

Optimization of reinforced concrete structures using AI

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Abstract

Optimization of reinforced concrete structures has traditionally relied on mathematical methods to find rational combinations of geometric parameters, material characteristics, and reinforcement while meeting strength, rigidity, and structural suitability requirements. The development of artificial intelligence and machine learning significantly expands the capabilities of this approach. Modern algorithms allow not only to search for optimal design solutions but also to approximate the results of labor-intensive calculations, generate surrogate models, predict structural characteristics, and combine multiple optimality criteria into a single procedure.

This research article provides an analytical review of methods for applying artificial intelligence to the optimization of reinforced concrete structures. It examines genetic algorithms, neural networks, machine learning methods, metamodels, hybrid algorithms, and deep reinforcement learning. Particular attention is paid to multi-criteria optimization, computational cost reduction, environmental performance, and the need for regulatory verification of results.

The scientific novelty of the article lies in the proposed conceptual model of AI-oriented optimization of reinforced concrete structures, which combines a digital model of the structure, a computational database, a ML surrogate, an intelligent optimizer, and independent finite element and regulatory verification into a single iterative process.

Keywords: Reinforced concrete structures, artificial intelligence, machine learning, neural networks, genetic algorithms, optimization, surrogate model, multi-criteria optimization, structural design.

Introduction

Optimization of reinforced concrete structures is one of the most complex problems in structural design. Unlike simply determining the load-bearing capacity of an individual element, optimization requires simultaneous consideration of geometry, material characteristics, reinforcement scheme, operational impacts, process limitations, and regulatory requirements. Moreover, the designer must strive not only to achieve a workable structure, but also to find a rational solution in terms of cost, material consumption, weight, carbon footprint, and other indicators.

Classical optimization methods are successfully applied to solving such problems, but increasing the number of design variables quickly leads to increased computational complexity. This is particularly evident in the optimization of spatial reinforced concrete systems, where each change in cross-section or reinforcement requires a repeat calculation. A critical review of reinforced concrete optimization methods shows that traditional algorithmic approaches already significantly reduce material consumption, but their effectiveness is limited by the complexity of the computational space and the cost of repeated calculations [1].

Artificial intelligence is ushering in a new era of development in this field. Machine learning enables the construction of approximate models of the relationship between design parameters and calculation results. As a result, some expensive calculations can be replaced with rapid predictions. A review of the application of artificial intelligence methods in construction and structural engineering shows that neural networks, machine learning methods, and hybrid algorithms are gradually moving from the experimental stage to practical engineering applications [2, 3].

Evolution of methods for optimizing reinforced concrete structures. In the traditional approach, the designer specifies a set of variables characterizing the structure: section dimensions, concrete grade, diameter and number of reinforcing bars, transverse reinforcement spacing, and other parameters. The optimization procedure searches for a combination of variables that results in the objective function achieving its minimum or maximum value while satisfying the specified constraints.

In the simplest case, the objective function can characterize the cost of the structure and include the cost of concrete, reinforcement, and formwork: ($F = C_c + C_s + C_f$). Constraints are determined by regulatory requirements for strength, crack resistance, deformation, and design parameters.

The main advantage of this approach is its mathematical certainty. However, real-world reinforced concrete structures are characterized by discrete design variables, nonlinear dependencies, and a large number of constraints. Therefore, classical methods for finding the optimum often require a significant number of calculation iterations [1].

Genetic algorithms. The development of evolutionary methods has become an important step in the optimization of reinforced concrete structures. Genetic algorithms allow for working with discrete and nonlinear design variables without requiring an analytical representation of the objective function.

During the search process, multiple design options are generated and evaluated according to specified criteria. The most promising solutions are then used in subsequent selection, crossbreeding, and mutation processes. This mechanism allows for exploration of a large space of possible design solutions.

Studies of the optimal detailed design of reinforced concrete frames have demonstrated the effectiveness of genetic algorithms for the simultaneous selection of element sizes and reinforcement parameters [5]. Hybrid methods combining genetic search with local optimization have been further developed. For example, an integrated genetic algorithm with direct search was used to improve the optimization efficiency of reinforced concrete frames [6]. Thus, genetic

algorithms have become an important foundation for modern intelligent optimization, but by themselves they do not yet solve the problem of the high cost of each calculation cycle.

The transition from algorithmic optimization to artificial intelligence. The fundamental difference between artificial intelligence methods is the ability not only to search for solutions but also to learn the relationship between initial parameters and calculation results.

While a traditional optimizer repeatedly accesses a computational model, machine learning can pre-form an approximating relationship between input and output parameters. Generally, this can be viewed as an approximation ($y \approx \hat{f}_{ML}(x)$), where (x) is the set of design characteristics and (y) is the predicted computational result. Once trained, such a model can produce a prediction significantly faster than the original finite element calculation. This is especially important in optimization, where thousands or tens of thousands of variants must be evaluated.

Recent reviews of machine learning in structural engineering demonstrate the expanding scope of such models' applications, from predicting individual parameters to optimization tasks and supporting design decisions [3, 4]. However, artificial intelligence should not be viewed as a replacement for engineering calculations. A more feasible architecture is one in which the ML model accelerates the search, while final verification is performed using traditional calculation methods.

Neural networks for reinforced concrete optimization. One of the first applications of artificial intelligence to reinforced concrete structures was the use of neural networks to determine optimal design parameters.

A neural network can be trained on a variety of previously calculated design variants. Inputs can include span, cross-section dimensions, concrete properties, reinforcement parameters, and loads. The output can be the structure's cost, mass, load-bearing capacity, or other design parameters. Early studies demonstrated the feasibility of using neural network models to determine the optimal cost of reinforced concrete slabs [4]. Despite the relative simplicity of these early models, it was this approach that laid the foundation for the modern concept of surrogate modeling.

Modern neural networks are capable of handling significantly more complex nonlinear relationships. However, their effectiveness is directly related to the quality of the training data. If the training data does not cover the required ranges of loads, materials, and geometric parameters, the model may produce incorrect predictions when designing new structures.

Machine learning as a surrogate for finite element analysis. One of the most promising areas involves creating an ML surrogate for a computational model. Finite element analysis is a crucial tool for assessing the performance of reinforced concrete structures, but running it repeatedly in an optimization cycle can be computationally expensive. A surrogate model allows for the replacement of some of these operations with rapid prediction.

The sequence can be organized as follows: first, a set of design options is generated, then each option is calculated using a traditional method, after which the resulting database is used to train the machine learning model. In the next stage, the optimizer works primarily with the ML model, periodically submitting promising solutions for precise computational verification. This approach

combines the advantages of both systems. Machine learning ensures search speed, while finite element analysis maintains physical and engineering accuracy.

Of particular interest is the metamodel approach to optimizing reinforced concrete frames, taking into account the interaction of the structure with the foundation. Research shows that the use of metamodels in conjunction with metaheuristic algorithms allows for a reduction in the number of costly calculations while maintaining the optimization procedure [9].

Hybrid ML-metaheuristic algorithms. The next stage of development is the combination of machine learning with genetic and other metaheuristic algorithms. In this architecture, the ML model serves as a fast estimator, while the metaheuristic algorithm is responsible for searching the design space. This allows for the separation of two tasks: predicting the design's behavior and finding the optimal combination of parameters.

Hybridization is especially effective when there are a large number of discrete variables. For example, the diameter and number of reinforcing bars cannot be considered as completely continuous parameters. Therefore, the optimizer must work with real design variants, and the ML model must quickly evaluate their characteristics.

Research on hybrid models for designing reinforced concrete columns demonstrates the feasibility of combining artificial intelligence with traditional search algorithms [8]. More recent research utilizes gradient-boosted models in conjunction with metaheuristic optimization to improve the efficiency of design solution searches [10]. Thus, the promising approach is not to replace one method with another, but to develop a hybrid computational-intelligence system.

Optimization of reinforced concrete columns. Columns are a convenient object for developing intelligent optimization models, as their design involves a limited, yet relatively large, number of interrelated variables. These include cross-sectional dimensions, concrete grade, longitudinal and transverse reinforcement, element length, design loads, and anchorage conditions. The objective function may include cost, mass, or environmental performance.

Modern hybrid models are capable of predicting optimal column parameters based on given input data. It's crucial that the trained system not limit itself to searching for the mathematical minimum value. The design solution must simultaneously meet strength requirements and structural constraints.

In studies of optimal design of reinforced concrete columns using machine learning, environmental criteria are also considered, which indicates a transition from cost minimization to a multi-criteria formulation of the problem [8, 9].

Multi-criteria optimization. Modern design can rarely be reduced to a single criterion. Minimizing cost does not always mean minimizing mass or carbon footprint. Reducing the cross-section can lead to increased rebar consumption, while increasing the concrete grade can lead to a reduction in geometric dimensions, while cost and environmental impacts change. Therefore, the objective function may include several components, such as cost, CO₂ emissions, weight, and the technological complexity of the design. In this case, the problem becomes multicriterial.

Instead of searching for a single, absolute optimum, multiple compromise solutions are generated, from which the engineer selects an option based on the design situation. For practical design, this

approach has a significant advantage: artificial intelligence is not required to independently determine the final solution. It can generate multiple feasible options, and the engineer selects a specific configuration based on regulatory, technological, and operational factors.

Environmental optimization of reinforced concrete. Environmental performance is becoming an increasingly important component of building structure optimization. Cement production is associated with significant greenhouse gas emissions, and steel production requires significant energy resources. Therefore, reducing the material intensity of reinforced concrete structures can have not only an economic but also an environmental impact. In this regard, machine learning can be used to evaluate the environmental performance of various design solutions. Studies of the optimal design of reinforced concrete columns demonstrate the possibility of integrating environmental criteria directly into the intelligent search procedure [9].

A promising model must consider not only the mass of concrete and rebar, but also a full range of factors related to material production, transportation, construction, and subsequent operation. Thus, artificial intelligence can transform the problem from a "minimum cost" approach to a search for structurally and environmentally sustainable solutions.

Constructive feasibility as a limitation of AI optimization. One of the fundamental problems of automated optimization is the possibility of obtaining a mathematically optimal but practically inconvenient solution. For example, an algorithm might reduce the volume of concrete by using an unusual cross-section geometry or achieve savings in rebar by using a complex combination of diameters and spacings. Such a solution may prove inconvenient for fabrication, installation, or quality control. Therefore, intelligent optimization must take into account design constraints. These include minimum and maximum reinforcement diameters, permissible bar spacing, minimum cover layers, requirements for anchoring and reinforcement placement, concrete placement processability, and cross-section standardization.

Therefore, the objective function must be considered in conjunction with the constraint system, not separately. This is where the engineer's key role remains. Artificial intelligence can accelerate the search and evaluation of options, but the normative and constructive interpretation of the results must remain part of the engineering process.

Genetic algorithms and neural networks. A comparison of genetic algorithms and neural networks shows that these methods solve different problems. A genetic algorithm is primarily a search tool. It can explore a large solution space and work with discrete variables. A neural network is primarily a predictive tool. Once trained, it quickly estimates output parameters for new combinations of input data. Therefore, their combination has a natural structure: a neural network quickly evaluates a large number of options, and a genetic algorithm uses these evaluations to find a promising area of the design space.

This combination reduces the number of costly calls to the precise computational model. This is why hybrid AI-metaheuristic systems are of significant interest for design optimization [4, 8, 10].

Automated design using reinforcement learning. A more radical approach involves deep reinforcement learning. In this case, the system doesn't receive a predefined set of optimal solutions, but rather sequentially generates design actions and evaluates their results. For a reinforced concrete structure, such actions may include changing the cross-section dimensions, selecting the concrete grade, changing the amount of reinforcement or other design parameters. Research into the application of deep reinforcement learning to the automated design of reinforced concrete structures has demonstrated the ability to generate a sequence of design solutions directly during the learning process [7]. The key difference between this approach and classical optimization is that the system is potentially capable of generating a design strategy rather than simply selecting a solution from a predetermined set.

However, reinforcement learning requires large amounts of data, a correct reward function, and strict constraint control. Therefore, its practical use should primarily be considered a promising research direction for now.

The problem of training data quality. Data quality is one of the key factors in the reliability of intelligent optimization. For training, it is necessary to create a representative database of design variants. This should cover various load values, geometries, material classes, reinforcement schemes, and operating conditions. If the data is only generated for a narrow range of parameters, the model will perform well within the training domain, but may produce significant errors when going beyond it. The accuracy of the initial calculations is especially important. Errors in the finite element model or standard calculation are automatically transferred to the training set and then reproduced by the ML model.

Therefore, data preparation should be considered as a separate engineering task, including variant generation, calculation, quality control, anomaly detection, and data partitioning into training, validation, and test sets.

The extrapolation problem. Most ML models perform most reliably within the domain represented by the training data. Beyond this domain, the prediction becomes less predictable. This is especially important for structural design. The new structure may have geometry, loads, or material combinations that are not present in the original design. Therefore, an intelligent system must determine the scope of its model's applicability. One possible approach is to periodically submit new variants for precise calculation. The resulting results are then added to the training database. This is how an iterative cycle is formed: **ML forecast → selection of a promising solution → precise calculation → replenishment of the database → retraining of the model**. This mechanism allows for a gradual increase in the reliability of the intelligent system.

Interpretability of AI results. Another challenge is the explainability of decisions. It's not enough for a designer to simply be informed that a certain cross-section is optimal. It's also necessary to understand the factors that led to this result.

In engineering practice, the ability to verify the relationship between input parameters and output decisions is particularly important. Therefore, models in which the forecast is accompanied by an assessment of the impact of key factors are promising. Interpretability is also important from a regulatory perspective. The final design solution must be verifiable, documentable, and

reproducible. Therefore, for the construction industry, the most promising option is not a fully autonomous "black box," but a system of intelligent support for engineering decisions.

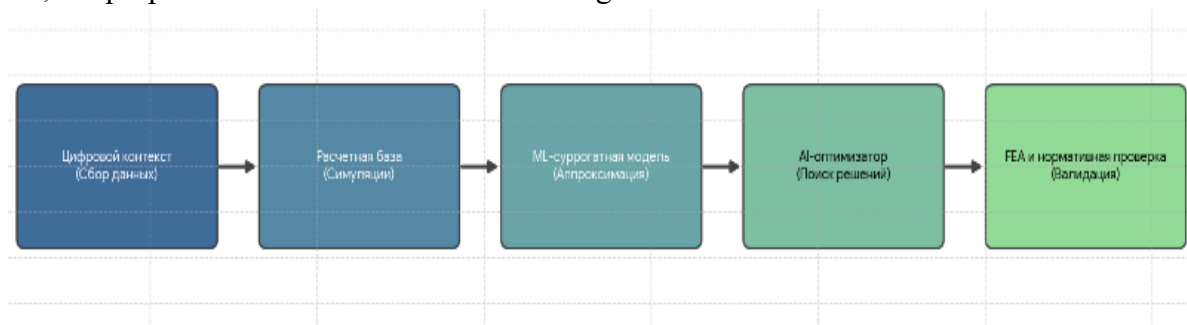
Table 1. Comparative characteristics of methods for optimizing reinforced concrete structures

Method	Main purpose	Advantage	The main limitation
Mathematical optimization	Finding the extremum of the objective function	Formal certainty	Complexity in nonlinear and discrete problems
Genetic algorithms	Search in a large solution space	Working with discrete variables	A large number of iterations
Neural networks	Forecast of design characteristics	Quick forecast after training	Dependence on data quality
ML surrogate	Replacement of some settlement operations	Significant reduction in time	Limited scope of applicability
Hybrid ML metaheuristics	+ Intelligent search	Combining forecasting and optimization	Increased system complexity
Reinforcement learning	Automated decision making	Opportunity to learn design strategy	High demands on data and training

Thus, the methods do not so much compete with each other as they form successive levels of development of the optimization system.

Conceptual model of AI-based optimization. Based on the studies reviewed, it is appropriate to consider the optimization of reinforced concrete structures as a multi-level process. In the first stage, a digital context is created: the structure's geometry, materials, loads, design model, and regulatory constraints. In the second stage, a design database is created. A precise calculation is performed for a variety of variants, after which the design parameters and corresponding results are recorded. In the third stage, an ML surrogate model is constructed, which establishes the relationship between the structure's parameters and its design characteristics. In the fourth stage, the AI optimizer searches for promising solutions. Depending on the problem statement, genetic algorithms, metaheuristic methods, gradient methods, or reinforcement learning can be used. In the fifth stage, independent finite element and regulatory verification of the selected solution is performed.

Thus, the proposed architecture has the following fundamental form:



The main advantage of this model is that artificial intelligence does not eliminate traditional engineering calculations, but is placed between the initial digital model and the final verification.

An analytical comparison of traditional and AI-driven design. Traditional design involves the sequential generation of several design variants and their verification using computational methods. Optimization is accomplished primarily based on engineering experience and a limited number of iterations.

An AI-centric approach significantly increases the number of options considered. With a trained model, evaluating a large number of solutions can be performed significantly faster than fully calculating each option. However, changing the nature of design doesn't eliminate the engineering role. On the contrary, the engineer shifts from the level of directly evaluating options to the level of problem definition, constraint monitoring, results interpretation, and final solution selection. This transformation appears to be the most realistic for the practical implementation of artificial intelligence in structural design.

Key benefits of using AI. The key advantages of artificial intelligence in the optimization of reinforced concrete structures include:

- 1. Reducing computational costs.** ML surrogates can quickly evaluate a large number of design options.
- 2. Working with a large number of variables.** Intelligent algorithms are capable of analyzing complex nonlinear relationships.
- 3. Taking multiple criteria into account.** Simultaneous optimization of cost, weight, material consumption, and environmental performance is possible.
- 4. Automated search.** Algorithms allow exploration of areas of the design space that are difficult to analyze manually.
- 5. Integration with digital design.** AI models can use data from BIM, calculation programs, and digital design databases.
- 6. Adaptation to accumulated data.** As the computational base expands, the ML model can retrain and improve forecasting accuracy.

Reviews of machine learning methods in structural engineering point to the combination of high prediction speed and the ability to work with complex nonlinear dependencies as key reasons for the development of this area [2–4].

Limitations of Artificial Intelligence. Despite its significant potential, AI has a number of limitations.

The first is the dependence on data quality. Insufficient representativeness of the training sample limits the model's scope of reliable application.

The second problem is extrapolation. A model may demonstrate high accuracy on a test sample, but exhibit significant errors when applied to a fundamentally new design configuration.

Third, regulatory verification is necessary. Even the high accuracy of ML forecasts is no substitute for a calculation check in accordance with current regulations.

The fourth limitation is interpretability. The engineer must understand why the algorithm proposes a specific solution and how it corresponds to the physics of the structure.

Finally, responsibility for the final design decision remains an important factor. Therefore, a modern AI design concept should be built around the **human-in-the-loop principle**, whereby the engineer retains control over defining the task and approving the result.

Promising directions. Further development of AI-based optimization of reinforced concrete structures can take place in several directions.

The first area involves integrating ML models directly into the BIM environment and calculation software. This will enable optimization directly on the digital building model.

The second direction is related to the development of multi-criteria algorithms that simultaneously take into account cost, weight, carbon footprint, durability, and manufacturability.

The third area is the creation of digital libraries of design solutions that will be used to train models and subsequently transfer the accumulated knowledge to new projects.

The fourth direction is related to the development of physics-informed machine learning, which integrates machine learning with physical and mechanical constraints. This approach has the potential to reduce the model's dependence on large volumes of experimental data.

The fifth area is the development of automated systems that combine generative design, machine learning, finite element analysis, and regulatory verification in a single cycle.

Conclusion

The conducted analysis shows that modern optimization of reinforced concrete structures is evolving from individual search algorithms to integrated intelligent systems. Genetic algorithms laid the foundation for the automated search for rational design solutions [5, 6]. Neural networks expanded this concept by rapidly predicting design characteristics [4]. Modern machine learning methods allow the use of surrogate models to reduce the number of expensive calculations [3, 9]. Hybrid approaches combine the advantages of ML and metaheuristic optimization [8, 10]. Finally, deep reinforcement learning creates the preconditions for the automated generation of a sequence of design actions [7].

However, these approaches should not be viewed as a sequential replacement of one method for another. The most promising approach appears to be the integration of various tools into a single system. In such a system, precise calculations retain the function of benchmarking, machine learning provides accelerated forecasting, and an optimization algorithm performs search. The engineer then defines the initial constraints, monitors the model's scope of applicability, and makes the final decision.

Therefore, it is advisable to consider artificial intelligence not as an independent designer, but as an intellectual layer that increases the speed and breadth of engineering search.

Artificial intelligence is shaping a new direction for the optimization of reinforced concrete structures. Unlike traditional methods, which focus primarily on directly searching for the optimal solution, machine learning enables the creation of rapid, approximate models of structural behavior and their use as part of the optimization cycle.

The most promising are hybrid systems that combine ML surrogate models, metaheuristic algorithms, and traditional finite element analysis. This architecture allows for a significant expansion of the range of design options while maintaining engineering control over the outcome.

Of particular importance is the transition from single-criteria cost optimization to multi-criteria assessment, taking into account material consumption, environmental performance, and design feasibility. Moreover, the reliability of intelligent optimization is determined not only by the accuracy of the algorithm, but also by the quality of the training data, the model's scope of applicability, the accuracy of the initial calculation, and the ability to independently verify it. Thus, the most efficient model for applying artificial intelligence in reinforced concrete design is to combine a digital model of the structure, a computational database, a machine learning surrogate, an intelligent optimizer, and traditional engineering verification. This approach leverages the benefits of artificial intelligence without abandoning the fundamental principles of structural reliability design and design.

References

1. Afzal M., Liu Y., Cheng JCP, Gan VJL Reinforced concrete structural design optimization: A critical review. *Journal of Cleaner Production* . 2020. Vol. 260. Article 120623. DOI: 10.1016/j.jclepro.2020.120623.
https://www.researchgate.net/publication/339409346_Reinforced_concrete_structural_design_optimization_A_critical_review
2. Salehi H., Burgueño R. Emerging artificial intelligence methods in structural engineering. *Engineering Structures* . 2018. Vol. 171. P. 170–189. DOI: 10.1016/j.engstruct.2018.05.084.
https://www.researchgate.net/publication/325626988_Emerging_artificial_intelligence_methods_in_structural_engineering
3. 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>
4. Ahmadkhanlou F., Adeli H. Optimum cost design of reinforced concrete slabs using neural dynamics model. *Engineering Applications of Artificial Intelligence* . 2005. Vol. 18, No. 1. P. 65–72. DOI: 10.1016/j.engappai.2004.08.025.
<https://www.sciencedirect.com/science/article/abs/pii/S0952197604001071>
5. Govindaraj V., Ramasamy JV Optimum detailed design of reinforced concrete frames using genetic algorithms. *Engineering Optimization* . 2007. Vol. 39, No. 4. P. 471–494. DOI: 10.1080/03052150601180767.
https://www.researchgate.net/publication/245310696_Optimum_detailed_design_of_reinforced_concrete_frames_using_genetic_algorithms
6. Kwak H.-G., Kim J. An integrated genetic algorithm complemented with direct search for optimal design of RC frames. *Computer-Aided Design* . 2009. Vol. 41, No. 7. P. 490–500. DOI: 10.1016/j.cad.2009.03.005. <https://dl.acm.org/doi/abs/10.1016/j.cad.2009.03.005>
7. Jeong J.-H., Jo H. Deep reinforcement learning for automated design of reinforced concrete structures. *Computer-Aided Civil and Infrastructure Engineering* . 2021. Vol. 36, No. 12. P. 1508–1529. DOI: 10.1111/mice.12773.
<https://www.sciencedirect.com/science/article/pii/S1093968726021870>
8. Nigdeli S.M., Yücel M., Bekdaş G. A hybrid artificial intelligence model for design of reinforced concrete columns. *Neural Computing and Applications* . 2023. Vol. 35. P. 7867–

7875. DOI: 10.1007/s00521-022-08164-7. <https://link.springer.com/article/10.1007/s00521-024-09998-z>
9. Aydın Y., Bekdaş G., Nigdeli SM, et al. Machine Learning Models for Ecofriendly Optimum Design of Reinforced Concrete Columns. *Applied Sciences* . 2023. Vol. 13, No. 7. Article 4117. DOI: 10.3390/app13074117. <https://www.mdpi.com/2076-3417/13/7/4117>
10. Metamodel-assisted meta-heuristic design optimization of reinforced concrete frame structures considering soil-structure interaction . *Engineering Structures* . 2023. Vol. 293. Article 116657. DOI: 10.1016/j.engstruct.2023.116657. <https://www.sciencedirect.com/science/article/pii/S0141029623010726>
11. Prayogo H., Yang I.-T., Cheng M.-Y. Dynamic Gradient Boosted Metaheuristic approach for efficient reinforced concrete structure optimization. *Journal of Building Engineering* . 2024. Vol. 97. Article 110864. DOI: 10.1016/j.jobbe.2024.110864. <https://www.sciencedirect.com/science/article/abs/pii/S235271022402432X>