quality Index	67.291	68.342	71.299	71.300	71.270

Table 18 Correlation matrix of proposed attributes and estimated quality index through fuzzy model

Attributes	Crushing value	Impact value	Abrasion value	Particle shape	Fine aggregate grading	Water absorption [Fine aggregate]	Elongation of reinforcement	Quality index
Crushing value	1	0.884	0.914	0.830	0.939	0.903	0.877	0.982
Impact value	0.884	1	0.964	0.866	0.965	0.865	0.962	0.817
Abrasion value	0.914	0.964	1	0.746	0.962	0.808	0.912	0.825
Particle shape	0.830	0.866	0.746	1	0.823	0.883	0.856	0.853
Fine aggregate grading	0.830	0.866	0.746	1.000	1	0.883	0.856	0.853
Water absorption [fine aggregate]	0.939	0.965	0.962	0.823	1.000	1	0.981	0.890
Elongation of reinforcement	0.903	0.865	0.808	0.883	0.934	1.000	1	0.922
Quality index	0.877	0.962	0.912	0.856	0.981	0.949	1.000	1

4.3Overall quality rating of considered RCC construction

The overall quality indexing model is based on the highest degree of quality of each attribute of every quality consideration. The numerical values of each quality consideration are combined through an arithmetic mean to form a holistic quality indexing of RCC construction. Certain attributes significantly influence the quality parameter of construction. This was due to the relative weightages of particular attributes, which significantly impacted the quality of RCC construction.

The overall quality rating of each building was the summation of all the parameters of material quality consideration, construction quality considerations, and hardened state quality considerations. The overall quality index of building 1: 76.847 was categorized as Excellent RCC construction, building 2: 73.883 was categorized as Good RCC construction, and building 3 was rated as Good RCC construction, having a quality index value of 72.221, as shown in *Figure 10*.

Building 1 received the highest overall quality rating (76.847) due to superior workmanship and the use of high-quality materials, which resulted in minimal cross-sectional deviations and enhanced compliance strength of RCC components. The elevated rating in material quality considerations was attributed to the improved properties of constituent materials used in Building 1. In terms of construction quality, Building 1 exhibited better compaction and more precise cross-sectional dimensions compared to the other two buildings, largely due to the effective use of high-quality formwork. This significantly reduced dimensional deviations and improved the structural performance of RCC elements. Furthermore, in the hardened state quality assessment, Building 1 achieved a higher rating due to its better-compacted concrete, enhanced resistance to water permeability, and well-maintained concrete cover. These factors collectively contributed to a robust and durable structural profile, reinforcing Building 1's superior quality index across all evaluation criteria.

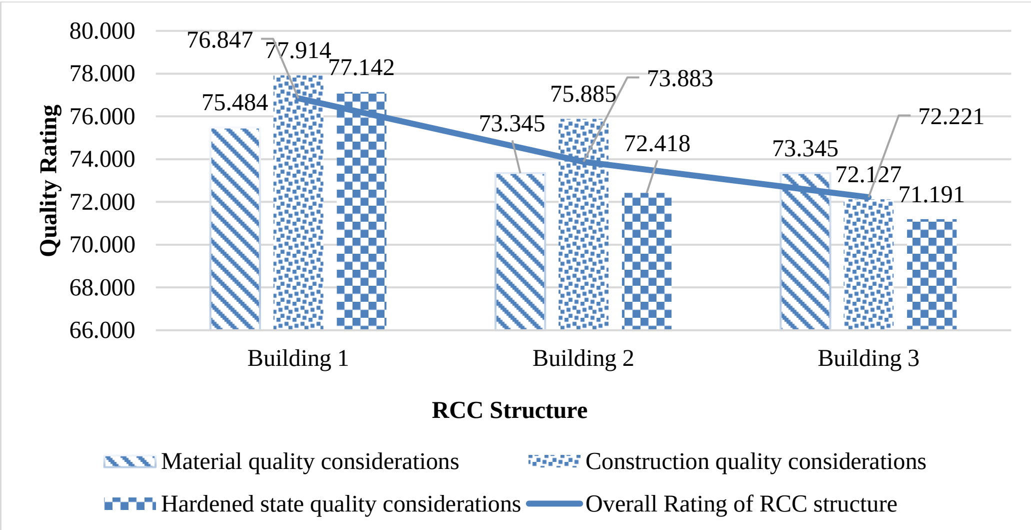

Figure 10 The overall quality rating of RCC structure of three buildings

5.Discussion

Concrete quality control is essential for reliable RCC construction, as it affects factors such as water content, aggregate size, surface texture, and angularity. The process considers various characteristics, such as aggregate, cement, reinforcement, water content, admixture, supervision, compaction, formwork deviation, workability, and homogeneity. Incorporating the fuzzy model and NDT techniques can effectively address construction-related issues like concrete quality and construction assessment. An expert system for quality evaluation and preliminary assessment criteria has been developed to help professionals make practical assessments.

Fuzzy set theory is a mathematical framework used in the construction industry to evaluate linguistic data, ensuring consistency and dependability in concrete quality. It uses fuzzy rules and reasoning to convert linguistic characteristics into logical descriptions, providing a degree of truthfulness similar to human thinking. The effectiveness of the fuzzy model is based on the shape and interval of fuzzy values. Defuzzification converts Ri into crisp values, optimizing model performance.

A comprehensive literature review was conducted to explore various dimensions of RCC quality assessment, with a specific focus on material quality considerations, construction quality considerations, and hardened state quality considerations. This review facilitated a deeper understanding of critical parameters influencing concrete construction quality, including workability, durability, compressive strength, and tensile strength. By examining existing research across these domains, the study established a foundational basis for evaluating and quantifying RCC construction quality through a structured and systematic approach. The overall quality assessment criteria in RCC construction comprised very few research investigations. A few studies have assessed the overall quality rating of RCC construction using a fuzzy model that incorporates condition evaluation of RCC structures. An effective way to assess the quality of an RCC structure is to combine the advantages of RCC construction with a fuzzy rule base.

This study aimed to develop a structured approach combining the fuzzy mathematical model with the relative importance of RCC attributes. The main goal of the suggested methodology was to use fuzzy mathematical models to assess the quality of the RCC structure. These models incorporate all identified attributes and their relative weights to generate a quality index measured on a scale of 100.

In the construction industry, quality is often assessed based on individual characteristics, which may not provide a comprehensive standard for overall quality assessment. The proposed fuzzy mathematical model, based on accepted codes of practice, integrates independent quality traits such as concrete cover, workability, and compressive strength. Assessments of overall construction quality can be ambiguous due to subjectivity, leading to variations in judgment among individuals. The proposed fuzzy model addresses this issue by providing a more objective evaluation, combining multiple quality attributes into a single numerical scale. To ensure a comprehensive and consistent assessment of building quality, this approach relies on both in situ and laboratory investigations guided by relevant standards and benchmarking norms.

This study used fuzzy mathematical modelling to rate the quality attributes of three RCC construction projects, assess their performance, and quantify the methods and workmanship of various construction agencies. The aim was to eliminate subjective evaluation from the overall RCC construction quality assessment. Three categories were created out of the chosen characteristics of RCC buildings: hardened state quality considerations, construction quality considerations, and material quality considerations. A triangular MF for different attributes was used to develop the fuzzy mathematical model, which was then validated by IS codes, the ACI, and literature. The study used a fuzzy mathematical model to analyze RCC constructions in Prayagraj, examining three buildings with G+10 to G+12 framed structures. Expert opinions, along with lab and in-situ values, validated the model's ability to analyze linguistic variables.

The crisp values of three RCC buildings were converted into fuzzy values using matrix methods, triangular MFs, and four linguistic values. The center-average defuzzification method then converted them back into crisp values. For example, the linguistic values of the crushing value were as follows: Excellent had a membership value of 0.929, Good had a membership value of 0.071, Fair had a membership value of 0, and Poor had a membership value of 0. The fuzzy composition matrix calculated material quality in RCC buildings by integrating relative weightage and Ri. The fuzzy composition values for the three buildings were 0.450, 0.500, and 0.500, respectively.

Under material quality considerations, Building 1 achieved the highest quality rating of 75.484, classified as Excellent, due to the superior quality of materials used compared to the other buildings. Buildings 2 and 3 both received a rating of 73.345, categorized as Good, indicating relatively similar material performance. In the construction quality assessment, Building 1 again outperformed the others with a score of 77.914 (Excellent), demonstrating a higher level of quality control and workmanship. This was notably higher than Building 2 (75.885, Good) and Building 3 (72.127, Good), highlighting Building 1’s superior execution of construction practices. The third aspect, hardened state quality, which evaluates parameters after the construction phase—such as curing time, water permeability, and concrete cover—also reflected Building 1’s excellence with a rating of 77.142 (Excellent). In comparison, Building 2 (72.418) and Building 3 (71.191) both fell into the Good category with marginal differences between them.

The overall quality rating further confirms these findings: Building 1 attained a quality index of 76.847, classified as Excellent RCC construction, while Building 2 (73.883) and Building 3 (72.221) were both categorized as Good. Building 1’s superior performance is attributed to its excellent workmanship, high-quality materials, reduced cross-sectional deviations, and enhanced compliance strength of RCC components. Additionally, effective compaction, improved water permeability resistance, and proper concrete cover—facilitated by efficient use of formwork—contributed significantly to its higher rating. The classification of Excellent signifies enhanced durability, greater structural strength, and superior overall performance when compared to lower tiers such as Good or Fair.

A complete list of abbreviations is listed in *Appendix I*.

Limitations

The primary drawback of the framework was its limitation to RCC construction projects. Adapting it to other industries would require continuous redefinition of associated parameters. Additionally, generating knowledge-based suggestions for a thorough assessment demands domain expertise. The method also involved rigorous mathematical calculations, which were time-consuming and prone to errors. Computer programs should develop and include relative weightage parameters in fuzzy modelling applications.

6.Conclusion and future work

The three quality considerations—material quality, construction quality, and hardened state quality—were used to assess and quantify RCC construction quality using a fuzzy mathematical model. This framework assesses RCC building quality by evaluating material, construction, and hardened concrete attributes. Material quality consideration involves evaluating the mechanical and physical properties of the constituent materials used in concrete production. The aggregate size distribution, fineness modulus, water absorption, and combined flakiness-elongation index are physical properties of both fine and coarse aggregates. The mechanical properties of coarse aggregate include impact, abrasion, and crushing values. Mechanical characteristics of reinforcement bars include the elongation of reinforcement, etc. Numerous construction quality factors have been considered, including achieving compliance strength on the job site and deviating from predetermined beam and column cross-section dimensions. Similarly, hardened quality considerations include concrete cover, minimum curing time, water permeability of concrete, etc. A systematic procedure for quality quantification of RCC construction has been proposed, considering the significant attributes of RCC construction facilities. The decision set or knowledge-based investigation developed a rule base and MFs. The fuzzy triangle MF serves as the basis for this quality category, which is categorized into four levels on a 100-point scale: Excellent: [75, 90, 100], Good: [55, 75, 90], Fair: [40, 55, 75], and Poor: [0, 40, 55]. The quality indexes of three RCC buildings, assessed using the fuzzy mathematical model, indicate that Building 1 has the highest construction quality, with an overall quality index of 76.847 out of 100. However, building 3 has the lowest quality of construction, with an overall quality index of 72.221, while the second-best quality index of building 2 was 73.883 on a scale of 100. Visual inspections and documented evidence, such as NDT results, have also confirmed the quality index. Numerical quality ratings for various buildings almost come under the same category. Still, it provides a definite value of quality in the form of a quality index, eliminating the subjective approach of quality evaluation and promoting numerical quantification. The proposed fuzzy mathematical model provides a standardized quality quantification method, reducing subjectivity in assessment and enabling a consistent quality index for RCC structures. The framework of a fuzzy mathematical model provides an edge for adding and modifying the attributes along with their relative weightage. This framework is also helpful in providing a competitive edge to construction companies, enhancing the overall quality of construction. The proposed model can be utilised in other sectors, such as roads, bridges, railways, etc, to obtain numerical determination of quality rating. The numerical quality indexing provides an integrated method for evaluating the quality of various facilities, regardless of their relationship to the RCC construction. Since the framework can rank construction facilities and prioritize projects, it serves as a crucial selection criterion for construction companies.

This model can be adapted to various fuzzy modeling platforms with modifications, such as adjusting the relative weightage of quality attributes. Future studies will evaluate the practicality of real-time applications. This research will be extended to develop a computer application integrating relative weights and knowledge-based criteria, aiming to create a universal fuzzy model for quality rating across various industries.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

The datasets generated and analyzed during this research are available from the corresponding author upon reasonable request.

Author’s contribution statement

Gaurav Singh: Analysis, procedures, information filtration, and graphics acquiring the original manuscript. **Laxmi Kant Mishra:** Writing-review, editing, conceptualization, visualisation, and supervision. **Virendra Kumar Paul:** Conceptualization, illustration, monitoring, and evaluation.

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Gaurav Singh is a research scholar in the Department of Civil Engineering at Motilal Nehru National Institute of Technology Allahabad, focusing on Concrete Quality Modeling. He completed his post-graduation in the field of Transportation Engineering in 2017.

Email: gauravsingh44511@gmail.com

Dr. Laxmi Kant Mishra is a Professor in the Department of Civil Engineering and currently serves as a dean of academics at Motilal Nehru National Institute of Technology (MNNIT) Allahabad, India. He has expertise in Structural Engineering & Concrete Technology, Construction Management, Building Science & Engineering. He holds a Ph.D. in Structural Engineering from MNNIT Allahabad, Prayagraj, and a postgraduate M.B.E.M. [Building Engineering & Management] from the School of Planning & Architecture, New Delhi.

Email: lkm@mnnit.ac.in

Dr. Virendra Kumar Paul is a Professor in the Building Engineering and Management department and currently serves as a director of the School of Planning and Architecture (SPA) Delhi, India. He has extensive experience in Indian architecture and building planning. He holds a Ph.D. and Master's in Building Engineering and Management. He also serves as a technical advisor on various building and construction projects.
Email: vk.paul@spa.ac.in.

Appendix I

S. No.	Abbreviation	Description
1	3D	Three-Dimensional
2	ACI	American Concrete Institute
3	AHP	Analytical Hierarchy Process
4	ANFIS	Adaptive Neuro-Fuzzy Inference System
5	ANN	Artificial Neural Network
6	FIS	Fuzzy Inference System
7	IS	Indian Standard
8	Lv_i	Individual Linguistic Value
9	ML	Machine Learning
10	MF	Membership Function
11	NDT	Non-Destructive Testing
12	O_i	Output Average Value of the Fuzzy Set
13	RCC	Reinforced Cement Concrete
14	R_i	Fuzzified Values
15	w_i	Individual Weightage