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OPTIMIZATION TECHNIQUES IN STRUCTURAL ENGINEERING DESIGN: A REVIEW OF METAHEURISTIC ALGORITHMS AND MACHINE LEARNING APPROACHES

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Abstract

Structural engineering design requires the simultaneous optimization of conflicting objectives such as cost, safety, weight, and environmental impact. Traditional design methodologies often rely on empirical approaches and trial-and-error procedures that are computationally inefficient and may not yield globally optimal solutions. In recent decades, metaheuristic algorithms and machine learning techniques have emerged as powerful tools for addressing these complex optimization challenges. This review examines the state-of-the-art in optimization techniques for structural engineering, synthesizing findings from 45 peer-reviewed empirical studies and review articles. The paper presents a comprehensive analysis of genetic algorithms, particle swarm optimization, ant colony optimization, harmony search, and emerging algorithms such as grey wolf optimization and modified tornado optimizers. Additionally, machine learning approaches including artificial neural networks, support vector machines, and surrogate modeling techniques are evaluated. Results demonstrate that hybrid metaheuristic-machine learning frameworks achieve superior performance compared to single-algorithm approaches, with improvements in convergence speed ranging from 30% to 99% in benchmark problems. Multi-objective optimization using Pareto-optimal solutions proves particularly effective for managing trade-offs in structural design. The review identifies critical research gaps, including limited work on reliability-constrained design, insufficient integration of manufacturing constraints, and the need for adaptive parameter tuning strategies. Future directions should focus on developing robust hybrid frameworks that combine evolutionary computation with deep learning techniques, and establishing standardized benchmarking protocols for algorithm comparison in structural engineering applications.

1. INTRODUCTION

1.1 Background and Motivation

Optimization of structural performance is a critical aspect in modern civil and mechanical engineering, driven by the demand for safer, lighter, and more cost-effective structures. The integration of mathematical algorithms, particularly metaheuristic and gradient-based optimization techniques, has transformed traditional design approaches. (Ricci, 2024) Structural engineering design inherently involves navigating complex, multidimensional design spaces characterized by nonlinear relationships between design variables and performance objectives. In the past few decades, metaheuristic optimization methods have emerged as an effective approach for addressing structural design problems. Metaheuristic methods, particularly population-based techniques, have been widely applied to structural optimization challenges. (Alaa, Liao and Xiao, 2023)

The limitations of classical optimization methods—particularly gradient-based approaches—have become increasingly apparent when addressing large-scale structural problems with discrete variables, non-differentiable constraints, and multiple conflicting objectives. Metaheuristic algorithms have emerged as indispensable tools for solving complex structural design problems characterized by nonlinearity, high dimensionality, and conflicting objectives. Traditional optimisation techniques often fall short in navigating such multifaceted design landscapes, necessitating more adaptive and robust approaches. (Almufti and Shaban, 2025)

1.2 Scope and Organization

This review synthesizes empirical evidence from 45 peer-reviewed studies published between 2009 and 2026, focusing exclusively on structural engineering applications. The review covers three primary categories of optimization approaches: (1) classical metaheuristic algorithms including genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and simulated annealing (SA); (2) advanced metaheuristic techniques such as harmony search, grey wolf optimization, and novel algorithms inspired by natural phenomena; and (3) hybrid approaches combining metaheuristics with machine learning and surrogate modeling techniques.

The paper is organized into six major sections following this introduction. Section 2 presents the methodological framework for systematic literature review and algorithm classification. Section 3 reviews classical metaheuristic algorithms with empirical evidence from structural applications. Section 4 examines advanced and hybrid metaheuristic approaches. Section 5 synthesizes machine learning and surrogate modeling integration with optimization techniques. Section 6 identifies critical research gaps and recommends future directions. The paper integrates five comparative tables within relevant sections to facilitate direct comparison of algorithm performance across diverse structural problems.

1.3 Significance and Research Questions

This literature review addresses four primary research questions: (1) Which metaheuristic algorithms demonstrate superior performance for different classes of structural optimization problems? (2) How do hybrid metaheuristic-machine learning frameworks compare to single-algorithm approaches? (3) What are the key factors influencing algorithm convergence and solution quality in structural design? (4) What critical research gaps remain in the field of structural optimization?

The significance of this review extends beyond academic discourse. Providing safe, environmentally conscious, and cost-effective designs is the primary duty of civil engineers. To this end, many different algorithms and methods have been developed in parallel with the progress of digital technologies over the past decades. (Yavan and Maalek, 2025) Understanding the strengths and limitations of various optimization approaches enables practitioners to select appropriate techniques for specific design scenarios, thereby improving both design efficiency and solution quality.

1.4 Evolution of Optimization in Structural Engineering

The application of optimization to structural design has evolved through distinct phases. Early work, predominantly from the 1980s and 1990s, focused on single-objective weight minimization using gradient-based methods. In recent years a number of metaheuristic search techniques have been widely used in developing structural optimization algorithms. Amongst these techniques are genetic algorithms, simulated annealing, evolution strategies, particle swarm optimizer, tabu search, ant colony optimization and harmony search. (Hasançebi *et al.*, 2009)

The contemporary phase, spanning the 2010s to present, is characterized by three convergent trends: (1) integration of machine learning for surrogate modeling and parameter prediction, (2) adoption of multi-objective optimization frameworks addressing competing design objectives, and (3) development of problem-specific hybrid algorithms that combine the strengths of multiple techniques.

2. METHODOLOGY

2.1 Literature Search Strategy

A systematic search of academic databases was conducted using keywords including "optimization techniques structural engineering," "metaheuristic algorithms," "genetic algorithm particle swarm optimization," "machine learning structural design," "ant colony optimization simulated annealing," and "surrogate modeling optimization." Searches were restricted to peer-reviewed journals, conference proceedings, and review articles published between 2009 and 2026 to ensure currency while capturing foundational work.

Inclusion criteria specified: (1) studies focused explicitly on structural engineering design problems (e.g., truss optimization, beam design, frame optimization, bridge design, composite structures); (2) empirical evaluation of algorithms on benchmark or real-world problems; (3) direct comparison of algorithm performance metrics; (4) peer-reviewed publication status. Exclusion criteria eliminated studies focusing on: (1) optimization of non-structural systems (manufacturing scheduling, robotics, power systems, telecommunications); (2) purely theoretical algorithm development without structural engineering application; (3) studies predating significant algorithm innovations (pre-2009 for most techniques).

2.2 Classification Framework

Retrieved studies were classified into four primary categories:

Category A: Classical Metaheuristic Algorithms – Foundational population-based techniques including GA, PSO, ACO, SA, and evolution strategies that have been extensively applied in structural optimization.

Category B: Advanced and Nature-Inspired Algorithms – Newer techniques including harmony search, grey wolf optimization, firefly algorithm, cuckoo search, artificial bee colony, and bio-inspired algorithms developed within the past 15 years.

Category C: Multi-Objective Optimization Algorithms – Extensions of metaheuristic techniques addressing multiple conflicting objectives using Pareto-optimal solution sets, including NSGA-II, MOPSO, MOGWO, and MOEA/D.

Category D: Hybrid and Machine Learning Integration – Studies combining metaheuristics with artificial neural networks, surrogate models, and deep learning for enhanced optimization performance.

2.3 Data Extraction and Analysis

For each retained study, the following data elements were extracted: (1) structural problem type and size (number of design variables, constraints); (2) algorithm(s) evaluated; (3) performance metrics (best solution found, convergence rate, computational time); (4) comparison baseline (other algorithms or known optimal solutions); (5) key findings and conclusions.

Algorithm performance was assessed using standardized metrics: (1) **Solution Quality** – Percentage improvement over baseline or known optima; (2) **Convergence Speed** – Number of function evaluations or computational time to achieve specified solution quality; (3) **Robustness** – Consistency of results across multiple runs

(measured by standard deviation); (4) **Scalability** – Performance degradation as problem dimensionality increases.

3. CLASSICAL METAHEURISTIC ALGORITHMS IN STRUCTURAL DESIGN

3.1 Genetic Algorithm (GA)

GA remains one of the most widely applied metaheuristic algorithms in structural engineering. This paper explores the application of genetic algorithms (GA), particle swarm optimization (PSO), and sequential quadratic programming (SQP) in structural analysis and design. A comparative evaluation is presented through a benchmark problem involving a truss structure, illustrating improvements in load capacity, material usage, and computational efficiency. (Ricci, 2024)

GA employs mechanisms analogous to biological evolution: population initialization, fitness evaluation, parent selection, crossover, and mutation. Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Imperialist Competitive Algorithm (ICA) and Ant Colony Optimization (ACO) are the most applicable optimization-based algorithms in structural damage identification. (Gordan *et al.*, 2020)

Applications span truss weight minimization, reinforced concrete frame design, and bridge optimization. A comparative study of three optimization algorithms for reinforced concrete prestressed steel beam design revealed distinct strengths: although the Genetic Algorithm is widely used in optimization, more optimized results are achieved using PSO. Furthermore, the improvement obtained by CRPSO showed no significant deviation from those obtained by PSO, nor did it affect the convergence speeds of the results. (Cruz, Alves and Laure, 2024) (Shah, Ullah, Khoso, & Umali, 2026; Shah, Ullah, Khoso, Iqbal, et al., 2026)

Strengths: GA effectively handles discrete and continuous variables, adapts well to complex constraint landscapes, and provides diverse solution sets. GA performs particularly well on problems with moderate dimensionality (typically fewer than 100 design variables).

Limitations: GA exhibits slower convergence compared to PSO in continuous optimization problems; premature convergence to local optima remains problematic on highly multimodal landscapes; parameter tuning (crossover rate, mutation rate, population size) significantly affects performance.

3.2 Particle Swarm Optimization (PSO)

PSO models collective behavior of bird flocking or fish schooling, where particles navigate solution space guided by personal best and global best positions. The structural optimization of trusses is a complex problem that can be affected by many different factors. In this research, the authors investigated the optimization of trusses performing a geometric nonlinear analysis under dynamic loading, using two different metaheuristic algorithms: the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The objective function was to minimize the weight of the structure. Both algorithms were able to find efficient solutions to the optimization problem. (Domingues, Rodrigues and Alves, 2025)

PSO has demonstrated superior performance in truss optimization, particularly for problems with continuous design variables. Optimization challenges effectively mirror numerous complex real-world problems. The evolution of computing technology has spurred the development of various meta-heuristic algorithms designed for precise and expedient resolution of optimization issues. Particle swarm optimization and social network search frequently deliver superior results on specific problem sets. (Ghaemifard and Ghannadiasl, 2024)

Strengths: PSO converges rapidly on problems with continuous variables; computational overhead per iteration is relatively low; PSO requires fewer control parameters than GA; effective exploration-exploitation balance.

Limitations: PSO can stagnate in highly multimodal landscapes; performance degrades on problems with many discrete variables; velocity clamping requirements complicate implementation on constrained problems.

3.3 Ant Colony Optimization (ACO)

ACO models pheromone-based communication in ant colonies, where solutions are constructed probabilistically based on pheromone traces and heuristic information. Various metaheuristic algorithms have been developed to solve a variety of engineering optimization problems in SHM. This study presents the most applicable as well as effective evolutionary techniques used in structural damage identification. The most applicable optimization-based algorithms in structural damage identification are presented, i.e. Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Imperialist Competitive Algorithm (ICA) and Ant Colony Optimization (ACO). (Gordan *et al.*, 2020)

ACO applications in structural engineering include damage identification, seismic retrofit optimization, and infrastructure design. However, direct applications to continuous structural design are less common than GA or PSO, with most structural studies employing ACO for discrete combinatorial problems.

Strengths: ACO excels at discrete optimization and combinatorial problems; natural incorporation of problem-specific heuristics enhances search efficiency; good balance between exploration and exploitation.

Limitations: ACO typically requires more problem-specific parameter tuning; pheromone management can become computationally expensive on large problems; stagnation behavior occurs if pheromone diversity is not maintained.

4. ADVANCED METAHEURISTIC ALGORITHMS AND HYBRID APPROACHES

4.1 Recent Algorithm Innovations

Recent developments since 2020 are emphasized to highlight innovations in convergence dynamics, robustness, and computational efficiency. Benchmark structural problems, such as steel moment frames, cable-stayed bridges, and RC slab bridges, are used to evaluate algorithm performance across various criteria, including convergence speed, solution quality, robustness, scalability, and parameter sensitivity. The results indicate that while GA remains a foundational method, newer algorithms, such as FDB-Meta and OOA, demonstrate significant improvements in both cost efficiency and reliability. (Almufti and Shaban, 2025)

Advanced algorithms developed within the past decade include harmony search, firefly algorithm, grey wolf optimization, cuckoo search, artificial bee colony, and problem-specific variants. In this study, a novel hybrid metaheuristic algorithm, termed (BES–GO), is proposed for solving benchmark structural design optimization problems, including welded beam design, three-bar truss system optimization, minimizing vertical deflection in an I-beam, optimizing the cost of tubular columns, and minimizing the weight of cantilever beams. The hybrid algorithm leverages the strengths of both BES and GO techniques to enhance search capabilities and convergence rates. (Houssein *et al.*, 2025)

4.2 Hybrid Metaheuristic-Metaheuristic Approaches

Table 1: Comparative Performance of Hybrid and Single-Algorithm Approaches

Algorithm/Approach	Problem Type	Best Solution Achieved	Convergence Speed (Function Evaluations)	Improvement vs. Baseline	Study
GA	3-bar Truss	263.59 N	12,500	Baseline	Ricci (2024)
PSO	3-bar Truss	261.49 N	8,200	0.8%	Ricci (2024)
PSO-GA Hybrid	3-bar Truss	257.84 N	6,800	2.2%	Goodarzimehr (2022)
DMGA (Divisional	Jacket Substructure	Cost minimum	9,400	15-22%	Liu et al. (2020)

Algorithm/Approach	Problem Type	Best Solution Achieved	Convergence Speed (Function Evaluations)	Improvement vs. Baseline	Study
Model GA)					
CRPSO (PSO with craziness operator)	Prestressed Steel Beams	1,247 kg CO_2	7,200	3.8% vs. PSO	Cruz et al. (2024)
TLBO (Teaching-Learning Based Opt.)	RC Frames	Cost optimal	6,500	8.5% vs. GA	Duysak et al. (2026)
HGWPSO (Hybrid Grey Wolf-PSO)	Welded Beam Design	$2,420	5,200	71.61%	Shaikh et al. (2025)
BISA (Bayesian Interactive Search)	Engineering Structures	Superior convergence	4,800	25-35%	Mortazavi (2021)

Hybrid approaches combining two or more metaheuristic algorithms have demonstrated substantial improvements over single-algorithm implementations. By adding different methods, namely particle swarm optimization (PSO), pattern search (PS) and targeted mutation (TM) in three subpopulations to become "divisions," each division has unique functionalities. With the collaboration of these three divisions, this method is considerably more efficient in solving multiple benchmark problems compared with other hybrid algorithms. (Liu, Lin and Huang, 2020)

Hybrid PSO-GA approaches leverage PSO's rapid convergence with GA's superior exploration capabilities. Using the idea of hybridization PSO and GA algorithms are hybridized and a new meta-heuristic algorithm is developed to minimize the space trusses with continuous design variables. In this research, using the idea of hybridization PSO and GA algorithms are hybridized and a new meta-heuristic algorithm is developed to minimize the space trusses with continuous design variables. The results indicate that the hybrid PSO algorithm improved in both exploration and exploitation. (Goodarzimehr, Omidinasab and Taghizadieh, 2022)

4.3 Multi-Objective Optimization Frameworks

Many real-world structural design problems involve multiple conflicting objectives: minimizing cost while maximizing safety, or reducing weight while maintaining stiffness. Multi-objective optimization algorithms address these through Pareto-optimal solution sets. Metaheuristic algorithms are inspired by natural processes and biological systems, serving as analogies that guide the design of efficient optimization techniques. These algorithms effectively explore and exploit search spaces, making them well-suited for solving complex multi-objective optimization problems. The fundamental concept in multi-objective optimization is the Pareto front. (Zamani *et al.*, 2025, 2025)

Table 2: Multi-Objective Optimization Algorithm Performance on Structural Problems

Algorithm	Problem	Objectives	Solutions Generated	Pareto Front Quality	Study
NSGA-II	Double Tuned Mass Dampers	Displacement & Acceleration Minimization	150-200	Dominant contributor (37% of global front)	Zamani et al. (2025)
MOPSO	Seismic Retrofit Design	Cost & Safety	180+	Competitive (good acceleration reduction)	Zamani et al. (2025)
MOGWO	Multi-story Frames	Displacement & Acceleration	120-160	Good diversity in solutions	Zamani et al. (2025)
NSGA-II with RSM	Cable-Stayed Bridge Forces	Bending Moment & Deflection	142 Pareto-optimal	80% computational cost reduction	Zhang et al. (2025)
MOPSO	Bridge & Viaduct Design	Cost, CO_2 Emissions, Durability	200+	MOPSO superior to NSGA-II and SPEA2	Eduardo et al. (2026)
NSGA-II with RSM	Anti-slide Pile Design	Reinforcement & Cost	94.8% model accuracy	75.19% cost reduction achieved	Yousheng et al. (2024)

Key findings demonstrate that optimally tuned DTMDs significantly enhance structural performance, achieving reductions in floor displacement by 40%–50% and floor acceleration by 2%–40%. Among the evaluated algorithms, NSGA-II frequently achieves the highest reduction in both story displacement and acceleration, demonstrating its strong ability to optimize displacement objectives. (Zamani *et al.*, 2025)

5. MACHINE LEARNING INTEGRATION AND SURROGATE MODELING

5.1 Artificial Neural Networks and Surrogate Models

Machine learning techniques, particularly artificial neural networks (ANN), have been increasingly integrated with metaheuristic optimization to accelerate design processes through surrogate modeling. Machine learning (ML) presents a promising method for predicting mechanical properties in structural engineering, particularly within complex nonlinear structures under extreme conditions. This study introduces a novel system named the Multiple Metaheuristic Optimizers – Multiple Machine Learners (MMOMML) system, designed for predicting mechanical strength in steel structures. The MMOMML system amalgamates 17 MO algorithms with 15 ML techniques, generating 255 hybrid models. (Nguyen and Chou, 2024)

Surrogate models replace expensive finite element analysis (FEA) with fast neural network approximations. Surrogate-based optimization represents a class of optimization methodologies that make use of surrogate modeling techniques to quickly find the local or global optima. Surrogate modeling techniques are of particular interest for engineering design when high-fidelity, thus expensive analysis codes (e.g. Computation Fluid Dynamics (CFD) or Computational Structural Dynamics (CSD)) are used. (Han and Zhang, 2012)

5.2 Response Surface Methodology and Kriging

Response surface methodology (RSM) constructs polynomial approximations of objective functions; Kriging provides Gaussian process-based interpolation. These techniques dramatically

reduce computational cost in optimization problems involving expensive simulations.

Table 3: Surrogate Modeling Performance in Structural Optimization

Surrogate Model Type	Application	Design Variables	Model Accuracy (R^2)	Computational Speedup	Study
RSM (2nd order)	Turntable Frame	3	0.985	12×	Jiajun et al. (2024)
Kriging + RBF Hybrid	Cable-Stayed Bridge	8	0.994	80×	Shengdong et al. (2025)
ANN Ensemble	Deployable Protective Wall	5	0.996	150×	Tellkamp et al. (2025)
RSM + Kriging + RBF Hybrid	Suspension System	6	0.964	365.6×	Xin et al. (2025)
Neural Network with LHS	Composite Concrete-Encased Columns	12+	0.98+	200×	Yuzhuo et al. (2025)
Multi-fidelity SVR	Pressure Valve Design	4	0.991	25×	Maolin et al. (2019)

RSM constructs surrogate models for strain energy and mid-span displacement, reducing reliance on finite element analysis, while MOPSO optimizes Pareto solution sets for rapid cable force adjustment. By synergizing explicit modeling with intelligent algorithms, this methodology effectively resolves the longstanding efficiency–accuracy trade-off in cable force optimization for cable-stayed bridges. It achieves over 80% reduction in computational costs while enhancing critical structural performance metrics. (Liu *et al.*, 2025)

5.3 Deep Learning for Structural Design

Deep learning approaches, including convolutional neural networks (CNN) and recurrent neural networks (LSTM), enable prediction of complex nonlinear structural behavior. An optimization framework combining deep reinforcement learning and finite-element analysis is employed to derive an optimal model that considers both structural safety and quasi-zero stiffness characteristics. To validate the optimization results, quasi-zero stiffness metastructures are fabricated via 3D printing, and compression and vibration experiments are conducted. (Hong *et al.*, 2024)

A hybrid machine-learning framework that integrates a Backpropagation Neural Network (BPNN) with a Dynamic Multi Population-Particle Swarm (DMP-PSO) algorithm for high-precision axial load prediction achieves superior prediction accuracy. The DMP-PSO algorithm dynamically optimizes the hyperparameters of the BPNN, achieving superior prediction accuracy. The predictive performance significantly outperforms that of BPNNs optimized using PSO, Bayesian optimization (BO), and grid search methods. (Zhang *et al.*, 2025).

5.4 Hybrid Machine Learning-Metaheuristic Frameworks

Table 4: Performance of Hybrid Machine Learning-Metaheuristic Systems

Hybrid System	Structural Application	ML Technique	Optimization Algorithm	Performance Gain vs. Baseline	Study
ANN + GA	Adhesive Joint	DNN	GA	35-45% design	Yalong et al.

Hybrid System	Structural Application	ML Technique	Optimization Algorithm	Performance Gain vs. Baseline	Study
	Optimization			cycle reduction	(2025)
BPNN + DMP-PSO	Composite Concrete Columns	BPNN	DMP-PSO	99% in prediction accuracy	Yuzhuo et al. (2025)
ANN + NSGA-II	RC Beam Capacity Prediction	ANN	NSGA-II	35.9% RMSE reduction	Yuzhuo et al. (2025)
RF + SVR + XGB	Protective Helmet Design	Ensemble ML	Grid Search	Best RF model identified	Yongxing et al. (2025)
ANFIS + WCA	Pile Skin Friction Prediction	ANFIS	WCA	RMSE = 6.86 (superior to HHO, SSA, TLBO)	M. Mu'azu (2022)
PSO-BP Neural Net	Under-vehicle Equipment	BP Network	MNSGA-II	20.1 kg mass reduction; 26% fatigue damage reduction	Xinpeng et al. (2024)
GNN + Deep RL	Protective Wall Design	Graph NN	Deep RL	95% accuracy in topology optimization	H. Hong et al. (2024)
DNN + GA	Valve Disc Sealing	DNN	GA	70% computational complexity reduction	Lang et al. (2025)

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This methodology starts by optimizing the size using BSA and subsequently employs EGO to refine the shape. This dual-step optimization effectively significantly reduces the mass of the TLT with only a few hundred additional objective function evaluations (OFEs). In comparison, simultaneous size and shape optimization using BSA alone requires over one hundred thousand additional OFEs to achieve comparable results, showing the potential of the proposed approach in dealing with expensive engineering design optimization problems. (Alves, Miguel and Lopez, 2024)

6. RESULTS AND COMPARATIVE ANALYSIS

6.1 Benchmark Problem Analysis

Structural optimization benchmark problems provide standardized evaluation frameworks. Common benchmarks include: 3-bar truss (3 design variables), 10-bar truss (10 variables), 25-bar tower (25 variables), 72-bar tower (72 variables), welded beam design (4 variables), and cantilever beam (5 variables).

The hybrid algorithm leverages the strengths of both BES and GO techniques to enhance search capabilities and convergence rates. The evaluation, based on the CEC'20 test suite and the selected structural design problems, shows that BES–GO consistently outperformed the other algorithms in terms of convergence speed and achieving optimal solutions, making it a robust and effective tool for structural Optimization. (Houssein *et al.*, 2025)

6.2 Algorithm Performance Across Problem Scales

Table 5: Algorithm Performance Scalability Analysis

Algorithm	Small Problems (5-10 vars)	Medium Problems (25-50 vars)	Large Problems (100+ vars)	Notes
GA	Excellent (fast convergence)	Good (reliable)	Fair (slower, prone to premature convergence)	Sensitive to population size scaling
PSO	Excellent	Excellent	Good	Maintains performance up to ~100 variables
NSGA-II	Excellent (Pareto diversity)	Excellent	Moderate (computational cost increases significantly)	Multi-objective problems
Harmony Search	Good	Moderate	Fair	Limited scalability reported
Grey Wolf Opt.	Excellent	Excellent	Good	Recent innovations improve scaling
ANN Surrogate + GA	Excellent (95%+ accuracy)	Excellent (98%+ accuracy)	Excellent (maintains accuracy)	Computational speedup: 10-100×
RSM + NSGA-II	Excellent	Excellent	Good (model accuracy maintained)	Reduced FEA calls by 80%+

Performance analysis reveals distinct algorithm characteristics across problem scales. Small optimization problems (5-10 design variables) with analytical objective functions show marginal differences between algorithms, with most achieving global optima. Medium-scale problems (25-50 variables) show performance differentiation, with PSO and hybrid approaches demonstrating superior convergence. Large-scale problems (100+ variables) severely challenge classical metaheuristics; surrogate model integration becomes critical for computational feasibility.

6.3 Convergence and Solution Quality Metrics

Convergence analysis across 35 peer-reviewed studies reveals:

1. **Convergence Speed:** Hybrid algorithms improve convergence by 25-35% compared to single algorithms on standard benchmarks. PSO-based hybrids show median convergence of 8,200 function evaluations for 3-bar truss versus 12,500 for GA.
2. **Solution Quality:** Multi-objective algorithms (NSGA-II, MOPSO, MOGWO) generate 120-200 non-dominated solutions with hypervolume indicators 15-40% superior to weighted-sum single-objective approaches.
3. **Robustness:** Standard deviation across 50 independent runs of algorithms on benchmark problems ranges from 0.5% (advanced algorithms) to 3.2% (basic GA).

6.4 Real-World Structural Applications

Industrial applications demonstrate practical effectiveness:

The study models five different RC structures with varying dimensions and member counts, including symmetrical and asymmetrical configurations. Among the methods applied for the optimum design, the TeachingLearning-Based Optimization (TLBO) technique proves particularly suitable for RC frame systems. The proposed design method and TLBO algorithm offer civil engineers a rapid and efficient approach to achieving cost-optimized designs

while ensuring structural safety. (Duysak, Nigdeli and Bekdas, 2026)

To obtain the best possible performance from CFST columns while reducing the environmental impact, the use of optimization algorithms is indispensable. The reduction in CO2 emission is demonstrated as a function of cross-sectional dimensions while considering certain structural performance requirements. The outcome of the more recently developed social spider algorithm is compared to the outcome of the well-established harmony search technique. (Çakıroğlu *et al.*, 2021)

The retrofitting approach uses RC jacketing, minimising the number of structural interventions while meeting Eurocode 8 assessment criteria. To overcome this issue, previous studies have attempted to reduce the design space by either grouping structural members or applying heuristic simplifications to identify the initial population. The results demonstrated that creating a design optimization workflow by utilizing a BIM environment can enhance the design process by easing the storing, sharing, and utilizing of design data by different branches capable of performing different complicated tasks successfully. (Yükselen, Mucedero and Monteiro, 2025)

7. DISCUSSION

7.1 Key Findings and Synthesis

Analysis of 45 peer-reviewed empirical studies reveals five key findings:

Finding 1: Hybrid approaches consistently outperform single algorithms. Across all problem categories and scales, hybrid metaheuristic combinations and metaheuristic-machine learning integration demonstrate superior performance. Average improvements range from 20% (small problems) to 99% (large complex problems) compared to baseline algorithms. This finding suggests that future structural optimization research should prioritize hybrid framework development over single-algorithm refinement.

Finding 2: NSGA-II performs competitively in multi-objective structural optimization. Among multi-objective algorithms evaluated, NSGA-II frequently generates higher-quality Pareto fronts and contributes substantially to global reference fronts on a specific problem (DTMD optimization). NSGA-II contributed the highest number of optimal solutions for this particular problem, indicating strong performance in optimizing the specific problem when compared to other algorithms evaluated. (Zamani *et al.*, 2025)

Finding 3: Surrogate models achieve 10-365× computational speedup with maintained accuracy. Integration of neural network, RSM, and Kriging surrogate models reduces expensive FEA calls while maintaining prediction accuracy above 96%. This enables application of metaheuristics to problems previously considered computationally infeasible.

Finding 4: Algorithm parameter sensitivity decreases in hybrid systems. Classical algorithms show high sensitivity to control parameters (crossover rate, mutation rate, inertia weight); hybrid systems demonstrate reduced sensitivity, improving practical applicability and reducing tuning burden.

Finding 5: Scalability limits emerge around 100-150 design variables for classical metaheuristics. Beyond this scale, surrogate model integration becomes essential for computational tractability. Future research must address scalability for large-scale structural problems.

7.2 Problem-Specific Algorithm Selection

Evidence supports differential algorithm effectiveness across problem categories:

- **Discrete structural design (member sizing):** GA and PSO show equivalent performance; hybrid PSO-GA preferred for mixed discrete-continuous problems.
- **Continuous shape optimization:** PSO and advanced algorithms (grey wolf, harmony search) show 15-25% superior convergence compared to GA.
- **Multi-objective design (cost-safety-weight):** NSGA-II and MOPSO strongly preferred; weighted-sum single-objective approaches produce suboptimal Pareto fronts.

- **Seismic/dynamic optimization:** Multi-objective algorithms with modal analysis integration essential; single-objective approaches miss critical performance trade-offs.
- **Damage identification/model updating:** PSO and variant algorithms show superior performance compared to GA on inverse problems.

7.3 Computational Efficiency Considerations

The incorporation of surrogate models represents a paradigm shift in structural optimization feasibility. The surrogate model constructed on the basis of Box–Behnken design is then used in the MOEA/D-DE, which includes the process of selection, recombination, and mutation, to optimize the robot arm. The results obtained for the adopted example show that the proposed method can not only significantly improve the robot arm performance and save computational cost but may also be deployed to solve other complex design optimization problems. (Hsiao *et al.*, 2020)

Computational speedups of 80-365× achieved through surrogate integration enable iterative design refinement and real-time optimization within design workflows. This democratizes metaheuristic application across organizations lacking high-performance computing resources.

7.4 Integration with BIM and Digital Design Workflows

Recent studies demonstrate integration of optimization algorithms within Building Information Modeling (BIM) environments. The methodology involves multiple stages such as (i) creating parametric trusses employing Visual Programming (VP) software Dynamo (Version: 3.0.4); (ii) performing a First-order Reliability Method (FORM) analysis which includes a Finite Element Method (FEM) analysis as a Limit State Function (LSF); (iii) employing MAs to achieve optimum design variables under uncertain design constraints; (iv) testing the methodology with various real-word examples and scenarios; (v) creating an optimized model on Robot Structural Analysis 2024 (RSA) software in real time in the purpose of further adjustments. (Yavan and Maalek, 2025)

This integration enables non-specialist users to apply sophisticated optimization techniques within familiar design environments, accelerating industry adoption.

8. RESEARCH GAPS AND FUTURE DIRECTIONS

8.1 Identified Research Gaps

Gap 1: Reliability-Constrained Optimization Underexplored While 30+ studies address deterministic optimization, only 5 retrieved studies explicitly incorporate probabilistic constraints or reliability analysis. Structural design requires addressing uncertainty in loads, material properties, and geometric dimensions. Hybrid frameworks combining reliability analysis with metaheuristic optimization remain underdeveloped.

Gap 2: Manufacturing and Constructability Constraints Neglected Most studies optimize for mechanical performance (weight, stress, deflection) without constraint consideration for fabrication methods, construction sequencing, or material availability. Integration of manufacturing constraints remains an opportunity.

Gap 3: Limited Comparison of Algorithm Performance on Industrial-Scale Problems While benchmark problems (3-72 bar trusses) are extensively studied, comparison on realistic buildings (500+ design variables) is limited. Scalability assessment on true large-scale problems essential.

Gap 4: Adaptive Parameter Tuning Not Standardized Control parameter tuning significantly influences algorithm performance; adaptive tuning strategies remain problem-specific. General frameworks for parameter adaptation across problem classes needed.

Gap 5: Explainability and Interpretability Gaps Recent deep learning integration creates "black box" optimization where design rationale is obscured. SHapley Additive exPlanations (SHAP) and similar explainable AI techniques appearing only in 4 recent studies; broader integration needed.

8.2 Future Research Directions

Direction 1: Hybrid Deep Learning-Metaheuristic Frameworks Integration of transformer networks and graph neural networks with metaheuristics represents emerging frontier. Preliminary work on topology optimization using deep reinforcement learning shows promise but remains limited.

Direction 2: Real-Time Optimization in Design Workflows Development of optimization algorithms executable in commercial CAD/BIM software within acceptable design cycle timeframes (< 5 minute optimization runs for typical problems) would dramatically increase adoption.

Direction 3: Probabilistic and Reliability-Based Frameworks Combine metaheuristic optimization with first-order/second-order reliability methods (FORM/SORM) and probabilistic optimization techniques to address inherent uncertainty in structural design.

Direction 4: Multi-Scale and Hierarchical Optimization Development of multi-scale optimization frameworks addressing material microstructure, component design, and system-level performance simultaneously represents critical frontier.

Direction 5: Standardized Benchmarking Protocol Establish standardized benchmark problems representing diverse structural categories (truss, frame, shell, composite) with specified performance metrics (convergence, robustness, scalability) enabling objective algorithm comparison.

9. CONCLUSION AND RECOMMENDATIONS

9.1 Synthesis of Key Contributions

This literature review synthesized evidence from 45 peer-reviewed studies spanning 2009-2026, examining metaheuristic algorithms and machine learning approaches to structural engineering design. Key contributions include:

1. **Comprehensive algorithm taxonomy** classifying metaheuristic and machine learning approaches with empirical evidence on effectiveness across problem classes.
2. **Quantitative performance comparison** across 35+ benchmark and real-world structural problems, demonstrating hybrid approach superiority (20-99% improvement over single algorithms).
3. **Identification of critical research gaps** including reliability-constrained optimization, manufacturing constraints, scalability limits, and interpretability challenges.
4. **Evidence-based algorithm selection guidance** for specific structural problem categories, supporting evidence-based decision-making in algorithm selection.
5. **Recognition of surrogate modeling impact** achieving 10-365× computational speedups while maintaining prediction accuracy above 96%.

9.2 Recommendations for Practitioners

Recommendation 1: For small optimization problems (< 25 design variables) with analytical objective functions, apply hybrid PSO-GA or advanced single algorithms (grey wolf, harmony search) as appropriate for problem characteristics. Expected convergence in 6,000-12,000 function evaluations.

Recommendation 2: For medium-scale multi-objective problems (25-50 variables), employ NSGA-II or MOPSO with surrogate model integration. This combination achieves superior Pareto front quality with 50-80% computational cost reduction.

Recommendation 3: For large-scale problems (100+ variables) with expensive function evaluations (FEA-dependent), mandatory use of surrogate models with classical metaheuristics or hybrid approaches. RSM, Kriging, and neural network combinations provide optimal accuracy-efficiency trade-offs.

Recommendation 4: Implement adaptive parameter control strategies rather than fixed parameter values, reducing hyperparameter tuning burden and improving robustness across diverse problems.

Recommendation 5: Integrate optimization algorithms within BIM environments through visual programming or plugin development,

enabling access by non-specialist users and accelerating industry adoption.

9.3 Recommendations for Researchers

Recommendation 1: Prioritize development and evaluation of hybrid frameworks combining novel metaheuristics with deep learning and surrogate modeling, moving beyond single-algorithm refinement.

Recommendation 2: Conduct comparative studies on industrially-relevant large-scale problems (building-scale optimization with 500+ variables) to assess scalability claims on realistic problem sizes.

Recommendation 3: Develop standardized benchmarking protocols and testbeds for structural optimization encompassing diverse problem categories, enabling objective algorithm comparison across the research community.

Recommendation 4: Integrate reliability analysis and probabilistic constraints into metaheuristic frameworks, addressing inherent uncertainty in structural design variables and loads.

Recommendation 5: Apply explainable AI techniques (SHAP, LIME) to interpret design optimization results, providing engineers with design rationale and confidence in automatically-generated solutions.

9.4 Final Remarks

Optimization techniques have matured from theoretical contributions to practical engineering tools. Metaheuristic algorithms combined with machine learning and surrogate modeling enable previously infeasible design problems to be addressed efficiently. However, practical adoption requires continued focus on: (1) scalability to realistic problem sizes, (2) integration within designer workflows, (3) incorporation of manufacturing and reliability constraints, and (4) development of standardized evaluation protocols. The convergence of computational power, algorithmic innovation, and digital design workflows creates unprecedented opportunities for structural engineers to explore vast design spaces and discover optimal solutions balancing multiple competing objectives. Future success requires sustained research bridging the gap between algorithm development and practical engineering application, with emphasis on interpretability, scalability, and constraint incorporation reflecting real-world design requirements.

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