



ARTIFICIAL INTELLIGENCE IN THE DESIGN OF REINFORCED CONCRETE AND METAL STRUCTURES

Temirlan Bakhytzhan
Structural Engineer, USA

Abstract

Artificial intelligence (AI), particularly machine learning methods, is becoming one of the areas driving the digital transformation of the construction and structural engineering industries. In the design of reinforced concrete and metal structures, AI is used to predict material properties, assess the load-bearing capacity of elements, optimize structural systems, analyze emergency scenarios, and automate the search for design solutions.

The scientific novelty of this article lies in its systematization of modern approaches to the application of artificial intelligence in the design of reinforced concrete and metal structures and the development of an integrated conceptual model of intelligent design. Unlike studies focused primarily on individual forecasting or optimization tasks, this paper examines the application of AI as a holistic system, including digital context generation, AI forecasting, generation and optimization of design options, independent numerical calculations, and regulatory verification.

An analysis of scientific publications revealed a consistent pattern of expanding AI applications from predicting material properties to assessing structural elements, optimizing structural systems, and analyzing building behavior under extreme conditions. This analysis supports the rationale for using AI primarily as a tool for intelligent search and preliminary assessment of design solutions, while maintaining independent design and regulatory oversight.

Artificial neural networks, support vector machines, genetic algorithms, swarm intelligence methods, and other machine learning approaches are considered. It is shown that research is evolving from predicting material properties to predicting the behavior of structural elements and then to optimizing entire structural



systems. Particular attention is paid to the application of AI in conjunction with BIM, finite element analysis, and multi-criteria optimization. It is established that the main limitation remains the dependence of model reliability on the quality of training data and their scope of applicability. A conceptual model of intelligent design is proposed that integrates AI forecasting, variant generation and optimization, numerical calculations, and regulatory verification.

Keywords: Artificial intelligence, machine learning, reinforced concrete structures, metal structures, neural networks, optimization, BIM, structural design, load-bearing capacity.

Introduction

Designing building structures is a multi-parameter task that requires simultaneous consideration of strength, stability, rigidity, crack resistance, durability, cost, and material consumption. The traditional process involves sequentially selecting a structural design, calculating several options, selecting sections and reinforcement, and then verifying the resulting solutions.

The increasing complexity of buildings and the expanding number of parameters considered lead to a significant increase in the number of possible design solutions. This creates the preconditions for the application of artificial intelligence methods capable of quickly analyzing large data sets and identifying nonlinear relationships between design parameters and calculation or experimental results.

A systematic review by H. Sun, H.V. Burton, and H. Huang found that machine learning is being used in structural engineering to predict structural behavior, process experimental data, and assess structural health. The authors also note that a significant portion of the developed models remained primarily in the research stage at the time of publication.

A review by H.-T. Thai, published in 2022, expands on this picture and examines the application of machine learning to concrete, steel, and composite structures, including analysis, design, monitoring, and evaluation of behavior under extreme impacts.



Main methods of artificial intelligence in structural design. In the studies reviewed, artificial intelligence is represented primarily by machine learning and optimization methods. The most common are artificial neural networks (ANN), support vector machines (SVM/SVR), decision trees, Gaussian processes, genetic algorithms, and swarm optimization methods.

Their application can be conditionally divided into three interrelated tasks.

The first is prediction. The model is trained on experimental or calculated data and predicts the material strength, the load-bearing capacity of an element, deformations, or other parameters.

The second is optimization. The algorithm searches for a design solution within given constraints. The objective function may be cost, weight, material consumption, carbon footprint, or a combination of several criteria.

The third is design decision making. Machine learning is used to select or pre-select design options, such as the placement of connections, the dimensions of components, or the design layout.

Of particular interest is the use of ML models as surrogate models—approximate substitutes for labor-intensive numerical calculations. In this case, a large number of finite element calculations form a training set, after which the trained model allows for significantly faster evaluation of new options. Consequently, the use of AI is gradually expanding beyond the simple evaluation of individual characteristics and extending to the very process of finding a design solution.

Predicting Concrete Properties. Cheng et al. in *Automation in Construction* (2012) proposed a hybrid model combining fuzzy logic, support vector machines, and a genetic algorithm to predict the strength of high-performance concrete. A study on 1,030 specimens demonstrated the feasibility of modeling complex nonlinear relationships between concrete composition and strength.

Chou et al. in *Construction and Building Materials* (2014) continued this approach, using multiregional data and machine learning methods to predict concrete strength. The work demonstrated the potential of ensemble models for processing data from various sources. Both publications demonstrate that AI can be effectively used at the material design level. However, the resulting models are



primarily applicable within the characteristics of the training dataset and do not, by themselves, replace standard structural analysis.

Automation of reinforced concrete design. Tafraout et al. in *Automation in Construction* (2019) applied a genetic algorithm to the automated design of a reinforced concrete wall-slab system based on a BIM/IFC model. The significance of this study lies in its transition from predicting material properties to the automated generation of design options.

Gan et al. in *Advanced Engineering Informatics* (2019) investigated parametric modeling and evolutionary optimization of high-rise reinforced concrete buildings. Cost and embodied carbon were considered as criteria. The study demonstrated the feasibility of multi-criteria design solution search. Thus, AI is beginning to be used not only to answer the question "how will the structure perform?" but also to answer the question "which design option should be considered?"

Optimization of reinforced concrete frames. Esfandiari and Urgessa in *Structures* (2020) combined machine learning and particle swarm optimization to design reinforced concrete frames considering the risk of progressive collapse. The model considered various scenarios for removing critical elements and regulatory constraints. The study demonstrates the potential of using AI to accelerate solution searches in problems where traditional repeated calculations are computationally expensive. The final solution must also be verified by independent analysis and compliance with regulatory requirements.

Design of composite structures. Zarringol et al. in *Structures* (2020) used artificial neural networks to predict the ultimate load-bearing capacity of concrete-filled steel tubes (CFST). The authors used extensive experimental data for centric and eccentric loading and derived engineering dependencies from the ANN results. The study is significant in that it demonstrates the feasibility of moving from a "black box" to an engineering-interpretable dependency. This approach has the potential to accelerate the design of composite elements, but the applicability of the resulting dependencies is limited by the range of input data.



Artificial Intelligence for Steel Structures. Fu, in *the Journal of Constructional Steel Research* (2020), explored the feasibility of using machine learning to assess the potential for progressive collapse of steel-frame buildings during a fire. Numerical scenarios were used to create a database, after which decision trees, KNNs, and neural networks were compared. The study demonstrates the feasibility of using AI to quickly classify failure scenarios. This approach is particularly promising in areas where conducting a large number of full numerical simulations requires significant computational resources.

Sakaguchi, Ohsaki, and Kimura investigated the use of SVM to identify characteristics of approximately optimal tie arrangements in multi-story steel frames. The model was trained using optimization calculations and was able to identify patterns associated with tie arrangements. Together, these studies demonstrate that AI can be applied to steel structures both for behavior analysis and for structural design search.

Systematic reviews. Sun, Burton, and Huang, in *the Journal of Building Engineering* (2021), systematized the applications of machine learning in structural engineering and highlighted structural behavior prediction, experimental data processing, and structural health analysis as key areas.

Thai in *Structures* (2022) presented a broader review of the application of machine learning in structural engineering, covering concrete, steel and composite structures, design, monitoring and damage assessment.

These reviews allow individual studies to be viewed not as isolated experiments, but as parts of an emerging scientific field. At the same time, the authors point to persistent problems with data quality, interpretability, and the transfer of models from research to practical design. The studies reviewed demonstrate a consistent expansion of the application of artificial intelligence: from predicting material properties to calculating elements and then to optimizing structural systems.



Table 1. Comparative analysis of studies.

Study	Year	Material/object	AI method	The main task	Main result
Cheng et al.	2012	high-performance concrete	SVM + fuzzy logic + GA	strength forecast	hybrid predictive model
Chou et al.	2014	concrete	ML/ensemble	strength forecast	multiregional data analysis
Tafraout et al.	2019	reinforced concrete	genetic algorithm	computer-aided design	generation of a structural system from BIM
Gan et al.	2019	Reinforced concrete high-rise frame	evolutionary optimization	cost and carbon	multicriteria optimization
Esfandiari, Urgessa	2020	Reinforced concrete frames	ML + PSO	progressive collapse	automated search for solutions
Zarringol et al.	2020	CFST columns	ANN	bearing capacity	forecast and engineering dependencies
Fu	2020	steel frames	DT + KNN + NN	fire/collapse	classification of scenarios
Sakaguchi et al.	2021	steel frames	SVM	arrangement of connections	identification of patterns of optimal solutions
Sun et al	2021	buildings	ML	structural engineering overview	systematization of directions and restrictions
Thai	2022	Concrete, steel, composites	ML	structural engineering overview	comprehensive systematization of the field

An analysis of the table allows us to identify four levels of AI application:

material level - prediction of concrete properties;

element level - prediction of the load-bearing capacity of columns and other elements;

structural system level - optimization of frames, connections and structural design;

system level - assessment of the building's behavior under emergency impacts.

Thus, the main trend is the transition from individual predictive models to complex intelligent design systems.

The use of AI in the design of reinforced concrete structures. For reinforced concrete, the most promising tasks are section optimization, reinforcement selection, structural design, and load-bearing capacity prediction.

Machine learning can quickly evaluate the results of a large number of variants generated by varying section dimensions, concrete grade, and reinforcement parameters. Genetic and other optimization algorithms enable finding solutions



that minimize material consumption or cost while maintaining specified constraints.

Of particular interest is multi-criteria optimization, which simultaneously considers safety, cost, weight, and environmental performance. The work of Gan et al. demonstrates the fundamental feasibility of such an approach.

However, the AI model results should be considered a preliminary assessment. The final design of the reinforced concrete structure requires verification of strength, stiffness, crack resistance, anchorage, and the design requirements of the relevant regulatory document.

Application of AI in the design of metal structures. In metal structures, AI can be used for section selection, bracing optimization, stability assessment, and behavior analysis under extreme loads. The unique feature of such problems is the large number of possible combinations of standard profiles, joints, and bracing systems. This makes optimization methods particularly attractive.

A study by Sakaguchi et al. demonstrates the feasibility of using SVM to identify patterns in optimal bracing arrangements, while Fu's work demonstrates the application of machine learning to the analysis of steel frame fire behavior. A promising approach is the integration of ML with finite element models. In this case, the results of a large number of calculations form a training base, after which the AI model can be used to accelerate the preliminary analysis of new options.

Key Limitations of AI Applications: Despite the high accuracy of many models, their use in design is subject to a number of limitations.

The first limitation is data quality. Experimental and calculated datasets may contain differences in testing methods, parameter ranges, and measurement accuracy.

The second is the domain of applicability. A model that performs well within the training set may produce unreliable results when extended beyond its boundaries. Third, interpretability. Many neural networks are complex models whose physical interpretation is difficult.

Fourth, regulatory compliance. High forecasting accuracy does not automatically mean compliance with building codes.

Therefore, the application of AI in structural design should be based on the principle: **AI forecast** → **independent calculation** → **normative verification**.

AI should be used as a tool to speed up the search and analysis of options, rather than as an independent replacement for engineering verification.

AI, BIM, and numerical analysis. One of the most promising areas is the combination of artificial intelligence with BIM and finite element modeling. BIM provides structured information about the geometry, materials, and relationships between elements. AI can use this information to automatically generate and preliminarily evaluate design options. Conceptually, this process can be represented as follows:

BIM model → **variant generation** → **AI forecasting** → **optimization** → **finite element calculation** → **regulatory verification** → **updated BIM model**.

The work by Taфраout et al. demonstrates an early version of such integration. This approach has the potential to transform the design process, enabling engineers to analyze a significantly larger number of options than with manual selection.

Based on the studies reviewed, the following sequence of AI application is proposed:

Концептуальная модель интеллектуального проектирования



Обобщенная последовательность применения ИИ





The proposed model has the following structure: **data → AI forecasting → variant generation → AI optimization → numerical calculation → regulatory verification → engineering solution**. Its fundamental difference from the autonomous use of machine learning is the preservation of physical and regulatory control at the final stages.

Prospects for further research. Further development of this area is primarily related to the creation of large standardized databases, improving the interpretability of models, and integrating AI with physical computational models.

Particularly promising is hybrid design, which combines machine learning, finite element analysis, BIM, and optimization algorithms. Another approach is physics-informed machine learning, in which physical laws and constraints are directly incorporated into the learning process. This potentially reduces the risk of physically incorrect results.

In the future, artificial intelligence could become the intelligent layer of a digital design system, automatically generating and pre-evaluating a large number of design solutions, while an engineer would define initial constraints, monitor results, and make the final design decision.

Conclusion

An analysis of the latest, most relevant research on the application of artificial intelligence in the construction industry demonstrates a steady expansion of AI use in the design of reinforced concrete and metal structures. In its early stages, AI was primarily used to predict material properties. Machine learning methods later expanded to assess the load-bearing capacity of structural elements, and then to optimize frames, connections, and entire structural systems.

For reinforced concrete structures, the most promising areas are predicting material properties and load-bearing capacity, optimizing cross-sections and reinforcement, and automating structural design selection. For metal structures, significant potential lies in optimizing profiles and bracing, assessing stability, and analyzing behavior during fire and other extreme conditions.



However, AI should not yet be considered a standalone replacement for traditional calculations. The main limitations relate to data quality, the scope of model applicability, interpretability, and the need for regulatory validation.

The most promising approach appears to be an integrated one, in which BIM, machine learning, optimization, and numerical calculations are combined into a single digital workflow. In such a system, AI performs rapid analysis and search for options, while engineering calculations and regulatory verification ensure physical feasibility and safety.

Thus, the further development of artificial intelligence in structural design is associated not with the rejection of engineering methodology, but with its digital expansion and the transition from manual selection of a limited number of solutions to the intelligent analysis of a large space of design options.

References

1. Cheng M.-Y., Chou J.-S., Roy A.F.V., Wu Y.-W. High-performance concrete compressive strength prediction using time-weighted evolutionary fuzzy support vector machines inference model. *Automation in Construction* . 2012. Vol. 28. P. 106–115. DOI: 10.1016/j.autcon.2012.07.004. <https://sci-hub.box/10.1016/j.autcon.2012.07.004>
2. Chou J.-S., Tsai C.-F., Pham A.-D., Lu Y.-H. Machine learning in concrete strength simulations: Multi-nation data analytics. *Construction and Building Materials*. 2014. Vol. 73. P. 771–780. DOI: 10.1016/j.conbuildmat.2014.09.054. <https://www.sciencedirect.com/science/article/abs/pii/S0950061814010708>
3. Taфраout S., Bourahla N., Bourahla Y., Mebarki A. Automatic structural design of RC wall-slab buildings using a genetic algorithm with application in BIM environment. *Automation in Construction*. 2019. Vol. 106. Article 102901. DOI: 10.1016/j.autcon.2019.102901. https://www.researchgate.net/publication/334592062_Automatic_structural_design_of_RC_wallslab_buildings_using_a_genetic_algorithm_with_application_in_BIM_environment
4. Gan VJL, Wong CL, Tse KT, Cheng JCP, Lo IMC, Chan CM Parametric modeling and evolutionary optimization for cost-optimal and low-carbon



-
- design of high-rise reinforced concrete buildings. *Advanced Engineering Informatics*. 2019. Vol. 42. Article 100962. DOI: 10.1016/j.aei.2019.100962. https://www.researchgate.net/publication/336183912_Parametric_modelling_and_evolutionary_optimization_for_cost-optimal_and_low-carbon_design_of_high-rise_reinforced_concrete_buildings
5. Esfandiari M., Urgessa GS Progressive collapse design of reinforced concrete frames using structural optimization and machine learning. *Structures*. 2020. Vol. 28. P. 1252–1264. DOI: 10.1016/j.istruc.2020.09.039. <https://www.sciencedirect.com/science/article/abs/pii/S2352012420305178>
 6. Zarringol M., Thai H.-T., Thai S., Patel V. Application of ANN to the design of CFST columns. *Structures*. 2020. Vol. 28. P. 2203–2220. DOI: 10.1016/j.istruc.2020.10.048. <https://www.sciencedirect.com/science/article/abs/pii/S2352012420306056>
 7. Fu F. Fire induced progressive collapse potential assessment of steel framed buildings using machine learning. *Journal of Constructional Steel Research*. 2020. Vol. 166. Article 105918. DOI: 10.1016/j.jcsr.2019.105918. <https://openaccess.city.ac.uk/id/eprint/23386/>
 8. Sakaguchi K., Ohsaki M., Kimura T. Machine Learning for Extracting Features of Approximate Optimal Brace Locations for Steel Frames. *Frontiers in Built Environment*. 2021. Vol. 6. Article 616455. DOI: 10.3389/fbuil.2020.616455. <https://www.frontiersin.org/journals/built-environment/articles/10.3389/fbuil.2020.616455/full>
 9. Sun H., Burton H.V., Huang H. Machine learning applications for building structural design and performance assessment: State-of-the-art review. *Journal of Building Engineering*. 2021. Vol. 33. Article 101816. DOI: 10.1016/j.jobbe.2020.101816. <https://www.sciencedirect.com/science/article/abs/pii/S2352710220334495>
 10. Thai H.-T. Machine learning for structural engineering: A state-of-the-art review. *Structures*. 2022. Vol. 38. P. 448–491. DOI: 10.1016/j.istruc.2022.02.003. <https://www.sciencedirect.com/science/article/abs/pii/S2352012422000947>
-