International Journal of Advanced Engineering Research and Science (IJAERS)
Peer-Reviewed Journal
ISSN: 2349-6495(P) | 2456-1908(O)
Vol-13, Issue-9; Sep, 2026
Journal Home Page Available: https://ijaers.com/
Article DOI: https://dx.doi.org/10.22161/ijaers.139.3

AI-Based Durability Prediction of RCC Buildings with Floating Columns using STAAD.Pro Analysis

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Received: 18 Aug 2026,

Received in revised form: 15 Sep 2026,

Accepted: 18 Sep 2026,

Available online: 24 Sep 2026

***Keywords*— Artificial Intelligence, RCC Buildings, Floating Columns, Durability Prediction, STAAD.Pro, Structural Analysis, Machine Learning, Structural Safety.**

***Abstract*— The use of floating columns in reinforced cement concrete (RCC) buildings can significantly influence structural load transfer, stiffness, and durability, particularly under complex loading conditions. This review examines the application of Artificial Intelligence (AI) for predicting the durability and structural performance of RCC buildings with floating columns using STAAD.Pro analysis. The study reviews existing research on AI-based prediction techniques, structural modeling, load analysis, material behavior, and durability assessment. STAAD.Pro is considered as a computational platform for evaluating structural responses, while AI techniques can be used to identify patterns and predict performance-related parameters. The review highlights the potential of integrating AI with structural analysis to improve durability prediction, optimize design decisions, and support safer and more efficient RCC building design.*

I. INTRODUCTION

Reinforced Cement Concrete (RCC) buildings are widely used in modern construction because of their strength, durability, versatility, and ability to withstand different types of structural loads. With increasing urbanization and demand for functional architectural spaces, irregular building configurations have become common. One such configuration is the use of floating columns, where columns do not continue directly to the foundation but terminate at a beam or slab and transfer their loads to other structural members [1]. Although floating columns provide greater flexibility in architectural planning, they can create discontinuities in the load-transfer mechanism and may significantly affect the overall structural behavior of the building [2].

The presence of floating columns can influence important structural parameters such as storey displacement, lateral drift, bending moments, shear forces, stiffness, load distribution, and overall stability. These effects become particularly important when buildings are subjected to earthquake, wind, and other dynamic loads. Inadequate consideration of these irregularities may lead to undesirable stress concentrations and reduced structural performance. Therefore, reliable structural analysis is essential for evaluating RCC buildings incorporating floating columns [3].

STAAD.Pro is a widely used structural analysis and design software that enables engineers to model complex building configurations and evaluate their behavior under various loading conditions [4]. It can provide important structural responses such as axial forces, bending moments, shear forces, deflections, and support reactions. STAAD.Pro analysis can therefore serve as an important source of structural data for assessing the performance and durability of RCC buildings with floating columns [5].

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques have gained considerable attention in civil and structural engineering. AI-based models can process large datasets and establish relationships between structural parameters and performance indicators. Techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and other machine-learning approaches can potentially be used to predict structural response and durability-related parameters without performing detailed numerical analysis for every design condition [6].

The integration of AI-based prediction with STAAD.Pro analysis provides an emerging approach for improving the assessment of RCC structures. Results obtained from STAAD.Pro can be used to develop datasets containing structural and material parameters, which can subsequently be analyzed using AI techniques to predict durability and performance. Such an approach can reduce computational effort, support early identification of potentially vulnerable structural configurations, and assist engineers in making informed design decisions.

This review focuses on existing research concerning AI-based durability prediction of RCC buildings with floating columns using STAAD.Pro analysis. It examines the structural behavior associated with floating columns, the application of STAAD.Pro for structural assessment, the use of AI and ML techniques for prediction, and the potential integration of numerical analysis with intelligent prediction models. The review also identifies existing research gaps and discusses future opportunities for developing reliable AI-assisted frameworks for durability and structural safety assessment of irregular RCC buildings.

II. FLOATING COLUMNS

A floating column is a vertical structural member that terminates at an intermediate floor or beam instead of extending continuously to the foundation. Its load is transferred to a supporting beam, girder, or other structural element, which subsequently transfers the load to the columns and foundations below. Floating columns are commonly introduced in RCC buildings to satisfy architectural and functional requirements, such as providing large column-free spaces for parking, commercial areas, auditoriums, lobbies, or other open spaces [7].

In a conventional RCC framed structure, columns generally extend continuously from the foundation to the upper floors, providing a relatively direct and continuous load-transfer path. In contrast, the introduction of a floating column creates a vertical discontinuity in the structural system [8]. The gravity load from the floating column is transferred horizontally through the supporting beam before reaching the lower structural elements. Consequently, the supporting beam may experience significantly higher bending moments and shear forces than those in a conventional frame.

Floating columns can provide considerable architectural flexibility. For example, upper floors may require several columns to support residential or office spaces, while the ground floor may require a large open area for vehicle parking. Instead of continuing all upper-storey columns to the foundation, selected columns can be terminated at the first-floor level and supported by transfer beams. This arrangement allows architects and engineers to create more usable space; however, it also increases structural complexity [9].

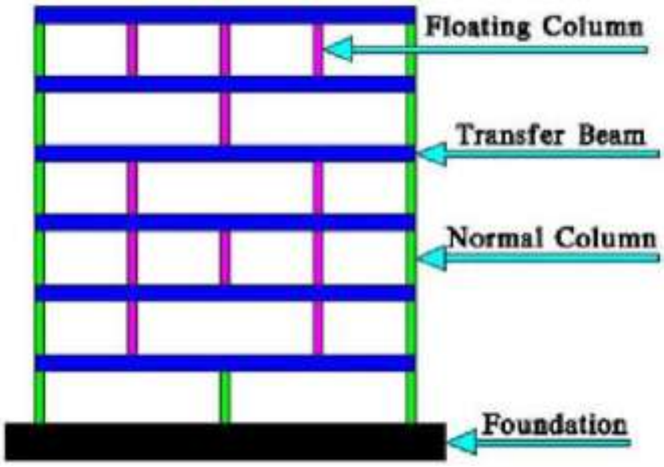

Fig.1. Floating column.

III. FLOATING COLUMNS IN STAAD.PRO ANALYSIS

STAAD.Pro can be used to model RCC buildings with and without floating columns and evaluate their structural response under different loading conditions. The model can incorporate building geometry, material properties, member dimensions, support conditions, dead loads, live loads, wind loads, and seismic loads [10]. The resulting analysis provides structural parameters that can be used to assess the behavior of floating-column systems.

For an AI-based durability prediction study, the results generated through STAAD.Pro can also serve as input data for machine-learning models [1]. Parameters such as axial force, bending moment, shear force, displacement, drift, stress, material properties, loading conditions, and structural configuration can be considered as potential input variables for predicting durability or performance-related indicators.

IV. IMPORTANCE IN DURABILITY PREDICTION

Although floating columns are primarily associated with structural irregularity and load transfer, their behavior can also influence the long-term durability of RCC structures [5]. Increased stresses, excessive deformation, cracking, and localized deterioration may contribute to reduced serviceability and durability over time. Environmental factors such as moisture, temperature variations, carbonation, chloride exposure, and corrosion of reinforcement can further affect the long-term performance of the structure [11].

Consequently, integrating STAAD.Pro-based structural analysis with AI techniques offers the possibility of developing predictive models capable of identifying potentially vulnerable structural conditions. Such models can support early assessment, maintenance planning, structural optimization, and improved decision-making [12-15].

V. REVIEW OF LITERATURE

1. Taffese et al. (2024)

Taffese et al. [1] investigated the application of machine-learning techniques for predicting the aging factor of concrete, which is an important parameter for durability-based reinforced concrete design. The researchers evaluated seven machine-learning algorithms, including Bagging, Random Forest, AdaBoost, Gradient Boosting, XGBoost, CatBoost, and LightGBM. The study considered parameters such as cement type, cement content, pozzolan content, water-to-binder ratio, exposure condition, and concrete age. The findings demonstrated that machine-learning models can effectively capture complex relationships between concrete characteristics and aging behavior. The study highlighted the potential of AI-based approaches for improving durability prediction and supporting performance-based RCC design.

2. Zhang et al. (2024)

Zhang et al. [2] developed a hybrid back-propagation neural-network approach for predicting the durability of reinforced concrete. The researchers developed a BPNN model and incorporated particle swarm optimization to improve its prediction capability. Concrete mix proportions and material-related parameters were considered as important input variables for predicting durability. The results indicated that the PSO-BPNN model provided effective prediction performance and was suitable for evaluating reinforced concrete durability. The study demonstrated that hybrid AI techniques can provide useful alternatives to conventional empirical approaches for durability assessment.

3. Liu et al. (2024)

Liu et al. [3] investigated the application of machine-learning algorithms for predicting chloride diffusion in concrete. The study examined the ability of data-driven models to estimate chloride migration characteristics using different concrete-related input parameters. The researchers emphasized that chloride penetration is an important factor affecting reinforced concrete durability because it can initiate reinforcement corrosion and reduce structural service life. The findings showed that machine-learning approaches can provide efficient predictions compared with conventional experimental procedures. The study is relevant to AI-based durability assessment because chloride diffusion can be considered an important durability indicator for RCC structures.

4. Elshaarawy et al. (2024)

Elshaarawy et al. [4] investigated the use of machine learning for predicting the compressive strength of concrete. The researchers developed a data-driven prediction approach and integrated the model with an interactive graphical user interface to improve practical usability. Various concrete parameters were used to establish the relationship between input variables and compressive strength. The study demonstrated that AI-based prediction can reduce the time and experimental effort associated with conventional concrete testing. The findings are significant for RCC structural assessment because concrete strength directly influences structural capacity, stiffness, and long-term performance.

5. Al-Khateeb et al. (2024)

Al-Khateeb et al. [5] investigated statistical and machine-learning models for predicting spalling in continuously reinforced concrete pavement. The study considered spalling as an important deterioration mechanism that affects durability, structural integrity, maintenance requirements, and service life. Different predictive approaches were evaluated to identify relationships between pavement characteristics and spalling occurrence. The results demonstrated the potential of machine-learning models for predicting deterioration-related phenomena. The study highlighted that AI can support preventive maintenance and durability assessment by identifying structures that may be vulnerable to deterioration.

6. Kazemi et al. (2024)

Kazemi et al. [6] reviewed machine-learning methods for estimating the performance of structural concrete members reinforced with fiber-reinforced polymers. The researchers examined the application of different ML approaches for predicting structural behavior and performance parameters. The review emphasized that machine-learning models can capture nonlinear relationships between material properties, structural characteristics, reinforcement parameters, and loading conditions. The study identified AI as a promising tool for improving prediction efficiency in structural concrete applications. The findings are relevant to the proposed research because similar AI techniques can be applied to RCC buildings using structural-analysis data.

7. Taffese et al. (2025)

Taffese et al. [7], through RILEM TC 315-DCS, reviewed the application of machine learning in concrete durability assessment. The study examined ML applications for important deterioration mechanisms including carbonation, chloride-induced deterioration, sulfate attack, frost damage, shrinkage, and corrosion. The researchers highlighted the importance of data quality, feature selection, model validation, and generalization when developing AI-based durability models. The review concluded that machine learning has considerable potential for improving concrete durability prediction but requires reliable datasets and appropriate validation procedures.

8. Li, Luo, and Niu (2025)

Li, Luo, and Niu [8] reviewed data-intelligence-driven methods for durability assessment, damage diagnosis, and performance prediction of concrete structures. The study compared traditional inspection and analytical approaches with modern machine-learning and deep-learning techniques. The researchers reported that conventional methods may be limited by the complexity of deterioration mechanisms and the availability of experimental data. AI-based methods were identified as promising approaches for intelligent damage detection and prediction of material performance. The study emphasized the potential of integrating data-driven techniques into the life-cycle assessment and maintenance of reinforced concrete structures.

9. Luo et al. (2025)

Luo et al. [9] reviewed the applications of artificial intelligence in concrete design, optimization, and performance prediction. The study examined the use of AI techniques for concrete mixture design, mechanical-property prediction, quality control, durability assessment, and performance optimization. The researchers highlighted the increasing use of artificial neural networks, ensemble-learning methods, and boosting algorithms for handling nonlinear relationships between concrete constituents and performance. The review indicated that AI can reduce experimental requirements and improve the efficiency of concrete performance prediction.

10. Kong et al. (2025)

Kong et al. [10] reviewed the application of machine learning for predicting concrete properties. The researchers examined ML applications in mechanical-property prediction, concrete mix design, durability assessment, and performance optimization. The study highlighted the advantages of machine-learning approaches in terms of prediction accuracy, computational efficiency, and reduced experimental requirements. However, the authors also identified limitations associated with dataset quality, model selection, and generalization. The study provides a useful foundation for selecting appropriate AI methods for durability prediction of RCC structures.

11. Wang et al. (2025)

Wang et al. [11] investigated machine-learning applications for the design, optimization, and assessment of steel-concrete composite structures. The study reviewed a large body of research on the use of ML in structural engineering and examined how AI can support structural design and performance assessment. The researchers emphasized that ML is particularly useful for complex structural systems where multiple material and geometric parameters influence structural behavior. The findings indicate that data-driven structural assessment can complement conventional numerical analysis and may be extended to irregular RCC building configurations.

12. Kumar et al. (2025)

Kumar et al. [12] reviewed artificial-intelligence-based techniques for predicting the mechanical properties of high-performance and ultra-high-performance concrete. The study examined machine-learning and deep-learning approaches used to predict strength, workability, and durability-related properties. The researchers reported that AI models can provide faster and more economical predictions compared with extensive laboratory experimentation. The study also emphasized the importance of selecting appropriate input parameters and validating prediction models using independent datasets. These findings are applicable to AI-based prediction of RCC material and structural performance.

13. Aziz et al. (2025)

Aziz et al. [13] reviewed the state-of-the-art applications of artificial intelligence techniques in structural engineering. The study examined AI methods including Artificial Neural Networks, Genetic Algorithms, Decision Trees, and XGBoost for structural performance prediction. Applications related to concrete, steel, and composite structures, as well as seismic performance, fire effects, structural frames, retrofitting, and life-cycle assessment, were considered. The researchers reported that AI models can achieve high prediction accuracy for several structural engineering problems while also identifying challenges related to datasets, evaluation metrics, and model selection. The study supports the integration of AI with conventional structural-analysis methods.

14. Li et al. (2025)

Li et al. [14] examined machine-learning-based approaches for durability, damage diagnosis, and performance prediction of concrete structures. The researchers emphasized that reinforced concrete structures are affected by multiple interacting deterioration mechanisms, making conventional prediction methods difficult to apply to complex situations. Machine learning and deep learning were identified as effective tools for learning relationships between environmental conditions, material characteristics, structural response, and deterioration. The study recommended further development of reliable datasets and intelligent predictive models for practical structural durability assessment.

15. Amini Pishro (2026)

Amini Pishro [15] presented a comprehensive review of machine-learning applications in reinforced concrete structures. The study covered prediction of material properties, load-bearing capacity of beams, columns, slabs and walls, structural damage detection, structural health monitoring, degradation, and fire-induced deterioration. The review found that ensemble algorithms such as Random Forest and XGBoost, together with neural-network and deep-learning methods, have significant potential for modeling complex nonlinear behavior of RCC structures. The study also identified data scarcity, model interpretability, and generalization across different structural configurations as major challenges. The findings strongly support the development of AI-assisted structural-performance and durability prediction frameworks for RCC buildings.

Summary of the Literature

The reviewed studies indicate that recent research has developed along two major directions. The first focuses on the structural and seismic behavior of RCC buildings containing floating columns, where increased drift, stress concentration, altered load transfer, and changes in structural stability have been reported. The second focuses on the application of AI and machine learning to concrete durability, structural response, damage detection, seismic vulnerability, and service-life prediction.

However, there is comparatively limited research integrating these two areas into a single predictive framework. In particular, limited attention has been given to developing an AI model using STAAD.Pro-generated structural response data from RCC buildings with floating columns to predict durability or long-term structural performance. This represents an important research gap.

Therefore, the proposed research can contribute by developing a systematic framework in which RCC buildings with different floating-column configurations are modeled and analyzed in STAAD.Pro, relevant structural parameters are extracted, and these parameters are subsequently used as inputs to AI/ML models for predicting durability-related performance. Such an integrated approach may provide a faster and more efficient alternative for preliminary structural assessment, performance prediction, and maintenance-oriented decision-making.

VI. CONCLUSION

This review indicates that floating columns significantly influence the load-transfer mechanism, stiffness, and seismic response of RCC buildings. STAAD.Pro provides an effective platform for evaluating important structural parameters such as displacement, drift, bending moment, shear force, and axial force. Recent studies also demonstrate the growing potential of AI and machine-learning techniques for predicting concrete durability, structural performance, damage, and service life. However, limited research has integrated STAAD.Pro-based analysis of RCC buildings with floating columns and AI-based durability prediction. Therefore, combining numerical structural analysis with AI offers a promising approach for faster, reliable, and intelligent assessment of the long-term performance and durability of irregular RCC buildings.

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