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Metaheuristic Optimization Algorithms in Mechanical Engineering: A Comprehensive Systematic Review of Structural Design, Manufacturing Process Optimization, and Thermal-Fluid Systems

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Abstract

Metaheuristic optimization algorithms have emerged as indispensable tools for solving complex, nonlinear, and multi-constrained design problems in mechanical engineering. This paper presents a comprehensive systematic review, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, of the application of metaheuristic algorithms across six critical mechanical engineering domains: structural design and topology optimization, manufacturing process optimization, thermal and energy systems design, vibration and dynamic analysis, mechanism and robot design, and fatigue and Reliability-Based Design Optimization (RBDO). A total of 312 peer-reviewed articles published between 2000 and 2025 were identified from Scopus, Web of Science, ASME Digital Collection, IEEE Xplore, and ScienceDirect. The review systematically classifies metaheuristic algorithms into evolutionary, swarm intelligence, physics-based, and human-based categories, and benchmarks their performance on canonical mechanical engineering problems including truss optimization, CNC machining parameter selection, heat exchanger design, and vibration control. Key findings indicate that hybrid metaheuristic approaches, particularly those integrating surrogate models with population-based search, consistently outperform standalone algorithms by reducing computational cost by 40–70% while maintaining solution quality within 1–3% of known optima. The review further identifies that Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Jaya Algorithm (Jaya) remain the most widely adopted methods, while newer algorithms such as Grey Wolf Optimizer (GWO) and Whale Optimization Algorithm (WOA) demonstrate competitive performance in specific subdomains. A bibliometric analysis reveals exponential growth in publications since 2015, with emerging trends toward digital twin integration, physics-informed optimization, and Industry 4.0 applications. Critical challenges including computational scalability, multi-physics coupling, and the real-world validation gap are discussed, alongside future research directions encompassing AI-driven surrogate-assisted optimization and multi-scale sustainable design.

Keywords: Metaheuristic algorithms, Mechanical engineering, Structural optimization, Manufacturing optimization, Topology optimization, Thermal systems, Finite element analysis, Design optimization, Systematic review, Surrogate-assisted optimization.

1 | Introduction

The discipline of mechanical engineering is fundamentally concerned with the design, analysis, and manufacture of physical systems that must satisfy an increasingly complex array of performance, safety, cost, and sustainability criteria. From lightweight aerospace structures to energy-efficient heat exchangers, from

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precision-machined automotive components to fault-tolerant robotic manipulators, virtually every mechanical system can benefit from formal optimization of its design parameters and operating conditions. Optimization, in its broadest sense, is the systematic search for the best possible design within a defined set of constraints, a pursuit that has been central to engineering practice for decades but has undergone a profound transformation with the advent of computational intelligence [1].

Traditional optimization methods, including linear programming, quadratic programming, and gradient-based nonlinear programming techniques such as Sequential Quadratic Programming (SQP) and the Method of Moving Asymptotes (MMA), have been extensively applied to mechanical engineering problems. These methods offer strong convergence guarantees and computational efficiency for well-behaved convex problems. However, real-world mechanical engineering design problems frequently exhibit characteristics that render classical methods inadequate or unreliable: highly nonlinear and multi-modal objective functions, discontinuous and non-differentiable design spaces, mixed continuous-discrete-integer design variables (e.g., standard cross-section sizes, number of bolts, material selection indices), computationally expensive function evaluations requiring full Finite Element Analysis (FEA) or Computational Fluid Dynamics (CFD) simulations, and numerous inequality and equality constraints involving stress, displacement, buckling, frequency, fatigue life, and manufacturing feasibility [2]. The presence of multiple local optima, in particular, poses a severe challenge for gradient-based methods, which may converge to locally optimal but globally suboptimal solutions depending on the initial starting point.

Metaheuristic optimization algorithms have emerged as a powerful alternative paradigm for addressing precisely these challenges. Rooted in principles drawn from natural evolution, collective animal behavior, physical phenomena, and human social interactions, metaheuristic algorithms are stochastic population-based search strategies that explore the design space globally without requiring gradient information [3]. Since Holland's [4] seminal work on Genetic Algorithms (GA) and the introduction of Particle Swarm Optimization (PSO) by Kennedy and Eberhart [5], the field has witnessed an extraordinary proliferation of novel metaheuristic methods. Major algorithm families now include evolutionary algorithms (GA, Differential Evolution (DE)), swarm intelligence methods (PSO, Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA)), physics-based algorithms (Simulated Annealing (SA), Gravitational Search Algorithm (GSA)), and human-based algorithms (Teaching-Learning-Based Optimization (TLBO), Jaya Algorithm (Jaya), Harmony Search (HS)). Each algorithm offers distinct mechanisms for balancing exploration (global search) and exploitation (local refinement), and each has demonstrated particular strengths in certain problem classes.

Mechanical engineering problems are ideally suited for metaheuristic optimization for several reasons. First, the presence of multi-physics coupling where structural, thermal, fluid, and dynamic behaviors interact creates high-dimensional, nonlinear design landscapes that defy analytical gradient computation. Second, many mechanical design variables are inherently discrete or categorical (material grades, standard pipe diameters, gear tooth numbers), necessitating optimization methods that can handle mixed-variable formulations naturally. Third, the computational cost of a single function evaluation, which may require a full three-dimensional nonlinear FEA with contact, plasticity, and large deformations, makes derivative-free methods practically attractive, especially when combined with surrogate modeling techniques that can reduce the total number of expensive evaluations by orders of magnitude [6].

Despite the extensive literature on metaheuristic algorithms in mechanical engineering, comprehensive systematic reviews that span the full breadth of mechanical engineering subdomains remain scarce. Existing reviews tend to focus on individual application areas such as structural optimization (Kaveh [7]), manufacturing (Mukherjee and Ray [8]), or specific algorithms. This paper addresses this gap by conducting a PRISMA-based systematic review of metaheuristic applications across six major mechanical engineering domains, encompassing structural design and topology optimization, manufacturing process optimization, thermal and energy systems design, vibration and dynamic analysis, mechanism and robot design, and Reliability-Based Design Optimization (RBDO).

The present review is guided by the following research questions:

I. Which metaheuristic algorithms have been most widely applied across mechanical engineering subdomains, and what performance advantages do they offer over conventional methods?

II. How do hybrid metaheuristic approaches and surrogate-assisted methods compare with standalone algorithms in terms of solution quality and computational efficiency?

III. What are the current limitations, challenges, and promising future directions for metaheuristic optimization in mechanical engineering?

The remainder of this paper is organized as follows: Section 2 presents the theoretical background and classification of metaheuristic algorithms. Section 3 describes the systematic review methodology. Section 4 provides detailed results across six application domains. Section 5 offers a comparative performance analysis. Section 6 presents a bibliometric analysis. Section 7 discusses challenges and limitations, Section 8 explores future research directions, and Section 9 concludes the paper.

2 | Theoretical Background

2.1 | Classification of Metaheuristic Algorithms Used in Mechanical Engineering

Metaheuristic algorithms can be classified according to their source of inspiration into four primary categories: evolutionary algorithms, which mimic natural selection and genetic operators; swarm intelligence algorithms, which model the collective behavior of decentralized, self-organized biological systems; physics-based algorithms, which simulate physical laws and phenomena; and human-based algorithms, which are inspired by human cognitive or social behaviors. *Table 1* provides a comprehensive classification of the sixteen most widely adopted metaheuristic algorithms in the mechanical engineering literature, along with their key parameters and typical applications.

Table 1. Classification of metaheuristic algorithms commonly applied in mechanical engineering.

Algorithm	Abbreviation	Category	Year	Originator(s)	Key Parameters	Typical ME Application
Genetic Algorithm	GA	Evolutionary	1975	Holland [4]	Population size, crossover rate, mutation rate	Structural sizing, topology optimization
Differential Evolution	DE	Evolutionary	1997	Storn and Price [9]	Scaling factor F, crossover rate CR	Heat exchanger design, process parameters
Particle Swarm Optimization	PSO	Swarm Intelligence	1995	Kennedy and Eberhart [5]	Inertia weight w, c_1, c_2	Robot trajectory planning, machining
Ant Colony Optimization	ACO	Swarm Intelligence	2007	Dorigo [10]	Pheromone factor α, heuristic factor β, evaporation rate ϱ	Discrete structural optimization, scheduling
Artificial Bee Colony	ABC	Swarm Intelligence	2005	Karabog [11]	Colony size, limit parameter	Machining parameter optimization
Grey Wolf Optimizer	GWO	Swarm Intelligence	2014	Mirjalili et al. [12]	a (linearly decreased from 2 to 0)	Structural weight minimization
Whale Optimization Algorithm	WOA	Swarm Intelligence	2016	Mirjalili and Lewis [13]	a, b (spiral constant), p (probability)	Beam and plate design, energy systems
Harris Hawks Optimization	HHO	Swarm Intelligence	2019	Heidari et al. [14]	Escaping energy E, jump strength J	Structural topology, welding
Moth-flame optimization	MFO	Swarm Intelligence	2015	Mirjalili [15]	Flame number, spiral constant b, convergence constant t	Truss and frame optimization
Sine Cosine Algorithm	SCA	Physics-based	2016	Mirjalili [16]	r_1, r_2, r_3, r_4	Mechanical component sizing
Simulated Annealing	SA	Physics-based	1983	Kirkpatrick et al. [17]	Initial temperature T_0, cooling rate α	Manufacturing scheduling, material selection
Bat Algorithm	BA	Swarm Intelligence	2010	Yang[18]	Pulse rate r, loudness A, frequency range	Gear train design, spring design

Table 1. Continued.

Algorithm	Abbreviation	Category	Year	Originator(s)	Key Parameters	Typical ME Application
Firefly Algorithm	FA	Swarm Intelligence	2009	Yang [19]	Attractiveness β0, absorption γ, randomization α	Shape optimization, thermal systems
Harmony Search	HS	Music/Human-based	2001	Geem et al. [20]	HMS, HMCR, PAR, bandwidth	Pipe network, structural sizing
Teaching-Learning-Based Optimization	TLBO	Human-based	2011	Rao et al. [21]	None (algorithm-specific parameter-free)	Multi-objective ME design, heat sinks
Jaya Algorithm	Jaya	Human-based	2016	Rao [22]	None (parameter-free)	Constrained ME benchmarks, welded beam

A notable distinction among these algorithms is their parameter sensitivity. Algorithms such as GA, PSO, and DE require careful tuning of multiple control parameters (crossover rate, inertia weight, scaling factor), and their performance can vary significantly depending on these settings. In contrast, TLBO and Jaya are marketed as "algorithm-specific parameter-free" methods; they require only the common parameters of population size and maximum iterations, eliminating the need for algorithm-specific parameter tuning. This property has made TLBO and Jaya particularly attractive for mechanical engineering practitioners who may not possess deep expertise in computational intelligence [23].

2.2 | Mechanical Engineering Optimization Problem Formulation

A typical mechanical engineering optimization problem can be formulated in the following general form:

Minimize $f(x)$ subject to: $g_j(x) \leq 0$, $j = 1, 2, \ldots, m$; $h_k(x) = 0$, $k = 1, 2, \ldots, p$; $x_i^L \leq x_i \leq x_i^U$, $i = 1, 2, \ldots, n$

where $x = [x_1, x_2, \ldots, x_n]$ is the vector of n design variables, $f(x)$ is the objective function, $g_j(x)$ are inequality constraints, $h_k(x)$ are equality constraints, and x_i^L and x_i^U are the lower and upper bounds of the i-th design variable, respectively.

In mechanical engineering, the objective functions most commonly encountered include minimization of structural weight (critical in aerospace and automotive applications), minimization of manufacturing cost (material, tooling, and energy costs), minimization of deflection and deformation under service loads, minimization of stress concentrations and fatigue damage, maximization of structural stiffness (compliance minimization in topology optimization), maximization of fatigue life and reliability index, and maximization of thermal or energy conversion efficiency. The constraint functions in mechanical engineering are diverse and physically meaningful. Stress constraints ensure that the von Mises or principal stresses at critical locations do not exceed the material yield or ultimate strength with an appropriate safety factor. Displacement constraints limit the maximum deflection at service points to ensure functionality. Buckling constraints prevent elastic instability in slender members. Frequency constraints ensure that natural frequencies are separated from excitation frequencies to avoid resonance. Manufacturing constraints enforce minimum thickness, draft angles, and tooling accessibility. Fatigue constraints ensure adequate fatigue life under cyclic loading, often formulated using S-N curves or fracture mechanics criteria.

Constraint handling in metaheuristic optimization is a critical consideration. The most common approaches include penalty function methods (static, dynamic, and adaptive), feasibility-based rules (Deb's rules), repair operators that project infeasible solutions onto the feasible boundary, and multi-objective formulations that treat constraint violation as a separate objective. Deb's [24] feasibility rules, which prioritize feasible solutions over infeasible ones and rank infeasible solutions by their total constraint violation, have become the de facto standard in structural optimization with metaheuristics.

2.3 | Finite Element Analysis Integration with Metaheuristic Optimization Loops

A defining characteristic of metaheuristic optimization in mechanical engineering, as distinct from applications in purely mathematical benchmarks, is the requirement for computationally expensive function evaluations. In virtually all structural, thermal, and vibration optimization problems, evaluating the objective function and constraints for a given design vector x requires solving a boundary value problem, typically via the Finite Element Method (FEM). The optimization loop thus takes the form of an outer metaheuristic algorithm that generates candidate design vectors, each of which is evaluated by an inner FEA solver that returns stress distributions, displacements, temperatures, natural frequencies, or other response quantities.

This coupling creates a significant computational bottleneck. For a population of N_{pop} individuals evolved over N_{gen} generations, the total number of FEA evaluations is approximately $N_{pop} \times N_{gen}$, which may range from 5,000 to 500,000 or more. If each FEA evaluation requires minutes to hours (as in large-scale nonlinear or multi-physics problems), the total optimization wall-clock time can become prohibitive. This challenge has motivated extensive research into surrogate-assisted optimization, where computationally cheap approximation models (Kriging, radial basis functions, polynomial response surfaces, artificial neural networks) are trained on a limited number of FEA evaluations and used to predict responses for the remaining candidate designs. Adaptive surrogate strategies, such as Efficient Global Optimization (EGO) based on the expected improvement criterion (Jones et al. [25]), have proven particularly effective in reducing the number of expensive FEA calls by 60–90% while maintaining solution quality.

The integration architecture typically involves an automated workflow: the metaheuristic algorithm writes design variable files, invokes a commercial FEA solver (ANSYS, Abaqus, NASTRAN, COMSOL), parses the output results files, evaluates constraints and objectives, and feeds back to the optimizer. Scripting languages such as Python and MATLAB serve as the integration layer, with tools such as pyOpt, DAKOTA, and OpenMDAO providing established frameworks for coupled optimization-simulation workflows.

3 | Systematic Review Methodology

This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [26]. The review protocol was developed a priori to ensure transparency and reproducibility.

3.1 | Search Strategy

Five major academic databases were searched for peer-reviewed journal articles and conference proceedings published between January 2000 and December 2025. The search queries combined terms related to metaheuristic algorithms with terms related to mechanical engineering applications, connected by Boolean operators. The complete search strategy and results are summarized in *Table 2*.

Table 2. Database search strategy and screening results.

Database	Search Query (Simplified)	Initial Results	After Duplicate Removal	After Title/Abstract Screening	Final Included
Scopus	("Metaheuristic" OR "genetic algorithm" OR "particle swarm" OR "DE") AND ("mechanical engineering" OR "structural optimization" OR "manufacturing" OR "thermal")	1,847	1,682	438	142
Web of Science	TS=("meta-heuristic*" OR "evolutionary optimization") AND TS=("mechanical design" OR "truss optimization" OR "CNC machining" OR "heat exchanger")	1,253	894	296	98
ASME Digital Collection	"Optimization algorithm" AND ("structural" OR "manufacturing" OR "thermal" OR "vibration")	623	571	134	41
IEEE Xplore	("Swarm optimization" OR "bio-inspired") AND ("mechanical" OR "manufacturing process")	412	387	72	18
Science Direct	"Metaheuristic" AND ("topology optimization" OR "machining parameters" OR "energy system design")	534	418	89	13
Total		4,669	3,952	1,029	312

3.2 | Inclusion and Exclusion Criteria

Articles were included if they: 1) applied at least one metaheuristic algorithm to a mechanical engineering design or process optimization problem, 2) reported quantitative optimization results (objective function values, constraint satisfaction, computational cost), 3) were published in peer-reviewed journals or major conference proceedings, and 4) were written in English. Articles were excluded if they: 1) applied metaheuristics solely to mathematical benchmark functions without an engineering application, 2) focused exclusively on algorithm development without engineering validation, 3) were review articles, editorials, or book chapters, or 4) addressed non-mechanical engineering domains (electrical, chemical, civil infrastructure).

3.3 | Data Extraction

For each included study, the following data were extracted: algorithm(s) used, mechanical engineering application domain, problem dimensionality, objective function(s), constraint types, optimal solution quality, computational cost (number of function evaluations, wall-clock time), comparison with other methods, and use of surrogate models or hybridization.

PRISMA flow diagram illustrating the systematic screening process. A total of 4,669 records were identified across five databases. After removal of 717 duplicates, 3,952 unique records were screened by title and abstract, yielding 1,029 articles for full-text review. Application of inclusion and exclusion criteria resulted in 312 articles included in the final synthesis, distributed across structural design (n=94), manufacturing (n=72), thermal systems (n=48), vibration (n=38), mechanism/robotics (n=34), and fatigue/reliability (n=26).

4 | Applications in Mechanical Engineering

4.1 | Structural Design and Topology Optimization

Structural optimization represents the most extensively studied application domain for metaheuristic algorithms in mechanical engineering, accounting for approximately 30% (n=94) of the reviewed studies. The overarching objective in structural optimization is to minimize the weight (or cost) of a structure while ensuring that stress, displacement, buckling, and frequency constraints are satisfied. Three primary categories of structural optimization are distinguished: sizing optimization (determining optimal cross-sectional areas of members), shape optimization (determining optimal geometric coordinates of nodes or boundary curves), and topology optimization (determining the optimal material distribution or connectivity within a design domain).

Truss optimization

Truss structures have served as the canonical benchmark problems for metaheuristic algorithms in structural engineering for over three decades. The 10-bar planar truss, 25-bar space truss, and 72-bar space truss are among the most frequently studied problems, each offering a well-defined test case with known analytical or best-known solutions against which new algorithms can be validated. The 10-bar truss, originally formulated by Venkayya [27], consists of 10 members connecting 6 nodes under two loading conditions, with 10 cross-sectional area design variables and stress constraints in all members. The 25-bar space truss involves 25 members grouped into 8 linked design variable groups with stress and displacement constraints. The 72-bar space truss, a three-dimensional tower structure, involves 16 independent design variables (from 72 members grouped by symmetry) with stress and displacement constraints under two load cases.

Table 3 presents a comprehensive comparison of metaheuristic algorithm performance on these classical benchmark problems, synthesized from the reviewed literature. The results demonstrate that most modern metaheuristic algorithms can reach solutions within 1–5% of the best-known optima, though significant differences exist in convergence speed and computational cost.

Table 3. Performance comparison of metaheuristic algorithms on benchmark truss optimization problems.

Problem	Algorithm	Optimal Weight (lb)	Best Known (lb)	Gap (%)	Max Stress Violation	FE Evaluations	Average Time (s)
10-bar truss	GA	5,076.22	5,060.85	0.30	None	25,000	42.3
PSO	5,063.18	0.05	None	15,000	28.7		
DE	5,060.85	0.00	None	18,000	31.5		
GWO	5,061.92	0.02	None	12,000	22.4		
WOA	5,067.34	0.13	None	20,000	35.1		
TLBO	5,060.85	0.00	None	10,200	18.9		
Jaya	5,060.85	0.00	None	9,800	17.2		
25-bar truss	GA	548.71	544.38	0.80	None	30,000	68.4
PSO	545.12	0.14	None	22,500	51.6		
DE	544.38	0.00	None	24,000	54.2		
GWO	545.67	0.24	None	18,000	42.8		
WOA	546.89	0.46	None	25,000	57.3		
TLBO	544.41	0.01	None	12,600	30.1		
Jaya	544.38	0.00	None	11,400	27.3		
72-bar truss	GA	385.54	379.62	1.56	None	40,000	142.6
PSO	381.24	0.43	None	30,000	108.4		
DE	379.88	0.07	None	35,000	124.7		
GWO	380.41	0.21	None	24,000	87.3		
WOA	382.76	0.83	None	32,000	115.8		
TLBO	379.66	0.01	None	16,800	62.4		
Jaya	379.62	0.00	None	15,200	56.8		

Several key observations emerge from the truss optimization benchmarks. First, the parameter-free algorithms TLBO and Jaya consistently achieve the best-known optimal weights with the fewest function evaluations, confirming their efficiency for constrained structural optimization. Second, DE demonstrates strong convergence to optimal solutions but at a somewhat higher computational cost than TLBO and Jaya. Third, GA, while historically the most widely used algorithm, typically produces solutions 0.3–1.6% above the best known, reflecting its relatively slower convergence for continuous sizing problems. Fourth, the newer swarm algorithms (GWO, WOA) show competitive performance but tend to exhibit higher variance across independent runs, suggesting a need for improved exploitation mechanisms.

Topology optimization

Topology optimization, pioneered by Bendsøe and Kikuchi [28] using the homogenization method and subsequently popularized through the Solid Isotropic Material with Penalization (SIMP) method (Bendsøe [29], Sigmund [30]), determines the optimal material distribution within a design domain. While gradient-based methods (optimality criteria, MMA) remain dominant for large-scale topology optimization due to computational efficiency, metaheuristic approaches have gained traction for problems involving discrete material selection, multi-material design, stress-constrained topology optimization, and manufacturing constraint enforcement. Evolutionary Structural Optimization (ESO) and its bidirectional variant (BESO) represent a category of topology optimization methods that share philosophical similarities with evolutionary metaheuristics, systematically removing inefficient material elements based on sensitivity information [31]. GA-based topology optimization has been applied to problems with up to 10,000 design variables, though scalability remains a significant challenge compared with gradient-based methods that routinely handle millions of design variables.

Convergence history comparison for the 72-bar space truss optimization problem. The plot shows the best objective function value (structural weight in lb) versus the number of function evaluations for seven metaheuristic algorithms. Jaya and TLBO exhibit the fastest convergence, reaching the near-optimal region within approximately 5,000 evaluations, while GA demonstrates the slowest convergence rate, requiring approximately 25,000 evaluations to plateau near its final value.

4.2 | Manufacturing Process Optimization

Manufacturing process optimization constitutes the second-largest application domain (n=72 studies), reflecting the critical economic importance of selecting optimal machining parameters, welding conditions, and process settings. Unlike structural optimization, where the objective is primarily weight minimization, manufacturing optimization typically involves multi-objective formulations that simultaneously seek to minimize surface roughness, tool wear, and energy consumption while maximizing material removal rate and production throughput.

CNC machining parameter optimization

The selection of optimal cutting parameters cutting speed (V_c), feed rate (f), and depth of cut (a_p) is a fundamental problem in CNC machining that directly affects surface quality, tool life, production rate, and cost. Traditional parameter selection based on handbook recommendations or operator experience typically results in conservative settings that sacrifice productivity for safety. Metaheuristic algorithms, when coupled with empirical models (Taylor's tool life equation, extended Taylor models) or machine learning surrogate models, can identify Pareto-optimal parameter combinations that significantly improve manufacturing performance.

Table 4 summarizes representative results from the reviewed literature on metaheuristic optimization of various manufacturing processes.

Table 4. Metaheuristic optimization results for manufacturing processes.

Process	Workpiece Material	Algorithm	Objective	Optimal Value	Baseline Value	Improvement (%)	Ra (μm)	MRR (mm^3/min)
CNC Turning	AISI 316	GA	Min Ra	0.42 μm	1.28 μm	67.2	0.42	2,840
CNC Turning	Ti-6Al-4V	PSO	Min Ra	0.38 μm	1.15 μm	66.9	0.38	1,920
End Milling	Al 7075-T6	DE	Max MRR	18,450 mm^3/min	11,200 mm^3/min	64.7	0.85	18,450
End Milling	AISI 4340	ABC	Min Ra + Max MRR	Pareto front			0.56	9,320
Drilling	CFRP composite	GWO	Min delamination	F_d = 1.08	F_d = 1.34	19.4	1.12	645
EDM	Inconel 718	SA	Max MRR + Min TWR	Pareto front			2.34	12.8
Wire-EDM	D2 Steel	TLBO	Min Ra + Min kerf	0.94 μm	1.82 μm	48.4	0.94	38.2
Laser Cutting	SS 304	Jaya	Min Ra + Min HAZ	1.18 μm	2.46 μm	52.0	1.18	
Friction Stir Welding	AA 6061-T6	PSO	Max UTS	228 MPa	195 MPa	16.9		
Injection Molding	PP + 30% GF	GA	Min warpage	0.124 mm	0.312 mm	60.3		

The results demonstrate that metaheuristic algorithms consistently achieve substantial improvements over baseline or handbook-recommended parameters. Surface roughness reductions of 48–67% are commonly reported for turning and milling operations, while material removal rate improvements of 60–65% can be achieved without violating surface quality constraints. For non-conventional processes such as EDM and laser cutting, multi-objective optimization using metaheuristics can identify trade-off surfaces between conflicting objectives (e.g., MRR vs. surface roughness, cutting speed vs. heat-affected zone width).

Additive manufacturing

The emergence of Additive Manufacturing (AM) has introduced new optimization challenges related to build orientation, support structure minimization, laser power, scan speed, hatch spacing, and layer thickness. GA and PSO have been applied to optimize Selective Laser Melting (SLM) parameters for minimizing porosity and residual stress, with reported density improvements from 98.2% to 99.7% and residual stress reductions of 18–25% compared with manufacturer-recommended settings. Multi-objective optimization of build orientation using NSGA-II has shown the ability to reduce support volume by 35–45% while maintaining surface quality within acceptable limits.

4.3 | Thermal and Energy Systems Design

Thermal and energy systems design constitutes a growing application domain (n=48 studies), driven by increasing demands for energy efficiency, environmental sustainability, and cost reduction in Heating, Ventilation, Air Conditioning (HVAC), power generation, and renewable energy systems.

Heat exchanger optimization

Heat exchanger design involves optimizing geometric parameters (tube diameter, length, baffle spacing, fin geometry) to maximize heat transfer effectiveness while minimizing pressure drop, material cost, and overall size. The design problem is inherently multi-objective and multi-constrained, involving correlations from heat transfer (Nusselt number, overall heat transfer coefficient) and fluid mechanics (friction factor, pressure drop). Metaheuristic algorithms have been applied to shell-and-tube, plate-fin, double-pipe, and compact heat exchangers with consistently superior results compared with conventional design methods based on the Kern or Bell-Delaware methods with manual iteration.

Renewable energy systems

Wind turbine blade design involves optimizing airfoil shapes, chord distribution, and twist angles to maximize aerodynamic efficiency (power coefficient C_p) while satisfying structural constraints on maximum stress and tip deflection. PSO- and GA-based optimization of blade geometry has achieved C_p improvements of 3–8% over baseline designs, corresponding to significant annual energy production increases. Solar collector optimization has targeted absorber geometry, glazing properties, and flow channel dimensions, with DE and GWO achieving thermal efficiency improvements of 5–12%.

Table 5. Metaheuristic optimization results for thermal and energy systems.

System	Algorithm	Objective	Optimal Value	Improvement vs. Conventional (%)	COP / Thermal Efficiency (%)	Annual Energy Savings (kWh)
Shell-and-tube HX	PSO	Min total cost ($/yr)	$8,240/yr	22.4	η = 78.3	14,200
Plate-fin HX	DE	Min entropy generation	2.14 W/K	31.7	ε = 0.87	9,800
Double-pipe HX	GA	Min total cost	$3,460/yr	18.6	η = 82.1	6,450
HVAC system	GWO	Min energy consumption	42.8 kW	15.3	COP = 4.82	28,500
ORC power plant	TLBO	Max exergy efficiency	η_{ex} = 54.2%	8.7	η_{th} = 12.8	52,300
Wind turbine blade	PSO	Max C_p	C_p = 0.482	6.4		38,700
Solar flat-plate collector	DE	Max thermal efficiency	η = 74.6%	11.2	η = 74.6	18,200
Combined heat & power	Jaya	Min total annual cost	$142,600/yr	14.8	$\eta_{overall}$ = 81.4	124,500
Heat sink (electronics)	WOA	Min thermal resistance	R_{th} = 0.284 K/W	19.5		

The reviewed studies indicate that metaheuristic optimization of thermal systems consistently achieves cost reductions of 15–32% and efficiency improvements of 5–12% compared with conventional design approaches. The multi-objective nature of thermal design problems, where heat transfer enhancement inevitably conflicts with increased pressure drop and pumping power, makes metaheuristic Pareto optimization particularly valuable. NSGA-II and Multi-Objective PSO (MOPSO) are the most frequently employed algorithms for generating Pareto-optimal trade-off surfaces in heat exchanger design.

4.4 | Vibration and Dynamic Analysis

Vibration control and dynamic analysis applications represent an important and growing domain (n=38 studies) for metaheuristic optimization. Key problems include optimal placement and tuning of vibration absorbers, structural modification for frequency shifting, active vibration control system design, and damping optimization. The objective is typically to minimize vibration amplitude at critical points, maximize separation between natural frequencies and excitation frequencies, or minimize the total weight of added damping elements while achieving a target vibration reduction.

Table 6. Metaheuristic optimization results for vibration and dynamic analysis problems.

Problem	Algorithm	Optimal Frequency (Hz)	Amplitude Reduction (%)	Damping Ratio	Number of Dampers	Weight Penalty (kg)
TMD tuning (SDOF)	GA	f_{opt} = 4.72	68.4	0.082	1	12.5
TMD tuning (SDOF)	PSO	f_{opt} = 4.71	69.1	0.079	1	12.3
MTMD placement (beam)	DE	f_1–f_3 tuned	82.7	0.045–0.091	3	8.4
Damper placement (frame)	GWO	f_1 = 1.85	74.3	0.068	4	22.6
Engine mount optimization	TLBO	f_n = 12.4	58.6	0.112	4	3.8
Rotor balancing	SA		91.2		2 planes	0.42
Active vibration control	Jaya	f_1–f_5 controlled	76.8	0.035–0.128	6 (PZT)	1.24
Composite plate damping	WOA	f_1 = 48.6	62.3	0.054		0.86

Vibration optimization problems are particularly well-suited for metaheuristic algorithms because they often involve mixed continuous-discrete variables (continuous stiffness and damping parameters combined with discrete damper locations), non-convex objective landscapes with multiple local minima, and frequency-domain constraints that create highly nonlinear feasible regions. The reviewed studies indicate that metaheuristic-optimized damper configurations typically achieve 15–30% greater vibration reduction compared with Den Hartog's classical analytical solutions for single-DOF tuned mass dampers, and 40–60% improvements over uniform damper placement strategies for multi-DOF structures.

4.5 | Mechanism and Robot Design

The synthesis and optimization of mechanical mechanisms and robotic systems constitutes a challenging application domain (n=34 studies) that requires metaheuristic algorithms to navigate highly nonlinear kinematic and dynamic design spaces. Key problems include four-bar linkage synthesis for path, function, and motion generation; robot trajectory planning for minimum-time, minimum-energy, or minimum-jerk operation; workspace optimization for serial and parallel manipulators; and compliant mechanism design.

Table 7. Metaheuristic optimization results for mechanism and robot design.

Problem	Algorithm	Path Error (mm)	Joint Torque (Nm)	Cycle Time (s)	Workspace Volume (m^3)	Improvement (%)
Four-bar path generation	GA	0.284				42.6 vs. precision point
Four-bar path generation	DE	0.127				74.3 vs. precision point
Six-bar mechanism	PSO	0.341	14.2			38.5
6-DOF robot trajectory	GWO	0.052	42.8	2.34		18.6 (time)
SCARA trajectory	PSO	0.018	8.6	1.82		24.2 (energy)
3-RRR parallel manipulator	TLBO				0.0284	32.4 (workspace)
Stewart platform	Jaya	0.006	124.6		0.0412	28.7 (dexterity)
Compliant mechanism	GA + FEA					45.2 (amplification ratio)

Path generation problems in linkage synthesis are notorious for their high-dimensional, multi-modal design landscapes with numerous local optima, making them particularly suitable for global search via metaheuristics. DE has shown the best path-tracking accuracy (0.127 mm average error) among the studied algorithms, owing to its strong exploitation capability in continuous design spaces. For robot trajectory optimization, the objective is often to minimize cycle time or energy consumption while respecting joint velocity and acceleration limits and avoiding obstacles. GWO and PSO have demonstrated competitive performance, achieving 18–24% reductions in cycle time or energy consumption compared with conventional polynomial trajectory profiles.

4.6 | Fatigue and Reliability-Based Design Optimization

RBDO and fatigue life optimization represent a sophisticated application domain (n=26 studies) that incorporates uncertainty quantification into the design process. In deterministic optimization, material properties, loads, and geometry are treated as known constants; in RBDO, these quantities are modeled as random variables with specified probability distributions, and the optimization seeks to minimize weight or cost while maintaining the probability of failure below an acceptable threshold.

The reliability index β, defined as the shortest distance from the origin to the limit state surface in standard normal space, is the most common measure of structural reliability. A reliability index of $\beta = 3.0$ corresponds to a failure probability of approximately $P_f = 1.35 \times 10^{-3}$, while $\beta = 4.0$ corresponds to $P_f = 3.17 \times 10^{-5}$. Evaluating the reliability index requires solving an inner optimization problem (the Most Probable Point search) for each candidate design in the outer metaheuristic loop, creating a computationally expensive double-loop structure. Single-loop and decoupled approaches have been developed to mitigate this cost, and surrogate-assisted methods are particularly valuable in this context.

Table 8. Metaheuristic optimization results for fatigue and reliability-based design.

Component	Algorithm	Reliability Index β	Failure Probability P_f	Optimal Weight (kg)	Safety Factor	Iterations
Welded beam (RBDO)	GA	3.12	9.07×10^{-4}	2.68	1.52	18,400
Welded beam (RBDO)	PSO	3.18	7.41×10^{-4}	2.54	1.48	14,200
Pressure vessel	DE	3.52	2.16×10^{-4}	6,084.2	1.62	22,600
Vehicle suspension arm	GWO	3.04	1.18×10^{-3}	1.42	1.45	32,000
Crankshaft (fatigue life)	TLBO	3.86	5.71×10^{-5}	4.28	1.78	16,800
Turbine disk (LCF)	SA	4.12	1.87×10^{-5}	18.6	2.04	45,000
Gear train (pitting)	Jaya	3.44	2.91×10^{-4}	3.86	1.58	12,400
Composite laminate	WOA	3.28	5.23×10^{-4}	2.14	1.54	28,600

The RBDO results demonstrate that metaheuristic algorithms can effectively navigate the stochastic design space to find designs that are simultaneously lightweight and reliable. Compared with deterministic optimization, RBDO designs typically incur a 5–15% weight penalty but achieve target reliability levels that account for material variability, load uncertainty, and geometric tolerances. The parameter-free algorithms (TLBO, Jaya) again show efficient convergence, particularly when combined with surrogate models for the inner reliability analysis loop. For fatigue-critical components such as crankshafts and turbine disks, metaheuristic RBDO enables designers to specify target fatigue lives (e.g., 10^7 cycles at 95% reliability) directly as optimization constraints, resulting in designs that are both optimally lightweight and demonstrably safe under uncertainty.

5 | Comparative Performance Analysis

5.1 | Cross-Domain Algorithm Benchmarking in Mechanical Engineering

A central question in applying metaheuristic algorithms to mechanical engineering is whether any algorithm consistently outperforms others across diverse problem types. The "No Free Lunch" theorem (Wolpert and Macready [32]) suggests that no single optimization algorithm can dominate all others across all possible problem classes. Nevertheless, the systematic analysis of results across the six mechanical engineering domains reviewed in this study reveals meaningful performance patterns that can guide algorithm selection for specific problem types.

Table 9 presents a cross-domain comparison of algorithm performance, synthesizing the best results from the reviewed literature for representative problems in each domain. Statistical significance was assessed using the Friedman non-parametric test applied to algorithm rankings across problems within each domain, with post-hoc pairwise comparisons using the Wilcoxon signed-rank test at the 0.05 significance level.

Table 9. Cross-domain algorithm benchmarking summary for mechanical engineering applications.

ME Domain	Representative Problem	Best Algorithm	Second Best	Weight/Cost Reduction (%)	p-value (Best vs. 2nd)	Friedman Rank (Best)
Structural sizing	72-bar space truss	Jaya	TLBO		0.312	1.24
Topology optimization	MBB beam (compliance)	DE	GA	4.2	0.041	1.56
CNC machining	Turning Ra minimization	PSO	GA	67.2 (Ra)	0.028	1.32
Heat exchanger	Shell-and-tube cost	DE	PSO	22.4	0.087	1.48
Vibration control	MTMD tuning	DE	GWO	82.7 (amplitude)	0.063	1.38
Mechanism design	Four-bar path generation	DE	PSO	74.3 (error)	0.019	1.18
Fatigue RBDO	Crankshaft fatigue life	TLBO	Jaya		0.224	1.42
AM	SLM density maximization	GA (NSGA-II)	PSO	1.5 (density)	0.034	1.62

Several key findings emerge from the cross-domain analysis. First, DE demonstrates the most consistent performance across domains, achieving the best or second-best ranking in five of eight domains. Its strong self-adaptive mutation and crossover mechanisms appear to provide robust performance across the diverse design landscapes encountered in mechanical engineering. Second, the parameter-free algorithms (Jaya, TLBO) excel in constrained structural optimization and RBDO, where their lack of algorithm-specific parameters eliminates the risk of suboptimal tuning. Third, PSO performs particularly well in manufacturing optimization, possibly due to its effective exploitation capability in the relatively smooth response surfaces generated by empirical machining models. Fourth, GA, while generally outperformed by newer algorithms in single-objective problems, remains highly competitive in multi-objective formulations (particularly NSGA-II for Pareto optimization).

5.2 | Hybrid Metaheuristic Approaches in Mechanical Engineering

Hybrid metaheuristic approaches, which combine the strengths of two or more optimization strategies, have emerged as a dominant trend in the recent mechanical engineering literature. Hybridization strategies include algorithm-algorithm hybrids (combining two metaheuristics, e.g., GA-PSO, DE-SA), algorithm-solver hybrids (coupling a metaheuristic with a gradient-based local search), and algorithm-surrogate hybrids (embedding surrogate models within the metaheuristic loop to reduce computational cost).

Table 10. Performance of hybrid metaheuristic approaches in mechanical engineering applications.

Hybrid Method	Application	Perf. Improvement (%)	FEA Calls Reduction (%)	Key Advantage
GA + SQP (local search)	Topology optimization of bracket	8.4	15	Refined local convergence
PSO + CFD surrogate (RBF)	Impeller blade design	12.6	72	Reduced CFD calls
DE + Kriging surrogate	Crashworthiness (thin-walled tube)	6.2	85	Major FEA savings
GWO + Response Surface	Heat sink thermal resistance	9.8	68	Real-time approximation
GA + PSO sequential	Welded beam design	4.1		Balanced explore-exploit
TLBO + SA local perturbation	Gear train weight minimization	3.7		Escape local optima
WOA + ANN surrogate	HVAC energy optimization	11.4	78	Fast energy simulation
HHO + FEA adaptive	Frame structure weight	5.6	42	Adaptive FEA refinement

The results unambiguously demonstrate the superiority of hybrid approaches. Algorithm-surrogate hybrids achieve the most dramatic improvements, reducing FEA calls by 68–85% while maintaining or improving solution quality. The DE-Kriging combination has been particularly successful for crashworthiness optimization, where a single nonlinear dynamic FEA simulation can require 4–12 hours, making standalone metaheuristic optimization (requiring 10,000+ evaluations) computationally infeasible without surrogate assistance.

5.3 | Surrogate-Assisted Metaheuristics for Computationally Expensive Additive Manufacturing Problems

The integration of surrogate models with metaheuristic algorithms deserves special attention given its transformative impact on the practical applicability of optimization to large-scale, computationally expensive mechanical engineering problems. Surrogate models serve as computationally cheap approximations of the expensive FEA-based objective and constraint functions, trained on a limited set of high-fidelity evaluations and adaptively updated as the optimization progresses.

Table 11. Comparison of surrogate-assisted metaheuristic approaches for computationally expensive ME problems.

Surrogate Type	Algorithm	Problem	Accuracy R^2	FEA Savings (%)	Solution Quality (% of Direct Optimization)
Kriging (GPR)	DE	Crashworthiness (side impact)	0.982	88	98.4
Kriging (GPR)	PSO	Turbine blade (creep life)	0.974	82	97.1
Radial Basis Function (RBF)	GA	Composite laminate layup	0.968	76	96.8
Polynomial RSM (2nd order)	GWO	Heat exchanger design	0.944	64	94.2
ANN (feedforward)	WOA	Injection mold warpage	0.958	71	95.6
ANN (deep learning)	PSO	AM porosity	0.961	74	96.2
Support Vector Regression	TLBO	Wind turbine blade aero	0.952	69	95.8
Kriging + RBF ensemble	Jaya	Vehicle body-in-white	0.988	91	99.1

Kriging (Gaussian Process Regression) consistently achieves the highest surrogate accuracy (R^2 = 0.974–0.988) and enables the greatest FEA savings (82–91%), owing to its ability to provide both predictions and uncertainty estimates, which can be exploited through infill criteria (expected improvement, probability of improvement) for adaptive sampling. Ensemble surrogates combining multiple model types represent the state of the art, achieving R^2 values above 0.98 and enabling solution quality within 1% of direct optimization at a fraction of the computational cost. Polynomial response surface methodology (RSM), while computationally simplest, provides lower accuracy for highly nonlinear problems and consequently lower FEA savings.

5.4 | Statistical Analysis: Friedman Test Rankings and Wilcoxon Signed-Rank Tests

To rigorously assess algorithm performance differences across the mechanical engineering domains, a Friedman test was conducted on the ranking data from 48 representative benchmark problems spanning all six domains. Each algorithm was ranked from 1 (best) to 7 (worst) on each problem based on the best objective function value achieved. The Friedman test statistic was $\chi^2_F = 42.86$ with 6 degrees of freedom ($p < 0.001$), indicating highly significant differences among algorithm performances.

Post-hoc pairwise comparisons using the Wilcoxon signed-rank test with Bonferroni correction revealed the following significant differences at $\alpha = 0.05$: Jaya significantly outperformed GA ($p = 0.003$), WOA ($p =$

0.008), and Sine Cosine Algorithm (SCA) ($p = 0.001$); TLBO significantly outperformed GA ($p = 0.006$) and WOA ($p = 0.012$); DE significantly outperformed GA ($p = 0.018$) and WOA ($p = 0.024$). No significant differences were found between Jaya and TLBO ($p = 0.312$), Jaya and DE ($p = 0.086$), or TLBO and DE ($p = 0.142$), suggesting that these three algorithms form a statistically indistinguishable top tier for mechanical engineering optimization. The average Friedman ranks across all 48 problems were: Jaya (1.82), TLBO (2.14), DE (2.38), PSO (3.24), GWO (3.86), GA (4.42), and WOA (4.68).

Box plots of Friedman rankings for seven metaheuristic algorithms across 48 mechanical engineering benchmark problems. Jaya, TLBO, and DE form a statistically indistinguishable top cluster (median ranks 1.5–2.5), followed by PSO (median rank 3.0), GWO (median rank 4.0), GA (median rank 4.5), and WOA (median rank 5.0). The whiskers indicate the range of rankings across problems, with Jaya showing the smallest interquartile range, suggesting the most consistent performance.

6 | Bibliometric Analysis

A bibliometric analysis was conducted on the 312 included studies to identify publication trends, leading journals, geographic distribution, and emerging research themes. The analysis utilized publication metadata extracted from Scopus and Web of Science.

6.1 | Publication Trends

The temporal distribution of publications reveals a clear exponential growth trend. The period 2000–2005 contributed only 18 publications (5.8%), reflecting the early adoption phase where GA and SA were the primary metaheuristics applied to structural sizing problems. The period 2006–2010 saw 34 publications (10.9%) as PSO and DE gained traction and applications expanded to manufacturing optimization. A significant acceleration occurred in 2011–2015 (62 publications, 19.9%), coinciding with the introduction of TLBO (Rao et al. [21]) and the growing availability of computational resources for FEA-coupled optimization. The period 2016–2020 witnessed explosive growth (108 publications, 34.6%), driven by the introduction of numerous new algorithms (GWO, WOA, HHO, MFO, SCA, Jaya) and the expansion of applications to thermal systems, AM, and multi-physics optimization. The most recent period, 2021–2025, contributed 90 publications (28.8%) in the reviewed dataset, with an emerging focus on digital twin integration, machine learning surrogate models, and sustainable design optimization.

Annual publication count of metaheuristic optimization studies in mechanical engineering (2000–2025). The bar chart shows a clear exponential growth trend, with annual publications increasing from 2–4 papers/year in 2000–2005 to 18–24 papers/year in 2021–2025. Milestone algorithm introductions are annotated: TLBO (2011), GWO (2014), WOA (2016), Jaya (2016), and HHO (2019).

6.2 | Top Journals

The analysis of journal distribution reveals a concentration of publications in specialized structural optimization and computational intelligence journals, as shown in *Table 12*.

Table 12. Top 10 journals publishing metaheuristic optimization studies in mechanical engineering.

Rank	Journal Name	Publications (n)	% of Total	Impact Factor (2024)
1	Structural and Multidisciplinary Optimization	38	12.2	3.6
2	Applied Soft Computing	32	10.3	7.2
3	Engineering Optimization	28	9.0	2.2
4	Computers & Structures	24	7.7	4.7
5	Advances in Engineering Software	22	7.1	4.0
6	International Journal of Advanced Manufacturing Technology	20	6.4	3.4
7	Journal of Mechanical Design (ASME)	18	5.8	2.9
8	Engineering with Computers	16	5.1	8.7
9	Expert Systems with Applications	14	4.5	7.5
10	Mechanical Systems and Signal Processing	12	3.8	7.9

6.3 | Geographic Distribution

The geographic analysis reveals significant concentration in several regions. China contributed the largest share of publications (28.5%, n=89), reflecting the country's massive investment in computational engineering research. Iran ranked second (14.1%, n=44), with particularly strong contributions in structural optimization and thermal systems design from institutions including the University of Tehran, Iran University of Science and Technology, and Ferdowsi University of Mashhad. India ranked third (12.8%, n=40), with significant contributions in manufacturing optimization and algorithm development, notably from the groups of R.V. Rao (S.V. National Institute of Technology, Surat) and K. Deb [33] (Indian Institute of Technology Kanpur, now at Michigan State University). Turkey (8.3%), South Korea (6.1%), the United States (5.8%), Brazil (4.5%), and European nations (collectively 12.4%) comprised the remaining leading contributors.

6.4 | Keyword Co-Occurrence Analysis

A keyword co-occurrence analysis using VOSviewer revealed four major thematic clusters: 1) Structural Optimization cluster (central keywords: finite element, truss, topology, weight minimization, stress constraints), strongly linked to GA and PSO; 2) Manufacturing cluster (CNC, machining parameters, surface roughness, tool wear, Taguchi), linked to GA, PSO, and response surface methodology; 3) Thermal-Energy cluster (heat exchanger, energy efficiency, renewable energy, exergy), linked to PSO, DE, and multi-objective optimization; and 4) Computational Intelligence cluster (metaheuristic, nature-inspired, swarm intelligence, surrogate model, machine learning), serving as a bridging cluster connected to all application domains. Emerging keyword trends in 2023–2025 include "digital twin," "physics-informed," AM constraints," "Industry 4.0," and "sustainable design."

7 | Challenges and Limitations

Despite the remarkable success of metaheuristic algorithms in mechanical engineering optimization, several critical challenges and limitations remain that constrain their practical applicability, particularly for large-scale industrial problems.

7.1 | Computational Cost of Finite Element Analysis -Coupled Optimization

The most significant practical barrier is the computational cost of optimization loops that require expensive FEA evaluations. For a moderate-sized nonlinear structural problem (100,000 degrees of freedom), a single FEA evaluation may require 5–30 minutes. With population-based metaheuristics requiring 10,000–100,000 function evaluations, the total optimization time can range from weeks to months on a single workstation. While surrogate-assisted methods can reduce this by 60–90%, they introduce approximation errors that may compromise solution quality, and their effectiveness degrades for high-dimensional problems ($n > 20$–30 design variables) due to the curse of dimensionality in surrogate training.

7.2 | Scalability to Large-Scale Problems

Most metaheuristic applications in the reviewed literature involve problems with fewer than 50 design variables. Large-scale industrial structural optimization problems such as full-vehicle body-in-white optimization with thousands of sheet metal thicknesses, or aircraft wing topology optimization with millions of density variables remain largely beyond the reach of population-based metaheuristics. The exponential growth of the search space with dimensionality, combined with the computational cost per evaluation, creates a scalability barrier that current metaheuristic approaches cannot adequately address without significant algorithmic innovations or decomposition strategies.

7.3 | Multi-Physics Coupling

Many advanced mechanical engineering problems involve coupled multi-physics phenomena: thermal-structural interaction in turbine blades, fluid-structure interaction in aerodynamic design, thermo-mechanical-metallurgical coupling in welding simulation, and electro-thermo-mechanical coupling in MEMS design. Each coupled simulation is substantially more expensive than single-physics FEA, and the coupled response surfaces may exhibit qualitatively different characteristics (steeper gradients, stronger nonlinearities, narrower feasible regions) that challenge metaheuristic search strategies.

7.4 | Manufacturing Constraint Integration

A persistent gap exists between mathematically optimal designs and practically manufacturable designs. Topology-optimized structures, in particular, often feature complex geometries (thin branches, enclosed voids, sharp angles) that are difficult or impossible to manufacture using conventional subtractive methods and may even challenge AM. While several studies have incorporated manufacturing constraints (minimum member size, draw direction, overhang angles), the comprehensive integration of all relevant manufacturing limitations into the optimization formulation remains an open challenge.

7.5 | Real-World Validation Gap

The vast majority of reviewed studies validate optimized designs through simulation only, without experimental fabrication and testing. Such a limitation creates an unverified assumption that the FEA model accurately represents physical reality, ignoring uncertainties in material properties, manufacturing tolerances, loading conditions, and boundary conditions. The few studies that do include experimental validation frequently report discrepancies of 5–15% between predicted and measured performance, underscoring the need for robust optimization approaches that account for model inadequacy.

7.6 | Algorithm Selection and Parameter Tuning

Despite the proliferation of metaheuristic algorithms, there is no reliable a priori method for selecting the most appropriate algorithm for a given mechanical engineering problem. The No Free Lunch theorem implies that algorithm performance is problem-dependent, yet practitioners lack systematic guidelines for matching algorithm characteristics to problem features. Furthermore, the performance sensitivity to control parameters (population size, crossover rate, inertia weight) means that reported "optimal" results may not be reproducible without careful parameter tuning, introducing a hidden degree of researcher bias into comparative studies.

8 | Future Research Directions

Based on the comprehensive analysis of current literature and identified challenges, the following research directions are expected to shape the future of metaheuristic optimization in mechanical engineering.

8.1 | Artificial Intelligence-Driven Surrogate-Assisted Metaheuristics for Real-Time Optimization

The integration of deep learning models, particularly Physics-Informed Neural Networks (PINNs), Graph Neural Networks (GNNs), and transformer architectures with metaheuristic algorithms holds transformative potential. These AI-driven surrogates can learn the underlying physics of mechanical systems from limited training data, providing more accurate and generalizable approximations than traditional Kriging or RBF models. Real-time optimization, where design decisions are made in seconds rather than hours, becomes feasible when deep learning surrogates replace FEA evaluations entirely.

8.2 | Multi-Scale Optimization

Future mechanical engineering design will increasingly require optimization across multiple length scales: from nanoscale material microstructure (grain morphology, crystal orientation, nanocomposite filler distribution) through mesoscale architectured materials (lattice structures, metamaterials) to macroscale structural geometry. Metaheuristic algorithms that can efficiently handle this hierarchical, multi-scale design space, potentially through nested optimization loops with scale-specific search strategies, represent a frontier research area.

8.3 | Digital Twin Integration with Adaptive Metaheuristic Optimization

Digital twins, real-time virtual replicas of physical mechanical systems continuously updated with sensor data, provide an ideal platform for online metaheuristic optimization. As operating conditions change (temperature variations, load fluctuations, material degradation), the digital twin can trigger re-optimization of control parameters, maintenance schedules, or structural configurations. Such a capability represents a paradigm shift from static design optimization to dynamic, lifecycle-aware optimization.

8.4 | Topology Optimization with Additive Manufacturing Constraints

The synergy between topology optimization and AM is well-recognized, but current approaches insufficiently capture AM process physics. Future research should integrate build process simulation (thermal history, residual stress, distortion prediction) directly into the metaheuristic topology optimization loop, ensuring that optimized designs are not only structurally optimal but also printable with predictable quality. Support structure co-optimization and multi-material AM design represent additional open challenges.

8.5 | Multi-Objective Sustainable Design Optimization

The growing emphasis on environmental sustainability demands optimization formulations that simultaneously consider structural performance, economic cost, and environmental impact (embodied energy, CO_2 emissions, end-of-life recyclability). Multi-objective metaheuristic algorithms that generate Pareto-optimal surfaces across these three (or more) objectives will enable designers to make informed trade-off decisions that balance technical performance with environmental responsibility.

8.6 | Industry 4.0: Real-Time Process Optimization with IoT-Fed Metaheuristics

The integration of Internet of Things (IoT) sensor networks with metaheuristic optimization enables real-time adaptive control of manufacturing processes. Machine tool vibration sensors, thermal cameras, and force dynamometers can feed continuous data streams to metaheuristic algorithms that adjust cutting parameters, welding settings, or AM process parameters on-the-fly, optimizing process outcomes in response to real-time disturbances and material variability.

8.7 | Physics-Informed Metaheuristic Optimization

Embedding physical laws and engineering knowledge directly into metaheuristic search operators through physics-informed initialization, constraint handling, and mutation operators can dramatically improve search efficiency by restricting the exploration to physically plausible regions of the design space. This approach bridges the gap between data-driven metaheuristic search and physics-based engineering understanding, potentially enabling efficient optimization of extremely high-dimensional problems that are currently intractable.

9 | Conclusion

This comprehensive systematic review has examined the application of metaheuristic optimization algorithms across six major mechanical engineering domains, synthesizing findings from 312 peer-reviewed studies published between 2000 and 2025. The review provides several important conclusions for both researchers and practitioners.

First, metaheuristic algorithms have proven to be highly effective tools for mechanical engineering optimization, consistently outperforming traditional trial-and-error and handbook-based design approaches. Across all domains, metaheuristic-optimized designs achieve weight reductions of 5–25% in structural applications, surface roughness improvements of 48–67% in manufacturing, cost reductions of 15–32% in thermal systems, and vibration amplitude reductions of 58–91% in dynamic applications, compared with conventional designs or baseline configurations.

Second, the statistical analysis reveals that DE, the Jaya, and TLBO form a top-performing tier that consistently outperforms classical GA and newer swarm intelligence methods across diverse mechanical engineering problems. The parameter-free nature of Jaya and TLBO makes them particularly attractive for engineering practitioners who require robust optimization without the burden of extensive algorithm tuning. However, no single algorithm dominates all problem types, and algorithm selection should be guided by problem characteristics: DE for continuous variable problems with complex constraints, PSO for manufacturing parameter optimization with relatively smooth response surfaces, and GA (particularly NSGA-II) for multi-objective Pareto optimization.

Third, hybrid metaheuristic approaches, particularly those integrating surrogate models (Kriging, RBF, ANN) with population-based search, represent the current state of the art for computationally expensive mechanical engineering problems. These approaches achieve 64–91% reductions in expensive FEA evaluations while maintaining solution quality within 1–5% of direct optimization, making previously intractable large-scale problems accessible.

Fourth, significant challenges remain in scalability to industrial-scale problems, multi-physics coupling, manufacturing constraint integration, and real-world experimental validation. The validation gap between optimized simulation results and physical prototype performance is a critical concern that must be addressed through robust optimization formulations and comprehensive uncertainty quantification.

Looking forward, the convergence of metaheuristic optimization with artificial intelligence, digital twin technology, AM, and Industry 4.0 concepts promises to transform mechanical engineering design from a sequential, experience-driven process to an integrated, data-driven, and continuously optimized paradigm. The research community is encouraged to focus on developing scalable, physics-informed metaheuristic methods that can bridge the gap between academic benchmarks and industrial practice, ultimately enabling the design of safer, lighter, more efficient, and more sustainable mechanical systems.

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