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Article

Fuzzy Logic Applications in Civil Engineering: A Structured Review of Methods, Applications, and Research Gaps

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Abstract: Civil engineering systems are complex because materials, construction processes, environmental circumstances, and human judgement interact. Statistics and determinism neglect engineering decision-making's subjectivity and ambiguity. Fuzzy logic has been a popular soft-computing method for modelling imprecise data using linguistic variables and rule-based reasoning in recent decades. This work examines fuzzy logic in reinforced concrete quality evaluation, structural and geotechnical engineering, and construction management. A representative selection of peer-reviewed research is analysed by application areas, fuzzy inference system (FIS) types (Mamdani and Takagi–Sugeno), membership function design, rule-base formulation, defuzzification approaches, and integration with MCDM and hybrid intelligent models Under uncertainty in limited or subjective data, fuzzy logic-based frameworks are interpretable, transparent, and flexible. Model calibration, validation robustness, repeatability, and scalability are research and methodological constraints. Future civil engineering research should support BIM-enabled decision-support frameworks and data-informed fuzzy systems.

Keywords: Fuzzy Inference System (Fis); Mamdani Model; Civil Engineering; Multi-Criteria Decision-Making (Mcdm).

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1. Introduction

Civil engineering projects are unpredictable due to material variability, construction techniques, environmental influences, and human judgment. Quality, safety, risk, and performance optimization choices sometimes involve incomplete, incorrect, or subjective data. Deterministic and probabilistic methods work well for well-defined systems, but civil engineering problems are typically confusing. One metric cannot characterize reinforced concrete quality. Instead, materials, workmanship, curing conditions, execution accuracy, and standards impact it. Classical threshold-based techniques with clear boundaries may oversimplify complex interactions, leading to inaccurate judgments. We need decision-support systems that integrate quantitative and qualitative expert knowledge. Fuzzy logic provides a good mathematical and computational model for these problems. By allowing partial membership and gradual state changes, fuzzy logic may explain engineering concepts, such as acceptable quality, moderate risk, and high durability. Civil engineering applications that need expert opinions, empirical observations, and numerical measurements benefit from fuzzy logic. FISs go through fuzzification, inference, and defuzzification [1].

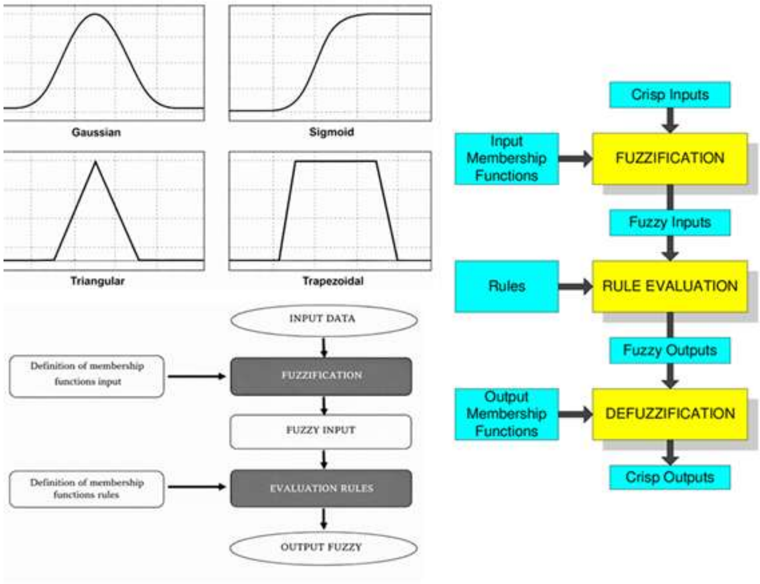


Figure 1. Broad civil engineering fuzzy logic system structure. Fuzzification blurs lab, field, and expert judgment data. Rule-based inference produces fuzzy outputs that are defuzzified into crisp values. Engineers use this paradigm to make ambiguous and difficult judgements [1].

Recent decades have seen fuzzy logic employed in structural, geotechnical, construction management, transportation systems, and water resources engineering. Researchers have proved its usefulness in quality indexing, safety assessment, contractor selection, risk analysis, and multi-criteria decision-making. When combined with AHP, artificial neural networks, and optimisation, fuzzy logic improves model robustness and decision accuracy. The literature is growing, although studies are scattered and focus on niche applications or case studies. Few thorough fuzzy logic technique evaluations, their usefulness across civil engineering fields, and research gaps exist. Variations in membership function design, rule-base formulation, and inference methods need more investigation [2].

This paper critically analyses fuzzy logic applications in civil engineering. The study synthesises and critically assesses peer-reviewed global publications by application areas, methodological frameworks, and integration approaches. This study examines merits, drawbacks, and future advances to enable civil engineering academics and practitioners build more reliable, transparent, and effective fuzzy-based decision-support systems [2].

Table 1. Functions of fuzzy inference system components in civil engineering.

Component	Description	Typical Role in Civil Engineering
Fuzzification	Converts crisp numerical inputs into fuzzy sets using membership functions	Transforms test results and field data into linguistic variables
Membership Functions	Define the degree of membership of inputs to fuzzy sets	Represent terms such as low, medium, and high quality

Rule Base	Collection of IF–THEN rules based on expert knowledge	Encodes engineering experience and standards
Inference Engine	Processes fuzzy rules to generate fuzzy outputs	Combines multiple criteria affecting performance
Defuzzification	Converts fuzzy outputs into a single crisp value	Produces quality indices or decision scores

Fuzzy logic applications in civil engineering are increasing quickly, although the literature is fragmented and methodological choices (e.g., membership function design, inference type selection, rule-base construction, and validation technique) are inconsistent. This work synthesises and critiques fuzzy logic-based civil engineering methods to address these issues [3].

1.1 The main objectives of this review are:

1. Summarize major fuzzy logic applications in civil engineering and research trends.

2. Classify fuzzy research by inference, membership function, and defuzzification.

3. To examine how fuzzy logic incorporates expert opinion and faulty field measurements into decision-support systems.

4. Compare fuzzy logic to ANN, ANFIS, and machine learning for interpretability and data demands.

5. To identify calibration, validation, scalability, and repeatability issues and propose a research plan for more reliable and implementable fuzzy frameworks.

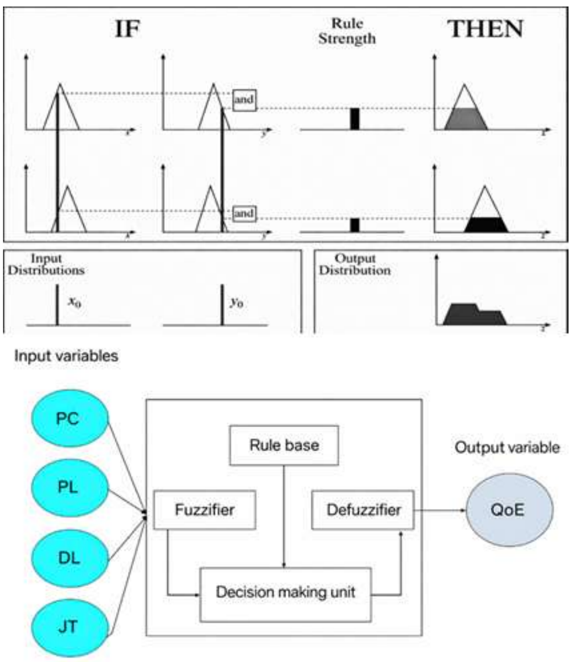


Figure 2. Popular civil engineering Mamdani-type fuzzy inference system structure. Crisp input fuzzification, fuzzy IF–THEN rule evaluation, rule output aggregation, and defuzzification give quantitative decision indicators.

Table 2. Key differences between fuzzy logic and deterministic civil engineering decision-making.

Aspect	Conventional Methods	Fuzzy Logic-Based Methods
Treatment of Uncertainty	Limited or ignored	Explicitly modeled
Input Data	Crisp numerical values	Crisp + linguistic variables
Expert Knowledge	Difficult to incorporate	Naturally integrated
Decision Boundaries	Sharp thresholds	Gradual transitions
Suitability for Complex Systems	Limited	High

1.2 Novelty of This Review

Novelly, the structured and methodology-oriented synthesis of fuzzy logic applications in civil engineering classifies studies by application domain and core fuzzy modelling components, such as inference system type, membership function design, rule-base formulation, defuzzification strategies, hybridisation approaches, and validation practises This study analyses methodologies and finds repeatability, calibration, and scalability difficulties, unlike previous reviews that focused on applications or presented findings descriptively. The paper directly relates fuzzy logic frameworks to digital construction environments, notably by combining fuzzy-based decision-support systems with BIM, revealing future research and application.

2. Methodology

To ensure openness, consistency, and replicability, this PRISMA-style systematic literature review gathered and synthesised civil engineering fuzzy logic research. Methodologically clear peer-reviewed research from key civil engineering fields was chosen and categorized. The protocol included several fuzzy logic applications in significant civil engineering disciplines and sought relevance and methodological clarity [4].

Review Design and Scope

Fuzzy logic-based decision-support and evaluation frameworks for civil engineering problems like reinforced concrete construction quality assessment, structural engineering condition evaluation, geotechnical stability assessment, construction management decision-making, transportation systems, and water resources were reviewed. The study assessed studies that used fuzzy logic as a modelling or decision-support tool in standalone fuzzy inference systems (FIS) or hybrid frameworks [4].

Data Sources and Search Strategy

Interdisciplinary studies on fuzzy logic applications in civil engineering were searched across Scopus, Web of Science, ScienceDirect, SpringerLink, and the ASCE Library using fuzzy modelling keywords (e.g., fuzzy logic, fuzzy inference system, Mamdani, Takagi–Sugeno, ANFIS) and civil engineering–related technical and managerial terms [5].

Eligibility Criteria (Inclusion and Exclusion)

Predefined inclusion and exclusion criteria were used to identify eligible papers that offer relevant and repeatable contributions to fuzzy logic applications in civil engineering to guarantee relevance to the study topic and methodological consistency [6].

This review included peer-reviewed journal articles or high-quality conference papers that explicitly addressed fuzzy logic in civil engineering and presented clearly defined fuzzy modelling structures with identifiable fuzzy inputs and outputs and at least one core methodological component, such as explicit membership function specification, rule-base development, fuzzy inference, etc. To apply to civil engineering issues, eligible research have to show quality indexing, risk evaluation, condition assessment, categorisation, ranking, or decision-support results [6].

The review excluded publications that were not directly related to civil engineering applications, mentioned fuzzy logic only superficially without a clear or reproducible methodological implementation, were duplicate records, editorials, non-scientific reports, or sources without a formal peer-review process. Research without sufficient methodological information to define and compare crucial fuzzy modelling traits was excluded to ensure analytical rigour and uniformity.

Screening and Selection Procedure (PRISMA-Style Workflow)

This review utilises PRISMA to search and identify relevant publications with openness, scientific rigour, and consistency. The initial identification stage used fuzzy logic and civil engineering application keywords to search academic databases for suitable publications. After then, a deduplication method removed duplicate items from many databases, guaranteeing that each study was screened once. After that, the titles and abstracts of the remaining records were carefully evaluated to remove non-fuzzy modelling or civil engineering studies. A full-text evaluation of remaining papers determined eligibility based on methodological clarity, fuzzy modelling implementation, and review scope relevance in the final step. This systematic selection approach preserved only qualitative synthesis and comparative analysis articles that matched review aims and data collection requirements [7].

Data Extraction and Classification Variables

For cross-domain comparability and methodological consistency, this review thoroughly extracted data from each study using a structured categorisation framework. The publication year, civil engineering application domain, and engineering problem type quality assessment, risk analysis, or stability classification were obtained [8]. Quantitative metrics, linguistic variables, and model outputs including indices, rankings, risk levels, and performance ratings were also collected. Each study was classed by fuzzy inference technique (Mamdani or Takagi–Sugeno) and membership function design (triangular, trapezoidal, Gaussian, or mixed). Documentation also examined expert-driven, hybrid, and data-assisted rule-base construction. Defuzzification technique information like centroid or mean-of-maxima enabled experiment comparison [9].

Final data extraction included fuzzy logic integration with hybrid or complementary methods like fuzzy-AHP, ANFIS, genetic algorithms, particle swarm optimisation, and machine learning, as well as each study's validation strategies like case studies, expert verification, benchmarking, or sensitivity-based analyses. Methodological trends, comparative assessment, and research requirements across civil engineering applications were synthesised using a detailed categorisation system [10].

Synthesis Approach

The included studies were synthesised using two complementary methods after extraction and classification:

- Grouped research by civil engineering field (structural, geotechnical, management, transportation, and water resources) for domain-based synthesis.
- Methodology-based synthesis compared fuzzy system properties (membership functions, inference processes, rule structures, hybridisation) across applications.

This structured synthesis identified prevalent methodological trends, recurrent restrictions, and research needs that affect fuzzy logic framework reliability and scalability in civil engineering.

Fundamentals of Fuzzy Logic

Mathematically, fuzzy logic describes complex system uncertainty, ambiguity, and imprecision. Unlike Boolean logic, fuzzy logic allows variables to have degrees of truth from 0 to 1. This makes replicating real-world engineering issues, particularly qualitative assessments and inadequate information, more realistic. Fuzzy logic uses fuzzy sets. Every fuzzy set element has a membership degree that defines its membership. Concrete compressive strength might be low, medium, or high. This adaptability helps civil engineering, where numerous elements change subtly. Membership functions translate input variables into degrees of membership between zero and one to construct fuzzy sets. The design and settings of membership functions strongly impact fuzzy model performance. Civil engineers use triangular, trapezoidal, and Gaussian membership functions. Membership function selection depends on data, expertise, and problem [10].

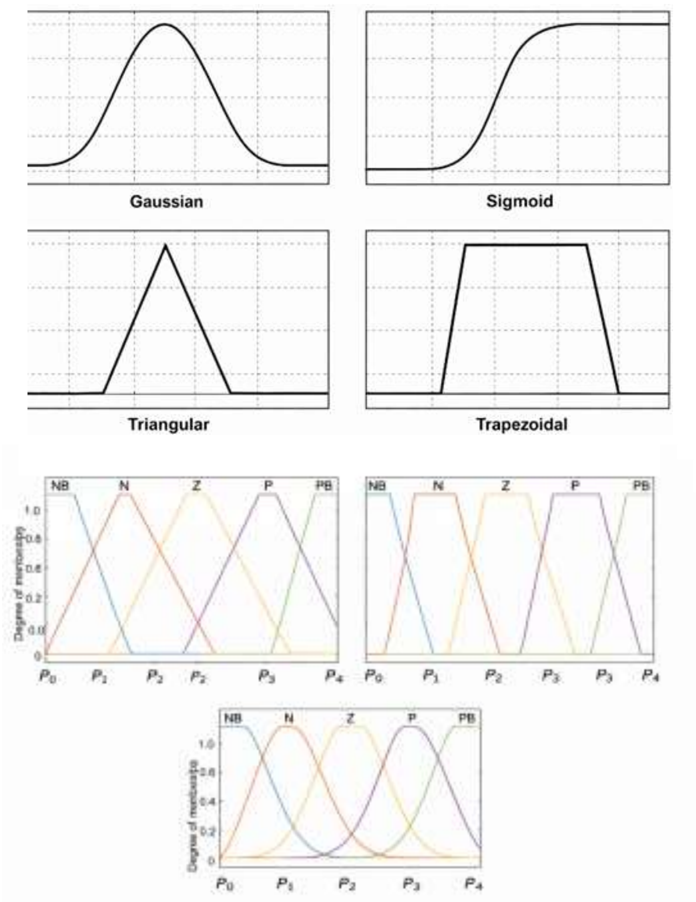


Figure 3. A fuzzy inference system (FIS) converts inputs to outputs in fuzzy logic [10].

The conventional FIS comprises three stages: fuzzification, inference, and defuzzification. Fuzzification uses specified membership functions to turn lab test, field measurement, and expert judgement values into fuzzy values. A rule base with IF–THEN statements is evaluated for inference input–output connections. Final defuzzification reduces fuzzy output into a clear value for decision-making or performance evaluation [11].

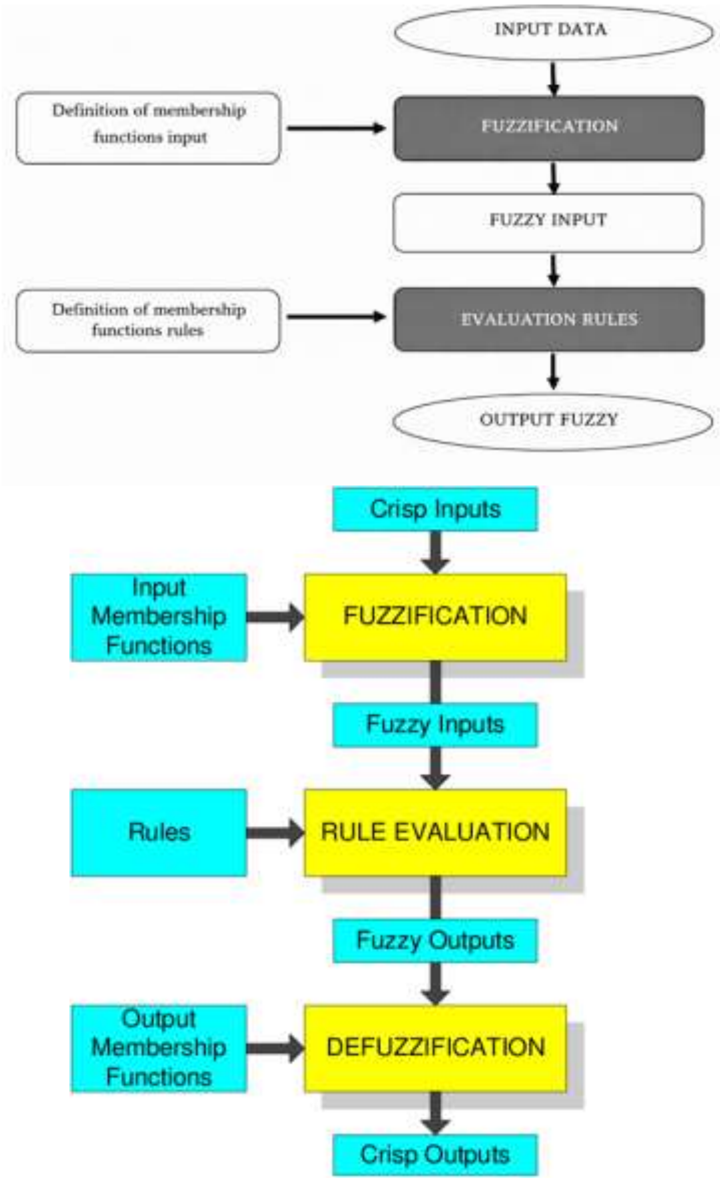


Figure 4. Mamdani- and Takagi-Sugeno-type fuzzy inference systems are employed in civil engineering research.

The intuitiveness and capacity to add expert reasoning via language standards make mamdani systems appealing. Takagi-Sugeno systems utilise mathematical functions in output rules for computationally efficient optimization and control. Fuzzy logic models are more transparent and interpretable than black-box AI. Engineers may directly analyse membership functions and rule bases to understand decision-making and build model confidence. Fuzzy logic can develop predictive models using multi-criteria decision-making and other AI technologies [12].

Table 3. Characteristics of commonly used membership functions in fuzzy logic-based civil engineering applications.

Membership Function	Shape	Advantages	Typical Applications
Triangular	Linear, simple	Easy to define and interpret	Preliminary assessments, limited data

Trapezoidal	Linear with plateau	Robust to small variations	Quality classification, decision support
Gaussian	Smooth, nonlinear	High accuracy and smooth transitions	Advanced modeling, data-driven systems

Literature Review

Fuzzy logic has emerged in civil engineering during the past 30 years to overcome ambiguity, subjectivity, and inadequate information in engineering decision-making. Fuzzy logic may replace deterministic systems, however current research focuses on hybrid models, performance optimisation, and real-world application. One of fuzzy logic's earliest and most renowned civil engineering applications was reinforced concrete quality assessment. Material quality, skill, curing conditions, and needs impact construction quality, researchers discovered. Traditional pass–fail criteria didn't represent quality change. Fuzzy-based quality indices combine qualitative and quantitative data into one performance score [13].

Structural engineers employ fuzzy logic for safety, damage, and health monitoring. Multiple studies employed fuzzy inference to classify structural condition states by fracture width, deflection, vibration, and material deterioration. Fuzzy models were more flexible and interpretable than standard safety factors, particularly for expert assessment. Geotechnical engineering applications including soil classification, slope stability analysis, and foundation performance assessment are questionable. Laboratory results, field observations, and expert knowledge have been merged using fuzzy logic due to soil quality variations and sparse site research data. Example: Fuzzy-based slope stability models reduce input parameter uncertainty [14].

Fuzzy logic is used in construction management for contractor selection, risk assessment, cost computation, and schedule review. Several studies employed fuzzy logic and multi-criteria decision-making methodologies like the Analytical Hierarchy Process to reduce subjectivity and enhance ranking alternatives. Decision-makers may integrate numerical and verbal data using these hybrid methods. Although beneficial, the literature mentions several downsides. Membership function selection, rule-base creation, and defuzzification may generate research inconsistencies. Case-specific solutions hinder generalisation and uptake in many applications. These results underline the need for extensive assessments and comparative studies to identify best practices and research goals [15].

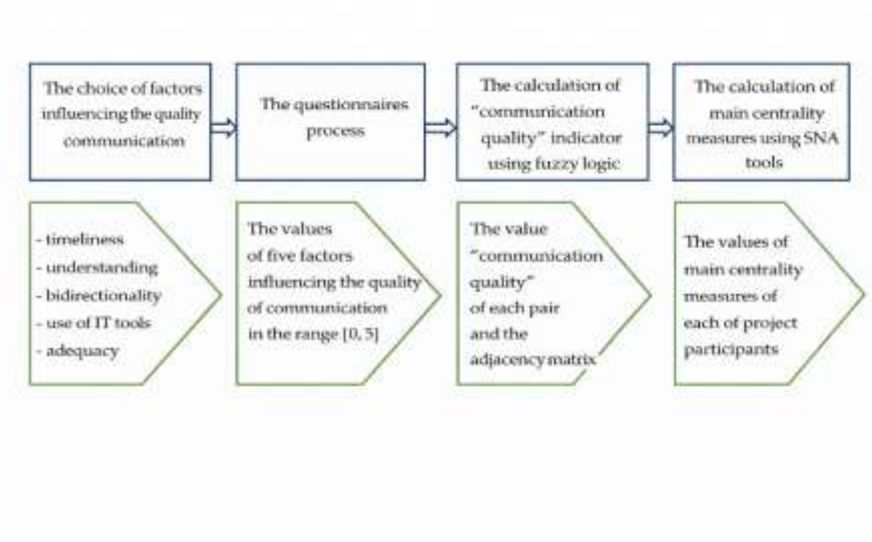


Figure 5. Example of fuzzy logic-based civil engineering decision-making that integrates technical data, expert judgement, and language factors for quality and performance evaluation [15].

Table 4. Enhanced comparative summary of representative fuzzy logic studies in civil engineering.

Application Area	Representative Study	Main Objective	Fuzzy Technique Used	Main Inputs (Examples)	Output / Decision Indicator	Key Findings
Bridge / Infrastructure Risk Assessment	Wang & Elhag (2007)	Bridge risk evaluation under uncertainty	Fuzzy group decision-making	Multiple risk criteria + expert judgments	Risk level score / ranking	Effective aggregation of subjective judgments within a consistent decision framework
Construction Risk Assessment	Ahn et al. (2013)	Construction risk assessment and prioritization	Fuzzy logic model	Qualitative & quantitative risk factors (safety, cost, schedule)	Risk index / level	Improved handling of linguistic risk descriptions and prioritization under uncertainty
Decision-Making / Contractor Selection	Zavadskas et al. (2015)	Contractor selection under multiple criteria	MCDM (often hybridizable with fuzzy)	Cost, time, quality, capability, experience	Ranking / selection decision	Demonstrates importance of multi-criteria structures commonly integrated with fuzzy-AHP frameworks

Emerging Direction: BIM + Fuzzy	Zhang et al. (2023)	Integration of fuzzy logic within BIM for quality management	Hybrid fuzzy–BIM decision support	Project digital information + uncertainty parameters	Quality control support	Demonstrates growing trend of fuzzy logic adoption in digital construction environments
Environmental / Water Resources	Chang et al. (2001)	Water quality identification and evaluation	Fuzzy synthetic evaluation	Water quality indicators (chemical/physical parameters)	Water quality class/index	Robust classification despite measurement uncertainty and natural variability
Fuzzy MCDM Foundations (Decision Support)	Chen & Hwang (1992)	Fuzzy multiple attribute decision making	Fuzzy MADM framework	Multi-criteria inputs in fuzzy environment	Ranking / decision output	Provides theoretical decision-support basis widely used in civil engineering fuzzy-MCDM models
Fuzzy TOPSIS Method Basis	Chen (2000)	Group decision-making under fuzzy environment	Fuzzy TOPSIS extensions	Fuzzy ratings + weights	Closeness coefficient ranking	Supports fuzzy ranking and selection problems relevant to engineering decision-making

Geotechnical: Slope Stability	Juang & Lee (2007)	Stability analysis under uncertain soil parameters	Fuzzy sets + expert rules	Soil shear strength, slope geometry, groundwater condition	Stability class / assessment	Reduced sensitivity to uncertain soil parameters compared to crisp safety factor-only approaches
Reinforced Concrete Quality	Huang & Hsieh (2012)	Construction quality evaluation	Mamdani-type FIS	Material/workmanship indicators, inspection results	Quality index / rating	Improved representation of gradual quality variations and reduced rigid pass/fail decisions
Structural Safety / Health Monitoring	Lee & Kim (2012)	Damage detection and condition assessment	Fuzzy rule-based inference	Damage-sensitive parameters (e.g., vibration features, inspection indicators)	Condition/damage level	Enhanced interpretability and ability to incorporate uncertain inspection data

Table 4 shows that fuzzy logic is used in civil engineering for assessment, categorisation, and uncertainty-based decision-support. Fuzzy frameworks are more interpretable than black-box learning methods and allow field data and language expert judgement to be combined. To improve repeatability and scalability, the evaluated research suggest greater validation techniques and clearer reporting of membership function parameters and rule-base structures.

Table 5. Classification framework for fuzzy logic studies in civil engineering.

Classification Dimension	Items (Examples)	Why It Matters
Application Domain	Structural, Geotechnical, Construction Management,	Enables domain-based comparison

	Transportation, Water Resources	
Defuzzification	Centroid, MOM, SOM/LOM	Converts fuzzy outputs into crisp decisions
FIS Type	Mamdani, Takagi–Sugeno, Hybrid	Impacts interpretability and computational behavior
Hybrid Models	Fuzzy-AHP, ANFIS, Fuzzy-Optimization (GA/PSO)	Enhances robustness and accuracy
Main Decision Task	Quality indexing, risk assessment, contractor selection, condition rating, stability classification	Clarifies the practical role of fuzzy logic
Membership Functions	Triangular, Trapezoidal, Gaussian	Affects smoothness and sensitivity
Rule-Base Design	Expert-based, data-assisted, hybrid	Determines transparency and reproducibility
Validation	Case study, expert validation, benchmarking, sensitivity analysis	Determines reliability and generalization

3. Results and Discussion

Applications of Fuzzy Logic in Civil Engineering

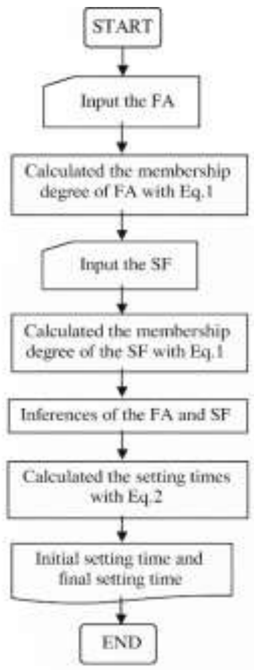
Applications in Structural Engineering

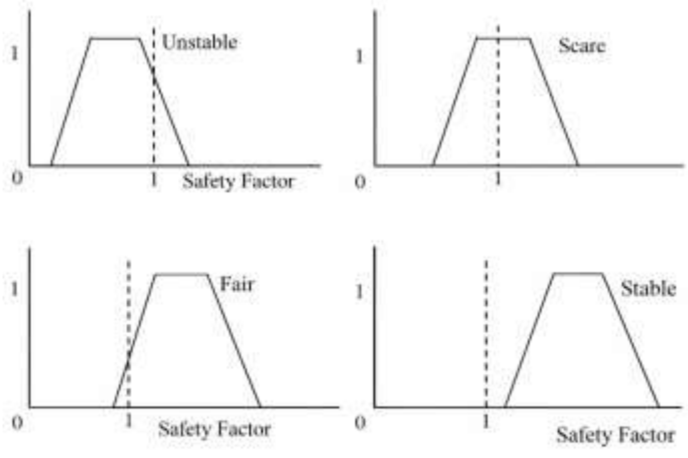
Material degradation, loading changes, environmental exposure, and poor inspection data increase structural engineering uncertainty. Traditional design and assessment methods employ deterministic safety factors, which may not reflect structural conditions. Fuzzy logic, which utilises quantitative data and qualitative expert opinions, is often employed to circumvent these constraints. Crack width, deflection, corrosion level, vibration characteristics, and visual inspection results are used in fuzzy inference algorithms to evaluate structural status. Fuzzy methods identify structural condition levels as good, moderate, and severe using linguistic variables instead of binary assessments [16].

Maintenance and structural reliability evaluations employ fuzzy logic. Fuzzy-based deterioration models prioritized maintenance and rehabilitation in many studies. Fuzzy models were more flexible and transparent than earlier systems, allowing engineers to monitor how elements influenced the final result. Optimization, fuzzy logic, and artificial neural networks increase structural application prediction. The hybrid models use data-driven learning with fuzzy rule-based interpretability [17].

Applications in Geotechnical Engineering

Spatial variability of soil properties, limited site investigation data, and measurement errors make geotechnical engineering uncertain. Fuzzy logic solves problems by combining laboratory test results, field observations, and expert opinion. In geotechnical engineering, slope stability analysis uses fuzzy logic. To measure stability, fuzzy models use soil strength metrics, slope geometry, groundwater conditions, and loading effects [18]. These models reduce uncertainty sensitivity and classify stability more realistically than factor-of-safety methods. Soil categorization and foundation performance assessment employ fuzzy logic. By allowing partial soil category membership, fuzzy models describe gradual soil type changes in reality. This improves foundation design in marginal or diversified soils [19].





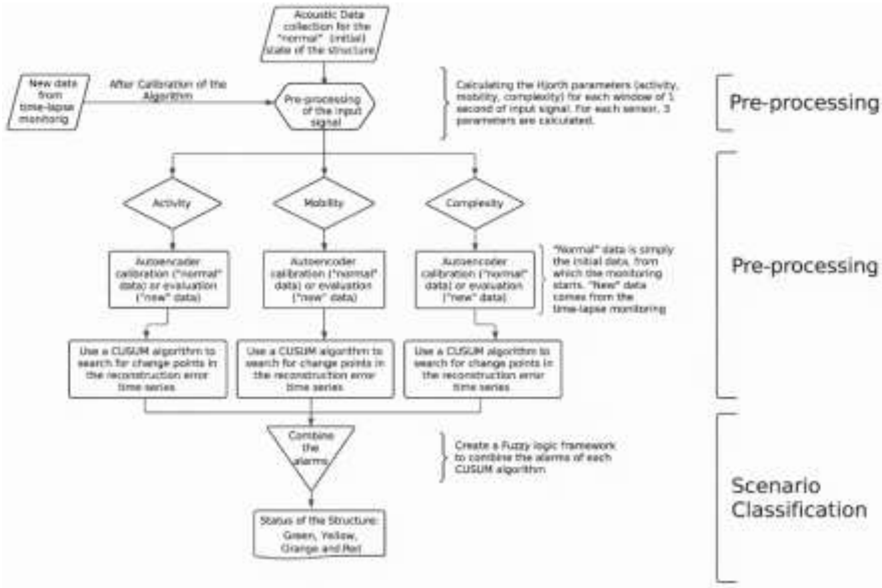


Figure 6. Representative applications of fuzzy logic in structural and geotechnical engineering, including structural condition assessment, damage classification, and slope stability evaluation under uncertain conditions [19].

Table 6. Summary of fuzzy logic-based applications in structural and geotechnical engineering.

Engineering Field	Typical Inputs	Fuzzy Output	Main Benefit
Foundation Assessment	Soil parameters, load conditions	Suitability level	Better handling of soil variability
Slope Stability	Soil strength, geometry, groundwater	Stability class	Reduced uncertainty sensitivity
Structural Engineering	Crack width, deflection, corrosion level	Structural condition index	Improved damage interpretation
Structural Maintenance	Age, exposure, deterioration indicators	Maintenance priority	Transparent decision support

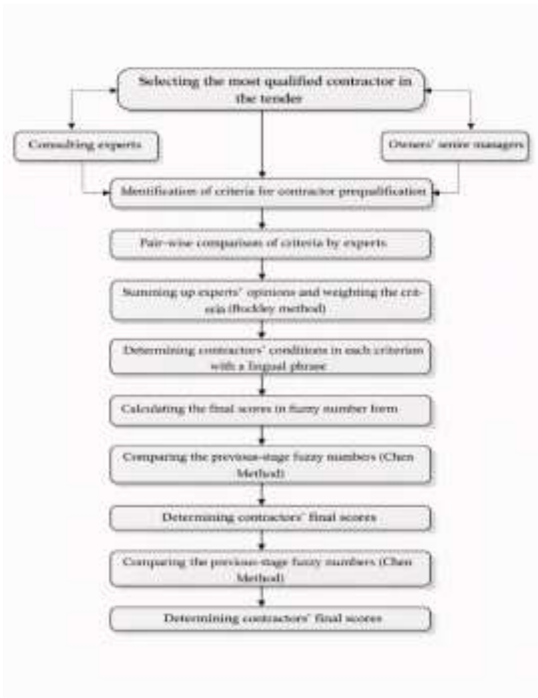
Applications in Construction Management

Construction management decisions are influenced by cost, time, quality, safety, and risk. Traditional quantitative methods cannot evaluate numerous qualitative elements, which depend on expert interpretation. For decision-making, fuzzy logic is commonly utilised in construction management. This region heavily employs fuzzy logic for contractor selection. Decision-makers may assess contractors using numerical (bid price, experience) and verbal (reputation, technical expertise) elements in fuzzy models. Researchers have shown that fuzzy logic and multi-criteria decision-making methods like the Analytical Hierarchy Process diminish contractor rating subjectivity and inconsistency [20].

Risk assessment and management employ fuzzy logic extensively. Construction safety, schedule delays, cost overruns, and environmental impacts are difficult to assess. Language-based fuzzy risk assessment tools assist managers identify hazards and mitigation priorities. Cost estimation and schedule performance evaluation use fuzzy logic. Fuzzy models accommodate for productivity, resource, and external variable uncertainty to provide more accurate forecasts than deterministic ones. These examples show fuzzy logic's use in complex uncertainty-based management decisions [21].

Applications in Transportation and Water Resources Engineering

Transportation and water resources engineering systems are dynamic, demand variable, and data limited. Fuzzy logic enhances system performance assessment and decision-making in several fields. Transportation engineers evaluate traffic congestion, service, and route selection using fuzzy logic models. Language indicates traffic, trip duration, and driving behaviour. Fuzzy traffic assessment methods are more flexible than threshold-based. For flood risk assessment, reservoir operation, and water quality evaluation, water resources engineering uses fuzzy logic. Measurement mistakes and natural variability render hydrological and environmental data inaccurate. Fuzzy models enhance decision-support systems by combining quantitative hydrological data with qualitative expert opinions [22].



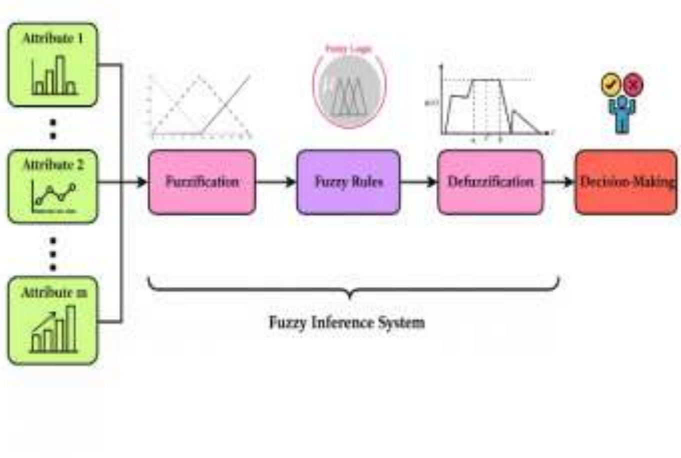


Figure 7. Fuzzy logic helps building, transportation, and water resources engineers make uncertain, multi-criteria decisions [22].

Table 7. Representative applications of fuzzy logic in construction management, transportation, and water resources engineering.

Application Domain	Decision Problem	Fuzzy Model Type	Main Advantage
Construction Management	Contractor selection	Fuzzy AHP	Reduced subjectivity
Construction Risk	Risk prioritization	Fuzzy linguistic model	Improved risk interpretation
Cost Estimation	Budget forecasting	Fuzzy inference system	Realistic estimates
Transportation	Traffic level of service	Fuzzy rule-based model	Adaptive classification
Water Resources	Flood risk assessment	Fuzzy multi-criteria model	Robust handling of uncertainty

Comparison with Other Artificial Intelligence Techniques

Recently, civil engineering problems have been solved using ANN, ANFIS, and ML algorithms. Situation, data, and decision-making demands determine the benefits and downsides of each strategy. Understanding fuzzy logic's advantages over other modelling methods helps choose the right one. Data-driven artificial neural networks may depict complex nonlinear input-output relationships. ANN models work well for civil engineering strength, damage, and performance forecasts. ANN models are often uninterpretable black boxes. Lack of transparency may diminish model output credibility, particularly in safety-critical engineering [23].

Neural network learning and fuzzy logic interpretation are in ANFIS models. These hybrid systems adjust membership functions and fuzzy rules based on training data to improve prediction accuracy. Despite its accuracy and interpretability, ANFIS requires massive datasets and computer power that many civil engineering applications lack. Support vector machines and decision trees are popular machine learning algorithms for their predictive strength and adaptability. These methods work for large datasets and complex pattern recognition. ANN models and other ML methods lack transparency and do not include qualitative expert knowledge [24].

Language thinking and uncertainty are explicitly represented by fuzzy logic. Unlike data-driven solutions, fuzzy logic models include expert opinion, technical knowledge, and qualitative assessments. Decision-support systems, quality assessment frameworks, and data-poor challenges benefit from fuzzy logic. Fuzzy models may have lower prediction accuracy than advanced machine learning algorithms in data-rich environments, but their transparency, flexibility, and resilience under uncertainty are practical advantages [25].

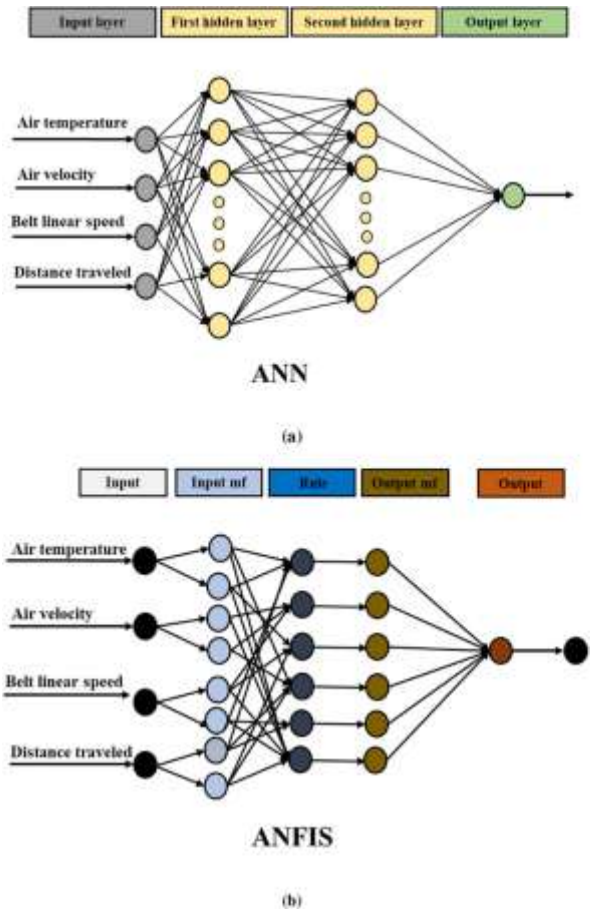


Figure 8. Conceptual comparison of fuzzy logic with other artificial intelligence techniques, highlighting differences in interpretability, data dependency, and suitability for uncertainty-driven engineering problems [25].

Table 8. Comparative assessment of fuzzy logic and commonly used AI techniques in civil engineering applications.

Criterion	**Fuzzy Logic**	**ANN**	**ANFIS**	**Machine Learning**
Interpretability	High	Low	Medium	Low–Medium
Handling Uncertainty	Explicit	Implicit	Explicit	Implicit
Data Requirement	Low–Medium	High	High	High
Integration of Expert Knowledge	Easy	Difficult	Moderate	Difficult
Computational Complexity	Low	Medium	High	High
Suitability for Decision Support	Very High	Moderate	High	Moderate

Discussion and Research Gaps

In civil engineering, fuzzy logic is a mature and frequently utilised method for addressing uncertainty and subjectivity, according to literature. In structural, geotechnical, construction management, transportation, and water resources, fuzzy models exceeded deterministic ones. Quantitative data and qualitative expert opinion work well with fuzzy logic in decision-support and quality evaluation systems. Despite these talents, methodological issues and research gaps persist. Subjective membership functions and rules are a problem. Many research define membership functions without calibration or sensitivity analysis using expert opinion. It may corrupt fuzzy models and prevent replication [26].

Many evaluations note inadequate validation and replication. Fuzzy logic models are effective for decision-making, although some research utilise single-case presentations, subjective membership function selection, and qualitative verification without calibration. Comparing project outcomes, transferring frameworks, and determining performance objectives are difficult. To improve fuzzy-based decision-support system reliability and adoption in civil engineering, future research should focus on multi-project validation, sensitivity analysis, data-driven parameter calibration, and standardised reporting of membership function parameters, rule-base size, and defuzzification Poor fuzzy model validation and generalisation is another issue. Many studies use tiny datasets or single projects for case-specific applicability. These studies show feasibility but not scalability or performance under different environmental and operational circumstances. Long-term monitoring validation and multi-site data have constraints [27].

The research also found civil engineering fuzzy logic implementation frameworks lacking. Differences in inference systems, defuzzification, and integration make study comparisons challenging. Fuzzy logic, machine learning, and optimisation hybrid models are promising, but data availability and processing restrict their application. To balance interpretability and prediction accuracy, future research should employ data-driven and hybrid fuzzy frameworks. Fuzzy logic in BIM, sensor-based monitoring, and real-time decision-support systems seem promising. Membership function design, rule formulation, and model validation standards may increase fuzzy-based engineering solutions' dependability and acceptability [28].

Table 9. Research gaps and recommended future research directions in fuzzy logic applications.

Identified Gap	**Description**	**Suggested Future Direction**
Hybrid Model Complexity	High data and computational demands	Efficient hybrid and reduced-complexity models
Lack of Standardization	Diverse fuzzy modeling approaches	Development of unified frameworks
Limited Validation	Case-specific and small-scale studies	Multi-project and long-term validation
Scalability Issues	Limited application to large systems	Integration with BIM and monitoring systems
Subjective Membership Design	Reliance on expert judgment without calibration	Data-driven and adaptive membership functions

Integration of Fuzzy Logic with Building Information Modeling (BIM)

Fuzzy logic with BIM may enhance uncertainty-based decision-making in digital construction. BIM uses data to depict construction projects throughout time, whereas fuzzy logic manages imprecise, incomplete, and linguistic data. Construction quality assessment, risk management, sustainability evaluation, and maintenance planning may benefit from fuzzy logic in BIM. Fuzzy-based decision-support models in BIM environments may improve transparency, reasoning, and decision-making in complex civil engineering projects. Fuzzy logic and BIM integration needs further research on interoperability, data standardisation, and real-time application [29].

Table 10. Advantages and Limitations of Fuzzy Logic in Civil Engineering Applications.

Aspect	Advantages	Limitations
Data Requirement	Works well with limited data	Lower accuracy with large datasets
Decision Support	Suitable for multi-criteria problems	Requires careful model calibration
Expert Knowledge	Easy incorporation of expert judgment	Subjectivity in rule formulation
Handling Uncertainty	Explicit representation of vagueness	Depends on membership function design
Interpretability	High transparency and explainability	Rule explosion for complex systems

Practical Implications

From an engineering practice perspective, fuzzy logic provides a highly interpretable platform for combining measured data with expert judgment in situations where uncertainties are unavoidable. For structural engineers, fuzzy-based systems support condition rating and maintenance prioritization using inspection indicators that are often uncertain or linguistic. For geotechnical engineers, fuzzy models enable more realistic classification and stability assessment under limited site investigation data. In construction management, fuzzy decision-support systems reduce subjectivity in contractor selection and risk prioritization by translating qualitative evaluations into consistent decision metrics. These practical benefits highlight the potential of fuzzy logic to enhance transparency and decision quality in civil engineering projects, particularly when integrated with modern digital construction environments [30].

Future Research Agenda

Civil engineering fuzzy logic research should promote standardised models and reporting frameworks for transparency, reproducibility, and cross-study comparability. Prioritise data-assisted and adaptive calibration of membership functions and rule bases to reduce subjectivity and increase model robustness. Beyond single-case demonstrations, future research should incorporate multi-project, multi-region, and long-term validation, sensitivity analysis, and benchmarking against existing decision-support and machine learning models. Fuzzy logic should be connected with BIM, sensor-based monitoring systems, and real-time data platforms to provide scalable and dynamic decision-support applications throughout the infrastructure lifetime. Creating computationally efficient hybrid fuzzy frameworks like reduced-complexity ANFIS or fuzzy–optimization models that balance interpretability and prediction accuracy is difficult. These study topics will convert fuzzy logic from academic implementations to reliable, scalable, and deployable civil engineering decision-support systems [31].

4. Conclusion

This systematic research examined fuzzy logic's ability to resolve ambiguity, vagueness, and subjectivity in complex civil engineering decision-making. Fuzzy logic clearly and adaptably integrates quantitative data with qualitative expert opinion in structural evaluation, geotechnical analysis, construction management, and risk assessments. Fuzzy algorithms outperform black-box AI in data-limited scenarios, rank performance incrementally, and are more interpretable than deterministic techniques. Subjective membership function design, inadequate validation, and unstandardised implementation exist in the literature. Future research should emphasise data-assisted calibration, rigorous validation methods, and fuzzy logic integration with digital platforms like Building Information Modelling to increase civil engineering scalability and practical applicability.

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