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Hybrid Finite Element Method and Artificial Intelligence Approaches for Efficient Structural Behavior Prediction: A Review

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ABSTRACT

The prediction of structural behavior under varying loading conditions is crucial in structural engineering, especially for critical infrastructures like bridges and high-rise buildings. Traditionally, the Finite Element Method (FEM) has been widely used for simulating structural responses, but its computational expense, particularly under complex conditions, necessitates the integration of Artificial Intelligence (AI). Hybrid FEM-AI approaches, leveraging machine learning techniques like neural networks and deep learning, have emerged to enhance efficiency without sacrificing accuracy. These methodologies enable faster predictions, making them highly relevant for intelligent infrastructure systems and real-time structural health monitoring.

Keywords: *Structural Behavior, Finite Element Method, Artificial Intelligence, Machine Learning.*

I. INTRODUCTION

The prediction of structural behavior under varying loading conditions has long been a fundamental concern in structural engineering, particularly for critical infrastructure such as bridges, high-rise buildings, and industrial systems. Traditionally, the Finite Element Method (FEM) has been the dominant numerical tool used to simulate stress distribution, deformation, and failure mechanisms in engineering structures due to its strong theoretical foundation in continuum mechanics. FEM allows engineers to discretize complex structures into smaller elements and solve governing differential equations to obtain accurate approximations of structural responses. However, despite its high accuracy and robustness, FEM is often computationally expensive, especially when dealing with nonlinear material behavior, large-scale structures, or time-dependent dynamic loading scenarios. These limitations have encouraged researchers to explore hybrid approaches that integrate Artificial Intelligence (AI) with FEM to enhance computational efficiency while maintaining predictive reliability. Recent advancements in machine learning (ML), deep learning (DL), and data-driven surrogate modeling have significantly transformed structural analysis by enabling rapid prediction of structural responses based on data generated from FE simulations (Bolandi et al., 2022; Ye et al., 2022).

In recent years, the integration of AI with FEM has emerged as a powerful hybrid modeling framework in structural engineering. AI techniques such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures have been increasingly used to emulate complex FE simulations and predict structural behavior under different conditions. These models are typically trained using datasets generated from high-fidelity FEM simulations or experimental results, enabling them to learn nonlinear relationships between input parameters and structural responses. For instance, Coulibaly et al. (2026) demonstrated that LSTM-based surrogate models can efficiently approximate nonlinear structural dynamic systems, although their performance may degrade in highly complex real-world scenarios, which necessitates hybrid improvements such as LSTM-RAMSS frameworks. Similarly, Zhao et al. (2025) developed a

Transformer-based deep learning model that accurately predicted mechanical responses and failure behavior in precast bridge joints, achieving high accuracy in strain-field-based analysis. Moreover, Ni et al. (2025) successfully applied deep neural network-based proxy models for finite element model updating in bridge structures, achieving highly precise deflection predictions validated through field measurements. These studies collectively indicate that AI-enhanced FEM frameworks are increasingly being adopted to overcome computational inefficiencies while preserving the physical interpretability of structural models.

Furthermore, the growing demand for intelligent infrastructure systems and real-time structural monitoring has significantly accelerated the adoption of hybrid FE–AI methodologies in structural engineering applications. The emergence of digital twin technology has further strengthened this integration by combining real-time data acquisition with physics-based and data-driven models for continuous structural health monitoring. Liu et al. (2024) highlighted the effectiveness of combining Bayesian Neural Networks with FEM-based response surface models for predicting bridge displacement under extreme wind conditions, demonstrating improved accuracy and computational efficiency. Additionally, Vaktskjold et al. (2026) provided a comprehensive mapping of AI applications in FEM-based structural engineering, reporting a significant surge in research focused on surrogate modeling and structural performance prediction after 2015. Similarly, Yang and Xia (2023) emphasized the role of AI-integrated Building Information Modeling (BIM) frameworks in enhancing structural damage recognition during bridge construction, showing the practical relevance of AI in real-world engineering workflows. Overall, hybrid Finite Element and Artificial Intelligence-based modeling represents a transformative shift in structural engineering, offering a balanced approach that combines the physics-based rigor of FEM with the adaptive learning capabilities of AI, thereby enabling efficient, accurate, and scalable structural behavior prediction for modern engineering challenges (Vaktskjold et al., 2026; Zhao et al., 2025).

II. RESEARCH BACKGROUND

Xu and Chen (2026) proposed a novel aluminum–timber composite column strengthened with CFRP to address the growing demand for green building materials and high-performance structural systems. The study was designed by integrating the durability of aluminum tubes, the high specific strength of timber, and the confinement effect of CFRP wrapping. Axial compression tests were conducted on ten specimens, along with finite element analysis, to evaluate failure behavior and the influence of parameters such as timber core size and CFRP layer number. It was reported that unstrengthened specimens mainly failed due to local buckling of the aluminum tube and crushing of the timber core, whereas CFRP wrapping effectively delayed buckling and improved failure progression. The load-bearing capacity was found to decrease with increasing timber core size, although a medium-sized core was identified as the most efficient configuration. CFRP strengthening significantly enhanced load capacity and buckling restraint, while ABAQUS simulations accurately validated the experimental findings and supported the development of a reliable axial compressive capacity prediction method.

Vaktskjold et al. (2026) systematically reviewed the application of artificial intelligence (AI) in finite-element (FE)-based structural engineering and provided a comprehensive mapping of the field. The study reportedly compiled a corpus of 5,995 unique English-language publications, of which 3,345 relevant papers were further classified according to discipline and application groups. In addition, a representative subset of 372 studies was subjected to detailed full-text analysis across seven analytical dimensions, including AI techniques, element formulations, materials, and structural objects. The authors observed a significant increase in research output after 2015, particularly in surrogate modelling and data-driven prediction approaches. It was further noted that structural engineering had gained greater prominence in recent years compared to earlier decades. While Optimization and Design remained the dominant application area, Structural Performance Prediction and FEM Acceleration/Surrogate Modelling were identified as the fastest-growing domains. Overall, the review indicated that AI had become increasingly integrated into FE-based structural analysis, design, and future industrial applications.

Coulibaly et al. (2026) addressed the challenge of high computational costs associated with nonlinear time history analysis (NLTHA) of high-fidelity finite element (FE) models in structural system design, particularly in Performance-Based Seismic Design (PBSD) and digital twin applications, by investigating data-driven machine learning surrogate models. The authors presented Part 1 of a two-part study focusing on the application of long short-term memory (LSTM) networks as fast emulators for nonlinear structural dynamic systems with varying material and geometric nonlinearities. Six structural engineering examples, ranging from academic cases to real-world applications, were introduced to evaluate the capabilities and limitations of LSTM models. It was observed that while LSTM performed effectively in simplified academic environments, its performance declined in capturing the complex nonlinear behaviour of practical systems. To overcome these limitations, the study proposed the LSTM Recursive Averaged Multi-step Sequence-to-Sequence (LSTM-RAMSS) framework, integrating CAE-based seismic record selection, dilation strategies, and hybrid LSTM-NARX and Seq2Seq architectures to enhance predictive accuracy and robustness.

Ni et al. (2025) investigated the difficulty of directly predicting the bearing capacity of existing concrete girder bridges due to design parameter uncertainties, construction deviations, and time-dependent material degradation such as shrinkage and creep. The authors proposed a finite element model (FEM) updating approach based on a proxy model (PM) to improve the accuracy of bearing capacity evaluation over conventional numerical estimation methods. In their study, a real-life plate girder bridge was simulated under random static vehicle loads, and a large dataset of deflection and fundamental frequency responses was generated. Based on these samples, a high-precision proxy model was developed using a deep neural network. Sensitivity analysis was further employed to identify the most influential mechanical parameters, including boundary restraint stiffness, concrete compressive strength, and reinforcement elastic modulus, which were then used for FEM updating. The updated model was validated with in-situ measurements, showing only 0.4% deviation in deflection prediction, thereby demonstrating high reliability and effectiveness for residual bridge capacity assessment.

Zhao et al. (2025) investigated the integration of artificial intelligence (AI) with finite element analysis (FEA) for predicting structural mechanical behaviour and displacement responses in composite structures. The authors noted that previous AI-FEA studies had mainly concentrated on single-material systems or simplified loading conditions and lacked a systematic framework for macro-scale response evaluation. To address this limitation, they proposed a failure analysis framework based on an enhanced U-shaped Transformer network, which effectively combined global dependency modelling with strain-field feature extraction. The framework was applied to an ultra-high performance concrete (UHPC)-headed bar joint in accelerated bridge construction systems. It was reported that the model accurately predicted internal rebar stresses and pull-out displacements, achieving low mean absolute errors. Furthermore, a logarithmic stress–displacement failure model was developed, and the proposed criterion attained 97.2% failure assessment accuracy under adverse conditions. The study also suggested potential applications in digital twin-based infrastructure lifecycle management.

Liu et al. (2024) examined the growing application of digital twin (DT) technology in bridge structural health monitoring amid advancements in big data and the Internet of Things (IoT). The study proposed a dual-driven framework that integrated data-driven and physical model-driven approaches to predict structural displacement and dynamic response under strong wind conditions. Specifically, a Bayesian

Neural Network (BNN) based on Bayesian inference and a finite element model (FEM) optimized through genetic algorithms (GAs), multi-objective optimization (MOO), and response surface methodology (RSM) were employed. Using data from the Forth Road Bridge under unusual strong wind events, the authors comparatively evaluated both methods in terms of prediction accuracy, computational efficiency, complexity, interpretability, and comprehensiveness. The findings indicated that the BNN model achieved superior prediction accuracy for Y and Z displacements and required significantly less computational time, whereas the FEM approach offered greater interpretability and full-structure response prediction. The study highlighted the value of integrating both approaches for robust large-span bridge monitoring.

Yang and Xia (2023) examined the transformative role of Building Information Modelling (BIM) in the construction industry and observed that its integration with Artificial Intelligence (AI) had gained increasing significance in interdisciplinary construction applications. The authors reported that, in China, the convergence of BIM, AI, and cloud data had contributed to notable advancements in intelligent construction practices; however, several limitations still constrained the comprehensive development of such technologies. Their study specifically addressed these issues by focusing on the design of intelligent recognition algorithms for monitoring structural damage during bridge construction. It was noted that earlier studies had largely relied on classical neural network algorithms, which had demonstrated certain shortcomings in performance and adaptability. To overcome these limitations, the authors proposed improved neural network-based recognition measures and validated their effectiveness through practical arithmetic examples. Furthermore, the improved algorithm was integrated into the BIM framework, enabling more efficient and accurate recognition and assessment of bridge structural damage during construction.

Ye et al. (2022) reported that although Finite Element (FE) methods had been extensively used in structural design for quantitatively analysing mechanical performance, their comprehensive models were often computationally expensive and time-consuming, which limited their applicability in real-time scenarios. To address this limitation, the authors had developed an FE-based machine learning (ML) framework for predicting structural displacement from temperature data during fire events. In their study, FE models of a steel frame structure had been created for fire analysis, and a numerical database containing responses under hundreds of fire scenarios had been established. Four ML models had then been trained using temperature as input and displacement as output. The findings indicated that Random Forest and Gradient Boosting had outperformed the other models, achieving an R^2 value of up to 0.99 with 1000 fire scenarios. The framework was also found to be robust against noise and showed strong potential for real-time fire response prediction.

Bolandi et al. (2022) reported that finite-element analysis (FEA) had been widely utilized for stress analysis in civil and mechanical engineering structures; however, conventional FEA methods had required the solution of large linear systems, making them computationally expensive. The authors observed that deep learning (DL) techniques could generate results much faster than traditional run-time analysis, which had been particularly beneficial for real-time structural assessment applications. In their study, a deep neural network based on convolutional neural networks (CNNs) was proposed to bypass FEA and predict high-resolution stress distributions in loaded steel plates under variable loading and boundary conditions. The model had used geometry, load, and boundary conditions as input parameters to estimate stress contours. Its performance was compared with finite-element simulations obtained through a partial differential equation solver. The findings indicated that the trained model had achieved a mean absolute error of 0.9% and an absolute peak error of 0.46%, demonstrating the feasibility and strong potential of DL-based stress prediction.

Rachedi et al. (2021) examined the limitations of using Peak Ground Acceleration (PGA) as a sole indicator in earthquake engineering for developing seismic vulnerability curves, noting that a single parameter could not adequately capture the complex relationship between structural damage and ground motion. To address this limitation, the authors proposed an Artificial Neural Network (ANN)-based approach for predicting nonlinear dynamic structural response by incorporating multiple ground motion intensities, soil variability, and soil–structure interaction (SSI). It was reported that the neural network was trained using a numerical database generated from a Finite Element Method (FEM) model, which was subsequently validated through experimental results. The study demonstrated that the ANN model achieved optimum prediction accuracy for nonlinear dynamic response. Furthermore, fragility curves were developed for three different soil classes while considering SSI effects. The findings indicated that SSI played a significant role in seismic damage evaluation and was essential for more reliable seismic risk assessment analysis.

Al-Rousan et al. (2020) investigated the vulnerability of reinforced concrete bridge deck slabs to environmental deterioration, particularly corrosion, and examined the potential of carbon and glass fiber reinforced polymer (FRP) bars as alternatives to conventional steel reinforcement. The study presented a three-dimensional nonlinear finite element analysis (NLFEA) to simulate the behaviour of full-scale concrete bridge deck slabs reinforced with FRP bars. Initially, a control slab model was developed, calibrated, and validated using previously published experimental data. Subsequently, a parametric analysis involving 27 NLFEA models was carried out by varying concrete compressive strength, reinforcement type (GFRP, CFRP, and steel), and bottom transverse reinforcement ratio. The findings indicated that CFRP and GFRP reinforcement had improved ultimate load, elastic stiffness, post-cracking stiffness, and energy absorption compared to steel reinforcement, while only slightly affecting ultimate deflection. Punching shear failure was predominantly observed, and increased concrete compressive strength was found to enhance slab load capacity and deflection.

III. KEY FINDINGS FROM STUDY

Author (Year)	Objective	Methodology	Key Findings	Contribution
Xu & Chen (2026)	Improve composite column performance using CFRP strengthening	Experimental axial tests + FEM (ABAQUS)	CFRP improved load capacity and delayed buckling failure	FE validated composite structural behavior
Vaktskjold et al. (2026)	Map AI applications in FE structural engineering	Systematic literature review (5,995 studies)	Rapid growth in AI-based surrogate and prediction models	Identified FE–AI integration trends
Coulibaly et al. (2026)	Reduce computational cost of nonlinear dynamic FE analysis	LSTM, Seq2Seq, hybrid LSTM-RAMSS	Standard LSTM limited; hybrid models improved accuracy	AI surrogate modeling for FE dynamics
Ni et al. (2025)	Improve bridge capacity prediction	FEM updating using deep learning proxy model	0.4% error vs field data	AI-enhanced FE model calibration
Zhao et al. (2025)	Predict structural failure using AI-FE integration	Transformer + strain field FE data	97.2% failure prediction accuracy	Advanced AI-based FE response modeling

Liu et al. (2024)	Predict bridge response under wind loads	FEM + Bayesian Neural Network	BNN improved speed and accuracy	Digital twin-based FE–AI hybrid system
Yang & Xia (2023)	Enhance bridge damage detection	AI-integrated BIM + neural networks	Improved structural damage recognition	AI-based structural monitoring system
Ye et al. (2022)	Predict fire-induced structural response	FEM + ML models (RF, GB)	RF & GB achieved $R^2 = 0.99$	FE-generated ML prediction framework
Bolandi et al. (2022)	Replace FE stress analysis with AI	CNN-based deep learning model	0.9% error in stress prediction	AI surrogate replacing FE computation
Rachedi et al. (2021)	Improve seismic risk prediction	ANN trained on FEM seismic data	Better fragility curves with SSI inclusion	FE-based ANN seismic modeling
Al-Rousan et al. (2020)	Study FRP reinforcement effects	Nonlinear FEM (3D simulation)	CFRP/GFRP improved slab performance	FE-based material performance evaluation

IV. CONCLUSION

The integration of Finite Element Method (FEM) with Artificial Intelligence (AI) has emerged as a transformative approach in structural engineering, significantly enhancing the accuracy, efficiency, and scalability of structural behavior prediction under complex loading conditions. The reviewed literature clearly demonstrates that while FEM remains a fundamental tool for simulating structural response based on physical laws, its limitations in terms of high computational cost, time consumption, and inefficiency in real-time applications have necessitated the adoption of AI-driven surrogate and hybrid modeling techniques. Studies such as Bolandi et al. (2022) and Ye et al. (2022) confirm that machine learning models, including convolutional neural networks and ensemble methods, can effectively replicate FEM-generated results with high accuracy while drastically reducing computational time. Similarly, Coulibaly et al. (2026) and Zhao et al. (2025) highlight the growing application of deep learning architectures such as LSTM and Transformer networks in capturing nonlinear structural dynamics and predicting failure mechanisms with remarkable precision. The integration of FEM with AI-based proxy models, as demonstrated by Ni et al. (2025), further strengthens the reliability of structural assessments by enabling accurate model updating using real-world measured data, thereby bridging the gap between theoretical simulations and actual structural performance. Moreover, advancements in digital twin frameworks and Bayesian neural networks, as discussed by Liu et al. (2024), indicate a shift toward real-time structural health monitoring systems that combine physics-based modeling with data-driven intelligence for continuous infrastructure evaluation. The systematic review by Vaktskjold et al. (2026) further confirms the rapid expansion of AI applications in FEM-based structural engineering, particularly in surrogate modeling, optimization, and predictive analysis domains, reflecting a global transition toward intelligent computational frameworks. Additionally, applications in BIM-integrated damage detection systems (Yang & Xia, 2023) and seismic vulnerability assessment using ANN models (Rachedi et al., 2021) demonstrate the practical relevance of FE–AI hybrid systems in real-world engineering problems. Overall, the convergence of FEM and AI represents a significant paradigm shift from purely numerical simulation toward intelligent, adaptive, and data-enhanced structural analysis systems. This hybrid approach not only improves predictive accuracy and computational efficiency but also enables real-time decision-making capabilities essential for modern infrastructure design, maintenance, and safety assessment. Therefore, the continued development of robust FE–AI integrated frameworks is expected to play a crucial role in advancing next-generation smart structural engineering systems and resilient infrastructure development.

V. FUTURE SCOPE

- **Development of Fully Autonomous FE–AI Hybrid Frameworks:** Future research can focus on developing fully automated hybrid systems where FEM simulations and AI models interact seamlessly without manual intervention. Such frameworks can dynamically generate training datasets from FEM, update AI models in real time, and continuously improve prediction accuracy. This will be highly beneficial for large-scale infrastructure systems such as bridges, high-rise buildings, and offshore structures, where continuous monitoring and adaptive analysis are required.
- **Integration with Digital Twin Technology for Real-Time Monitoring:** The combination of FEM–AI models with digital twin systems represents a major future direction. Digital twins can integrate sensor data from structures in real time and synchronize it with physics-based FEM and AI prediction models. This will enable continuous structural health monitoring, early damage detection, and predictive maintenance strategies, especially for critical infrastructure exposed to dynamic environmental and loading conditions.
- **Advanced Deep Learning Architectures for Nonlinear Structural Behavior:** Future studies can explore more advanced AI models such as Graph Neural Networks (GNN), Physics-Informed Neural Networks (PINNs), and hybrid Transformer-based architectures to better capture complex nonlinear structural responses. These models can improve prediction accuracy for failure analysis, seismic response, and material degradation, especially where traditional FEM becomes computationally inefficient.
- **Uncertainty Quantification and Reliability-Based Design Integration:** Another important research direction is integrating uncertainty quantification methods within FE–AI frameworks. Structural systems are often affected by variability in material properties, loading conditions, and environmental effects. Future hybrid models should incorporate probabilistic AI approaches to improve reliability-based design and risk assessment in structural engineering applications.
- **Application in Smart and Sustainable Infrastructure Systems:** The future scope also includes applying FE–AI hybrid models in smart cities and sustainable infrastructure development. These models can optimize material usage, improve energy efficiency, and support green building design by providing accurate predictions of structural performance over lifecycle conditions. This will contribute to cost-effective, safe, and environmentally sustainable construction practices.

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