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Real-World Applications of Metaheuristic Algorithms: A Comprehensive Review of the State-of-the-Art

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ABSTRACT

Metaheuristic algorithms have gained significant acceptance in large areas of optimization, giving unique and novel solutions to complicated problems across various areas. This research dives into the wide classification of state-of-the-art real-world applications that depend on metaheuristic algorithms, acknowledging their prevalence and the diversity of real-world applications where their performances are evaluated. The major goal is to evaluate forty-eight metaheuristic algorithms from 2020 to 2024 based on the results presented in their original research articles, emphasizing their effectiveness in tackling six prevalent real-world applications. In addition, the study classifies the algorithms and compares them to determine which ones are most effective for the particular applications. The results point out the necessity to solve the actual problems using opting for a metaheuristic algorithm. Nevertheless, it becomes very obvious that no algorithm works well in all the cases pointed out, as a demand for an informed selection based on the task complexity. This research contributes to the ongoing development and application of metaheuristic algorithms in diverse practical settings by providing valuable insights into the dynamic landscape of metaheuristics.

1. Introduction

In the world of optimization strategies, metaheuristic algorithms are adaptive tools borrowed from many different fields, providing a new way to solve the complex problems in diverse industries [1]. Worldwide, scientists are always trying to improve optimization methods. Several algorithms, such as bio-inspired/nature-inspired, population-based, and swarm-based, have become prevalent for their improved performance and ease [2-4]. These methods have enabled them to effectively manage the various challenges in different spheres.

Effective methodologies of optimization are extremely important in the complex world with many growing knowledge domains. Metaheuristic algorithms present a fascinating approach to the overcoming complex issues in engineering, biology, and many other fields [5-7]. Knowing these algorithms and their types is very critical for researchers, engineers, and practitioners looking for effective approaches to tackle the sophisticated optimization problems.

Optimization plays a crucial role in solving complex, constrained real-world problems, and metaheuristic algorithms have emerged as robust tools in this context due to their adaptability and efficiency [8,9]. These algorithms are increasingly recognized for their ability to address multidimensional engineering challenges, especially in electrical and civil domains, where standard solutions fall short [10]. Their design, often inspired by natural processes such as evolution and swarm

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behavior, equips them with the flexibility to be applied across diverse fields, including healthcare, economics, and computer science [11-13]. As high-level frameworks, metaheuristics offer generalizable approaches suitable for complex tasks [14] in planning, scheduling, and network systems [15]. Notably, specific techniques like the Teaching-Learning-Based Optimization (TLBO) algorithm have shown promising results in handling nonlinear, multidimensional problems and have been refined for broader applications [16]. In the domain of cybersecurity, advanced metaheuristics such as the Lion Optimization Algorithm and Grey Wolf Optimizer have enabled the development of more accurate and adaptive intrusion detection systems [17].

In recent years, there have been great discoveries and the utilization of metaheuristic algorithms. Bio-inspired/nature-inspired algorithms are inspired by the nature and can adapt to the changing environments [18]. Human behavior-based algorithms use the information about human activity to improve the decision making [19]. Swarm algorithms, which are based on the collective behaviors in nature and utilize the cooperation of multiple agents to achieve the optimal solutions [20]. These metaheuristics are very essential in addressing a wide range of optimization problems within the different domains for their flexibility and also effectiveness.

Previous reviews have broadly examined metaheuristic algorithms, focusing on their classification, theoretical foundations, and general applications. Studies such as [21-23] provide high-level overviews—detailing algorithmic types, inspirations, open challenges, and broad application domains—while offering insights into commonly used metaheuristics like PSO, GA, and ACO. These works aim to guide both new and experienced researchers in understanding the scope and versatility of metaheuristics. Some reviews narrow in on specific algorithms, such as [24], which focuses on the Bat Algorithm, and [25], which focuses on the Slime Mould Algorithm, offering in-depth analyses of their variants, applications, and potential research directions. In contrast, the uniqueness of the current review lies in its practical benchmarking of 48 recent metaheuristic algorithms (2020–2024) specifically against six real-world engineering problems. It not only categorizes these algorithms by their conceptual basis but also assesses their effectiveness in constrained, real-world tasks—offering performance-based insights and concrete guidance on algorithm selection, a dimension largely missing from prior general or algorithm-specific reviews.

Despite significant advancements in the research and application of metaheuristic algorithms, there is a substantial void in an all-inclusive classification and systematic assessment of these algorithms, especially for engineering optimization. The literature lacks a comprehensive analysis that describes such algorithms and evaluates their efficacy in various engineering problems. Filling this gap is extremely important for the progress of the field, as it allows the researchers to choose algorithms based on algorithmic properties tailored to their optimization problems.

This study delves into bio-inspired/nature-inspired, chemistry-based, game-based, human behavior-based, hybrid, math-based, physics-based, population-based, socio-inspired, and swarm-based metaheuristic algorithms. In order to cover a knowledge gap and contribute to the progress of problem-solving techniques, this paper deals with the specifics of these algorithms. It presents their practical application in engineering optimization. As a result, the following are the specific research objectives aimed at filling the identified knowledge gap:

Comprehensive Classification: Develop a detailed classification of metaheuristic algorithms, categorizing them into distinct groups based on their inspiration sources and underlying principles. Thus, A clear gap identified in the existing literature is the absence of a comprehensive survey that compares the results of metaheuristic algorithms in real-world applications. This lack of comparative analysis makes it difficult for developers to identify the generated algorithms for specific real-world problems, particularly those based on nature-inspired and bioinformatics-driven approaches. By addressing this gap, the current survey provides valuable insights that aid in the effective selection of metaheuristic methods for practical applications.

These benchmark problems are widely utilized due to their highly non-linear, constrained nature and strong relevance to real-world engineering applications. Their complexity makes them particularly suitable for evaluating the robustness, convergence behavior, and optimization accuracy of metaheuristic algorithms. Furthermore, while the No-Free-Lunch (NFL) theorem asserts that no single algorithm universally outperforms all others across every problem domain, several algorithms have demonstrated consistently strong performance within specific engineering contexts. This systematic review highlights that the effectiveness of each algorithm is problem-dependent, and its success is closely tied to the characteristics of the target application. By analyzing performance across standard benchmark problems, this review provides valuable insights into which algorithms are most capable of delivering optimal solutions efficiently in practical engineering and real-life scenarios.

Performance Assessment: Assess the effectiveness of these algorithms for a variety of constrained benchmark optimization problems in mechanical engineering, including the pressure vessel design, welded beam design, tension/compression spring design, speed reducer design, gear train design, and also three-bar truss.

The key contributions of this study are as follows:

- Provides a comprehensive classification of 48 recent metaheuristic algorithms based on their conceptual inspiration.
- Conducts a systematic performance assessment of these algorithms across six classical engineering optimization problems.
- Highlights the strengths and limitations of each algorithm in real-world applications.
- Offers practical guidance for selecting suitable metaheuristic algorithms tailored to specific optimization challenges.
- Fills a critical knowledge gap by benchmarking modern metaheuristics in constrained engineering design tasks.

The organization of the paper is outlined in the following manner: In Section 2, the methodology of the literature search is described, which also represents the research approach. Section 3 is devoted to the metaheuristic algorithms classification. Section 4 outlines the application of metaheuristic algorithms in engineering optimization and discusses the assessment of their performance. Section 5 engages in discussion, providing insights and analysis. Section 6 is devoted to the discussion, while the final section, Section 7, encompasses concluding remarks and outlines future directions.

2. Literature search methodology

Conforming to the PRISMA [26,27] guidelines, this systematic literature review investigates pertinent papers from credible sources, depicted in Figure 1. Employing a systematic literature review approach, the study concentrates specifically on evaluating the efficacy of algorithms for various constrained benchmark optimization problems within the realm of mechanical engineering. Following the evaluation phase, the primary studies singled out undergo thorough quantitative analysis to affirm the strength and relevance of the findings.

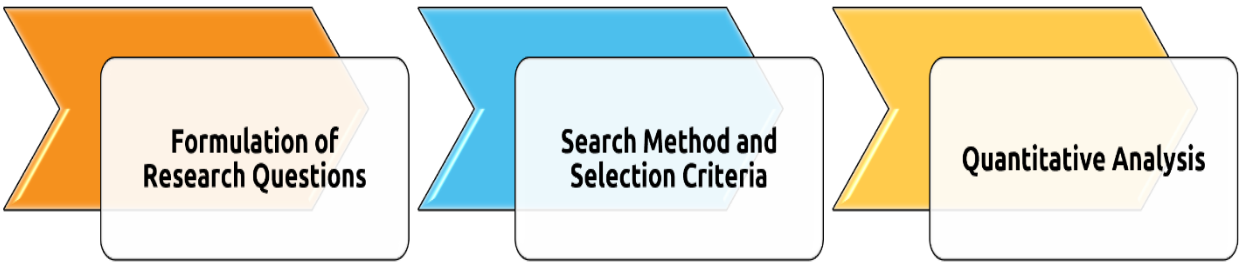

Figure 1. Systematic literature review paradigm.

2.1. Formulation of research questions

This review seeks to identify the research questions related to investigating the efficacy of several metaheuristic algorithms in resolving engineering issues. The set of questions below seeks to elucidate the role of metaheuristic algorithms in solving engineering problems:

- What are the dominant types of metaheuristic algorithms?
- What type of metaheuristic algorithm has resulted in the best performance in solving the various engineering optimization problems?
- Which classical engineering optimization problems are used the most frequently to assess the performance of the metaheuristic algorithms?

2.2. Search method and selection criteria

The literature review was composed of searching for English-language peer-reviewed research articles from three databases (PubMed, ScienceDirect, and IEEE). Additionally, the University of Toronto Libraries' OneSearch [28]. The search included records published in the year 2020-2024 and was conducted on April 9, 2025. The search terms used were: ("meta-heuristic" OR "metaheuristic" OR "Algorithm*") AND ("pressure vessel" OR "three-bar truss" OR "welded beam" OR "tension/compression spring" OR "gear train" OR "speed reducer design"). In total, 48 unique articles were incorporated in this review. To incorporate and embed relevant papers according to the research questions determined in the "Formulation of Research Questions" segment, the inclusion-exclusion criteria were created. The following criteria were applied to choose the most pertinent papers for this review:

Inclusion Criteria:

1. English-language peer-reviewed articles.
2. Publications spanning the years 2020 to 2024.
3. Pertinence to the application of metaheuristic algorithms on the six previously mentioned engineering optimization problems.

Exclusion Criteria:

1. Studies unavailable in the English language.
2. Studies devoid of engagement with metaheuristic algorithms.
3. Studies unrelated to the previously mentioned engineering optimization problems.
4. Studies presenting results solely through charts or graphs.
5. Studies released prior to the year 2020.
6. Studies lacking the inclusion of statistical measures for assessing metaheuristic algorithms.
7. Studies with inadequate topic definition.

2.3 Quantitative analysis

The final stage of our assessment methodology involved conducting comprehensive statistical analysis on quantitative data. This phase entailed collecting and analyzing quantitative data sourced from various sources such as conferences, journals, and book chapters. Subsequently, we conducted rigorous statistical analyses to explore our research topics in depth and identify emerging trends.

Figure 2 provides a detailed overview of our screening and assessment procedure for the statistical analysis of literature. The diagram illustrates the selection process involving two databases and a search engine for the review. Initially, out of the 783 papers identified for review and analysis, a significant portion was duplicated, leading to the removal of 89 entries before screening commenced. Publications were then screened based on predetermined inclusion and exclusion criteria, resulting in the assessment of 46 papers meeting the specified criteria. Additionally, two additional papers were sourced from alternative channels, bringing the total to 48 papers for analysis.

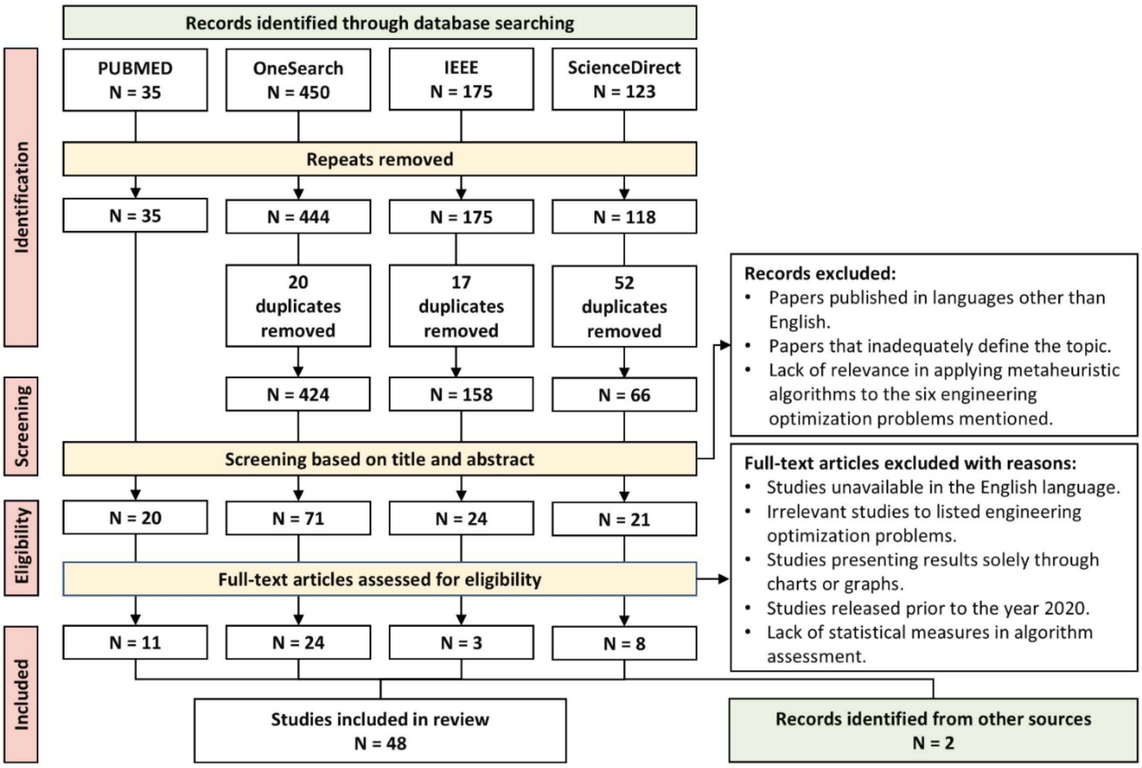

Figure 2. Systematic review screening process flowchart.

3. Metaheuristic algorithms classification

Metaheuristic algorithms comprise various optimization strategies derived from various areas, as shown in Figure 3. This innovative family of approaches includes bio-inspired/nature-inspired, chemistry-based, game-based, human behavior-based, hybrid, math-based, physics-based, population-based, socio-inspired, and swarm-based algorithms, each of which offers unique solutions to complex problems across multiple domains. Table 1 presents a list of algorithm abbreviations along with their full names.

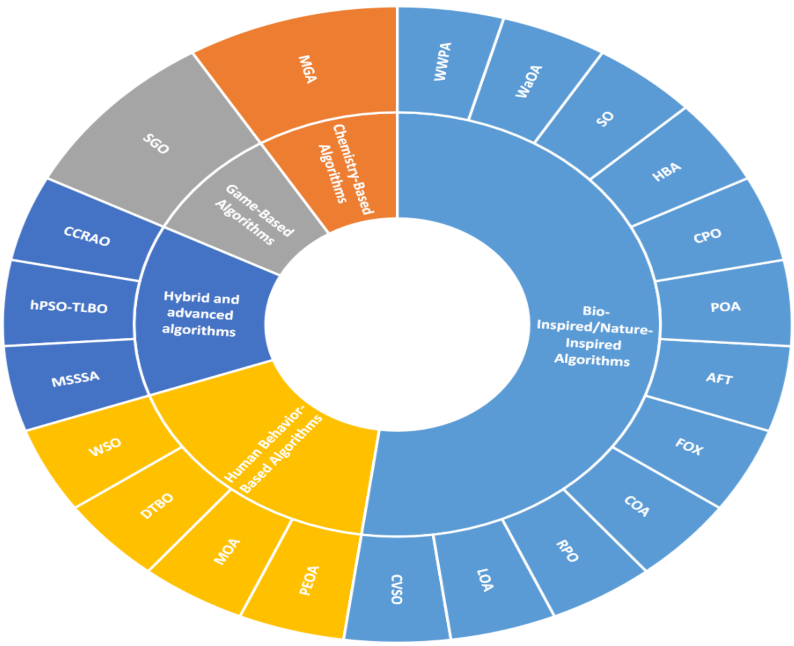

Figure 3. Classification of metaheuristic algorithms.

Table 1: The abbreviations mentioned in the text are listed in alphabetical order.

Abbreviations	Words
CVSO	Corona Virus Search Optimizer
AFT	Ali Baba and the Forty Thieves
AOA	Archimedes optimization algorithm
APO	Artificial Protozoa Optimizer
BOA1	Bobcat Optimization Algorithm
BOA2	Botox Optimization Algorithm
CCE	City Councils Evolution
CCRAO	Colonial Competitive RAO
COA	Coati Optimization Algorithm
COASaDE	Crayfish Optimization Algorithm Self-adaptive Differential Evolution
CPO	Crested Porcupine Optimizer
CWO	Carpet Weaving Optimization
DRA	Divine Religions Algorithm
DTBO	Driving Training-Based Optimization
EDO	Exponential Distribution Optimizer
EHO	Elk herd optimizer
FDA	Flow Direction Algorithm
FOX	Fox optimizer
GCRA2	Greater cane rat algorithm
GRO	Gold Rush Optimizer
GVOA	Griffon Vultures Optimization Algorithm
HBA	Honey Badger Algorithm
HBWO	hybrid Beluga Whale Optimization
HO	Hippopotamus Optimization
HOA	Hiking Optimization Algorithm
hPSO-TLBO	hybrid Particle Swarm Optimization–Teaching–Learning-Based Optimization
LCA	Learning cooking algorithm
LOA	Lyrebird Optimization Algorithm
MGA	Material Generation Algorithm
MOA	Mother Optimization Algorithm
MSSSA	Multi-Strategy-Sparrow Search Algorithm
NGO	Northern Goshawk Optimization
OOBO	One-to-One-Based Optimizer
OOPOA	Object-Oriented Programming Optimization Algorithm
PbA	Penalty-based Algorithm
PEOA	Preschool Education Optimization Algorithm
PO	Political Optimizer
POA	Pelican Optimization Algorithm
PSA	Propagation Search Algorithm
RBMO	Red-billed blue magpie optimizer
RPO	Red Panda Optimization
SABO	Subtraction-Average-Based Optimizer
SCO	Single Candidate Optimizer
SGO	Squid Game Optimizer
SO	Snake Optimizer
WaOA	Walrus Optimization Algorithm
WOA	Wombat Optimization Algorithm
WSO	War Strategy Optimization
WWPA	Waterwheel Plant Algorithm

Bio-inspired/nature-inspired algorithms harness the remarkable behaviors of diverse creatures to tackle complex optimization challenges. CVSO [29] draws inspiration from the movement and search strategies of the coronavirus within societies, exhibiting a balance between local and global search through evolutionary strategies. HBA [30] is inspired by the intelligent foraging behavior of honey badgers. SO [31] mimics the unique mating behavior of snakes, where each snake (male or female) competes for the best partner when sufficient food is available and the temperature is low. WaOA [32] is based on the natural behaviors of walruses, specifically feeding, migrating, escaping, and fighting predators. The WWPA [33] models the natural hunting behavior of the waterwheel plant. LOA [34] mimics lyrebirds' escape and hiding strategies, showcasing high exploration and exploitation capabilities in problem-solving spaces. RPO [35] emulates red pandas' foraging and tree-climbing behaviors, demonstrating effective optimization without parameter adjustment. COA [36] demonstrates an advantage in balancing the exploration and exploitation over multiple objective functions and real-world problems due to capturing coati behaviors that are related to attacking, hunting, and escaping. EHO [37] is inspired by the structured breeding behavior of elk, where dominance-based group formation and seasonal cycles guide the search process. GCRA [38] mimics the intelligent nocturnal foraging and mating behaviors of cane rats, using trail-following and territorial separation to enhance exploration and exploitation. HO [39] algorithm draws from the defensive, evasive, and movement strategies of hippos in aquatic environments to balance search dynamics. RBMO [40] models the cooperative hunting, chasing, and food storage tactics of magpies to efficiently explore and exploit the solution space. BOA [41] replicates the stalking and chasing behavior of bobcats during hunting to simulate adaptive exploration and targeted exploitation. APO [42]simulates the life cycle behaviors of protozoa, including foraging, dormancy, and reproduction, to dynamically navigate complex search spaces. WOA [43] is inspired by wombats' food-searching routines and evasive burrow-diving actions, enabling a robust exploration-exploitation trade-off in optimization tasks. GVOA [44] draws inspiration from the complex and adaptive foraging strategies of griffon vultures, modeling their cooperative and individual search behaviors to achieve a balanced and efficient global optimization process. FOX [45] takes cue from the foraging technique of the foxes, whereby it focuses on manageable jumps to chase the prey efficiently. AFT [46] creatively draws from the well-known story, infusing Ali Baba's search for the Forty Thieves with the exploration and exploitation processes. POA [47] implements a stochastic optimization process to explain the hunting behavior of the pelicans, which depicts an equilibrium between exploration and exploitation on different functions. CPO [48] utilizes the defensive characteristics of crested porcupines and proposes a population reduction cycle to improve the convergence and diversity. These bio-inspired/nature-inspired algorithms possess distinctive features that contribute to efficiently solving complex optimization problems.

The realm of human behavior-based algorithms introduces innovative optimization approaches, drawing inspiration from diverse aspects of human interactions. WSO [49] strategically mimics military tactics, while DTBO [50] emulates the driving learning process. MOA [19] reflects the care and guidance of a mother in its three phases, emphasizing education, advice, and upbringing. Meanwhile, referencing preschool activities, PEOA [51] models the incremental evolution of a teacher's influence and the development of individual knowledge. HOA [52] draws from the physical and strategic aspects of hiking through mountainous terrains; CWO [53] mimics the intricate coordination between a weaver and a pattern reader in traditional carpet-making; BOA [54] takes cues from the defect-correcting nature of cosmetic Botox procedures; DRA [55] models socio-religious dynamics and leadership evolution within spiritual communities; and LCA [56] reflects the intergenerational learning process observed in family cooking environments—all offering unique strategies to balance exploration and exploitation while effectively solving complex optimization problems. These algorithms showcase the potential of human-centric metaheuristics, offering unique perspectives in solving optimization problems.

Based on social organizations, the socio-inspired algorithms restate the optimization paradigms. CCE [57] cleverly reflects the evolutionary processes of the city councils. Political processes are translated by PO [58] into a dual role assignment, which allows for navigating the optimization landscapes with agility. SCO [59] goes against the conventions, depending on a lone candidate with a double-phased approach. The socio-inspired algorithms are very creative in that they give much better results than their counterparts on various benchmarks. Thus, their innovative style reveals a lot of new opportunities because the socio-inspired strategies transform the optimization landscapes.

Population-based algorithms are very unique solutions to complicated problems; each algorithm is influenced by many different sources [60]. The GRO [61] cleverly imitates the methods used by prospectors during the Gold Rush Era that involve migration, collaboration, and panning. OOBO [62] uses one-to-one interactions very innovatively, eliminating the dependence on particular persons for population changes. Moreover, PbA [63] is a population-based evolutionary model specifically designed for addressing continuous restricted optimization challenges within real-life engineering applications.

Swarm algorithms are based on collective behavior, which is very common in nature, where a group of simple entities, such as particles or agents, can collaborate to explore solution spaces and provide efficient and flexible optimization solutions for different problems. Based on the enactment of the northern goshawks, the NGO [64] combines prey identification and pursuit phases, showing a compromise between exploration and exploitation. Instead, SABO [20] uses the subtraction of average searcher agents to perform population position updates. SGO [65] proposes an original metaheuristic algorithm that borrows from the game dynamics of the traditional Korean Squid Game. In this game-based algorithm, offensive and defensive players make different strategic moves, leading to an innovative approach for the optimization challenges.

Chemistry-based algorithms use rules derived from chemical reactions for optimization. Math-based algorithms rely on mathematical models, and physics-based algorithms utilize physical laws, with both approaches working towards solving the problem-solving process. EDO [66] draws its inspiration from mathematics, utilizing the exponential probability distribution model. The MGA [67] based on material chemistry, uses the structure of chemical compounds and reactions in solving engineering problem optimizations. Math-based AOA [68] creatively uses Archimedes' Principle from physics to show the buoyant force principles confronting the intricate optimization problems. FDA [69] is a physics-based optimizer that approximates the direction of flow in a drainage basin, demonstrating its effectiveness in solving various mathematical benchmarks and also engineering design problems. Another physics-based optimizer PSA [70] is a great example of a physics-based optimizer that uses voltage and current wave propagation along the transmission lines to achieve superior results in engineering applications using just a few coding lines. OOPOA is motivated by object-oriented programming inheritance, where public, private, and protected traits guide population updates, promoting both exploitation through elite inheritance and exploration via mutation. These algorithms, MGA, AOA, FDA, OOPOA, and PSA, representing the different classes of metaheuristics, offer novel solutions to the optimization problems in diverse domains.

Hybrid and advanced algorithms combine the disparate optimization methods, bringing the advantages of different techniques to solve the problems more effectively. The CCRAO [71] introduces a powerful group algorithm by merging and modifying three Rao algorithms, exhibiting superior performance in optimizing real-parameter functions. The hPSO-TLBO [72] creatively combines the exploitation abilities of PSO with the exploration abilities of TLBO, proving effective in addressing various benchmark functions. HBWO [73] is inspired by the social swimming, foraging, and spiral predation behaviors of beluga whales, integrating quasi-oppositional learning, adaptive strategies, and the Nelder-Mead method to enhance search efficiency and convergence. COASaDE [74] draws from the foraging behavior of crayfish and the adaptability of self-adaptive differential evolution, combining symmetric exploration and exploitation to robustly solve diverse engineering optimization problems. The MSSSA [75] employs a circle map, adaptive survival escape strategy, and craziness factor, showcasing excellent feasibility and practicality in solving highly non-linear optimization problems, outperforming other state-of-the-art algorithms.

4. Classical engineering optimization using metaheuristic algorithms

In this section, we utilize six well-known constrained benchmark optimization problems in mechanical engineering: pressure vessel design, three-bar truss design, welded beam design, tension/compression spring design, gear train design, and speed reducer design, as depicted in Figure 4. These issues have distinct objective functions, design variables, and also constraints. The aim is to test the performance of the metaheuristic algorithms that are discussed in Section 2. The assessment is based on the results presented in the original research articles, focusing on solution quality, stability, and convergence rate. To evaluate the performance of the algorithms on the classical engineering application, five key statistical metrics are used: Best, Mean, Worst, Standard Deviation (Std. Dev.), and Optimal Cost. The Best value represents the lowest (most optimal) solution cost achieved by an algorithm across multiple independent runs, indicating its peak performance. The Mean (or average) denotes the average solution cost obtained over all runs, reflecting the algorithm's typical performance. The Worst value shows the highest solution cost recorded, which helps in assessing the algorithm's reliability in less favorable conditions. Standard Deviation (Std. Dev.) measures the variability or consistency of results across runs—a lower value signifies stable and reliable performance. Finally, the Optimal Cost refers to the best-known or theoretically ideal solution for the problem, used as a benchmark to compare the effectiveness of each algorithm.

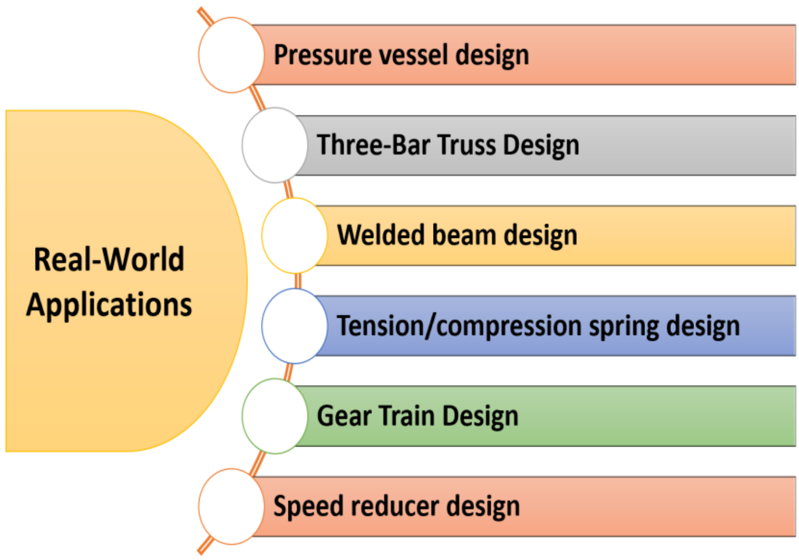

Figure 4. Real-world applications.

4.1. Pressure vessel design

The engineering challenge of pressure vessel design, focusing on optimizing costs for cylindrical pressure vessels, has a long-standing history. Pressure vessel design optimization involves finding the most efficient and cost-effective configuration for a vessel that contains pressurized fluids or gases, as depicted in Figure 5. The goal is to minimize construction costs while meeting safety and performance criteria. This process considers crucial factors such as the length of the cylindrical section (L), inner and head radii (R), head thickness (Th), as well as shell thickness (Th). These four factors play a pivotal role in the design of pressure vessels [71]. The design must adhere to constraints related to buckling load, end deflection, shear stress, and bending stress. By strategically adjusting these variables, engineers aim to balance structural integrity, functionality, and cost efficiency in pressure vessel construction. The complete optimization equation is detailed in equation (1) [29]. Various metaheuristic algorithms, as outlined in

Table 2, have been employed to address this intricate design problem.

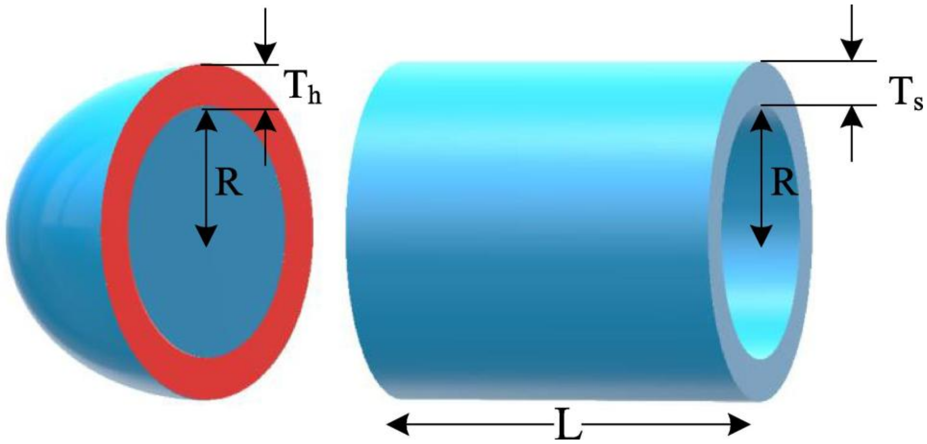

Figure 5. Schematic of the pressure vessel design [71].

$$
\begin{aligned}
&\textit{Consider}: && \bar{x} = [x_1 x_2\ x_3\ x_4] = [\,T_s\ \ T_h\ R\ L],\\
&\textit{Minimize}: && f(\bar{x}) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3,\\
&\textit{Subject to}: && g_1(\bar{x}) = -x_2 + 0.00954x_3 \le 0,\\
& && g_2(\bar{x}) = -x_1 + 0.0193x_3 \le 0,\\
& && g_3(\bar{x}) = x_4 - 240 \le 0.\\
& && g_4(\bar{x}) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1296000 \le 0,\\
&\textit{Variable range}: && 0 \le x1 \le 100, 0 \le x2 \le 100, 10 \le x3 \le 200, 10 \le x4 \le 200.
\end{aligned} \tag{1}
$$

In

Table 2, diverse algorithms were employed to address the pressure vessel design challenge, revealing noteworthy statistical outcomes. Most algorithms demonstrate comparable results regarding mean or average values, suggesting similar central tendencies. Notably, the HBA algorithm performs the best overall with the lowest mean (5876.70812), best case (5276.6792), and a low standard deviation (0.1001), indicating stable performance across trials. RPO, hPSO-TLBO, and BOA1 all exhibit nearly identical best, mean, and worst-case values, with extremely low deviations (1.87E-12, 2.06E-12, and 9.83E-14, respectively), reflecting highly consistent behavior. However, HBA still holds superiority in terms of the lowest mean and best overall cost.

OOBO, which previously ranked second, now demonstrates a mean of 5880.524, slightly higher than HBA, but with a lower worst case (5882.658) than several others and a higher standard deviation (9.125), indicating more variability. Several other algorithms like SABO, MOA, CWO, and PEOA also produce closely clustered performance near 5882.9, but do not surpass HBA in optimality or consistency.

Table 2: Optimizing statistical outcomes in pressure vessel design with diverse algorithms.

Algorithm	Best Case	Mean/Average	Worst Case	STD. Dev.	Optimal Cost
HBA	5276.6792	5876.70812	5877.20827	0.1001	5276.6792
OOBO	5870.846	5880.524	5882.658	9.125	5870.846
RPO	5882.895	5882.895	5882.895	1.87E-12	5882.895
hPSO-TLBO	5882.895451	5882.895451	5882.895451	2.06E-12	5882.895451
BOA1	5882.8955	5882.8955	5882.8955	9.83E-14	5882.8955
SABO	5882.901	5882.901	5882.901	1.87E-12	5882.901
MOA	5882.901	5882.901	5882.901	1.89E−12	5882.901
CWO	5882.901	5882.901	5882.901	2.94E-12	5882.901
PEOA	5882.901	5883.043	5884.245	0.316128	5882.901
LOA	5882.9013	5884.8955	5885.8955	1.87E-12	5882.9013
WSO	5885.246	5885.246	5885.246	4.287399E-13	5885.246
BOA2	5885.3263	5885.3263	5885.3263	2.32E-08	5885.3263
AFT	5885.332773	5885.332773	5885.332773	4.18E-12	5885.332773
RBMO	5885.332774	5885.333685	5885.348157	2.9161E−03	5885.332774
CPO	5885.43417	5885.434175	NA	5.85E-09	5885.43417
EDO	5885.3734	5885.5207	5885.7806	1.16E−01	5885.3734
LCA	5886	5887	5890	9.632E–01	5886
POA	5883.0278	5887.082	5894.256	24.35317	5883.0278
WaOA	5884.8824	5887.201	5894.172	21.041638	5884.8824
DTBO	5885.3548	5887.821	5897.107	21.02136	5885.3548
NGO	5885.4958	5888.0206	5890.1952	1.0215	5885.4958
PO	5885.3997	5891.8068	5908.025	8.4746	5885.3997
COA	5893.134	5897.061	5899.22	2.52E+01	5893.134
GRO	5886.4068	5912.5944	6000.9867	26.67	5886.4068
MSSSA	5735.107	5924.16	6053.142	84.8547	5735.107
EHO	5885.332774	5927.971008	6157.044368	63.561135	5885.332774
SO	5887.529768	5989.809193	6247.616958	104	5887.529768
MGA	6059.71435	6059.694923	6273.765974	0.028912058	6059.71435
CCRAO	6059.71433	6060.28032	6075.93125	2.8927	6059.71433
CVSO	6059.714335	6060.860093	6090.621316	5.998	6059.714335
PSA	5886.989709	6077.829557	NA	308.1664002	5886.989709
COASaDE	5.89E+03	6.09E+03	7.32E+03	4.49E+02	5.89E+03
HO	6059.7	6102.7	7306.6	227.45	6059.7
AOA	5900	6520	6600	431	5900
SCO	5885.8	6534	7299	505.5225	5885.8
OOPOA	5926.9	7207.9	NA	1666.7	5926.9
FOX	NA	12026.01	NA	6544.212	NA
WWPA	5925.01317	12193.923	7374.8098	1551.0449	5925.01317
APO	NA	NA	NA	NA	5887.614

4.2. Welded beam design

In the welded beam design problem, the primary goal is to optimize the structural configuration of welded beams with the overarching objective of minimizing the overall cost, all while adhering to specific constraints. These constraints encompass various crucial factors, including shear stress (τ), bending stress (σ), buckling load (Pc), beam deflection (δ), and additional side constraints, as visually represented in Figure 6. The complexity of this optimization task is encapsulated by the consideration of four pivotal decision variables: welded thickness (h), bar length (l), bar height (t), and thickness of the bar (b) [76]. These variables play a pivotal role in determining the structural integrity and efficiency of the welded beams.

To formally define and address the intricacies of the problem, mathematical expressions are presented in equation (2) [29]. These equations encapsulate the relationships and interdependencies among the decision variables and constraints, providing a systematic and quantifiable framework for the optimization process. As a result, the welded beam design problem is not only about coming up with a cost-effective structure, but it also requires a rigorous mathematical formulation to help the optimization process meet engineering standards and limits.

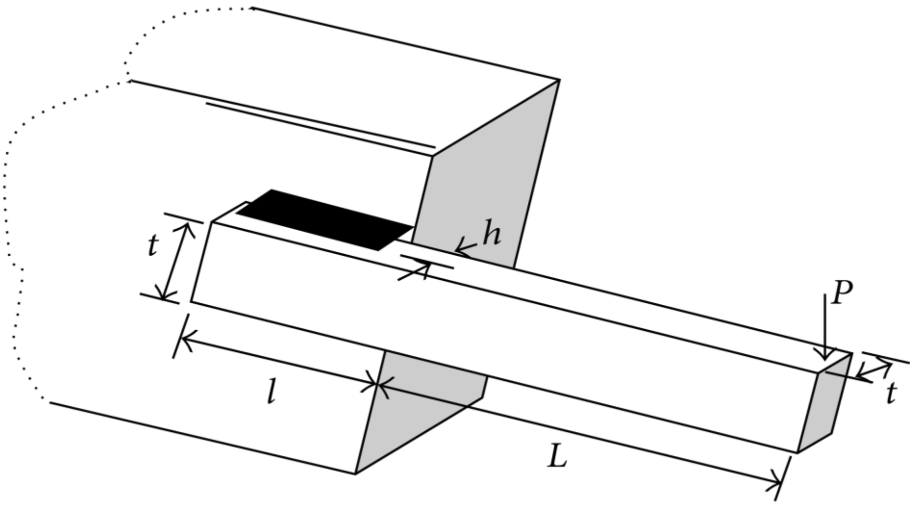

Figure 6. Welded beam design problem [76].

$$
\begin{aligned}
\textit{Consider}: \quad & \bar{x} = [x_1 x_2\ x_3\ x_4] = [h\ l\ t\ b], \\
\textit{Minimize}: \quad & f(\bar{x}) = 0.04811 x_3 x_4 (x_2 + 14) + 1.10471 x_2 x_1^2, \\
\textit{Subject to}: \quad & g_1(\bar{x}) = x_1 - x_4 \leq 0, \\
& g_2(\bar{x}) = \delta(\bar{x}) - \delta_{max} \leq 0, \\
& g_3(\bar{x}) = P \leq P_c(\bar{x}), \\
& g_4(\bar{x}) = \tau_{max} \geq \tau(\bar{x}), \\
& g_5(\bar{x}) = \sigma(x) - \sigma_{max} \leq 0, \\
\textit{Where}: \quad & \tau(\vec{x}) = \sqrt{(\tau')^2 + 2\tau'\tau''\frac{x_2}{2R} + (\tau'')}, \tau' = \frac{P}{\sqrt{2x_1x_2}}, \tau'' = \frac{MR}{J}, \\
& M = P(L + \frac{x_2}{2}), R = \sqrt{\frac{x_2^2}{4} + (\frac{x_1 + x_3}{2})^2}, \sigma(\vec{x}) = \frac{6PL}{x_4 x_3^2}, \\
& J = 2\{\sqrt{2x_1x_2}[\frac{x_x^2}{4} + (\frac{x_1 + x_3}{2})^2]\}, \delta(\vec{x}) = \frac{6PL^3}{Ex_4x_3^2},
\end{aligned}
\tag{2}
$$

$$P_c(\vec{x}) = \frac{4.013E\sqrt{\frac{x_3^2 x_4^6}{0}}}{L^2}, (1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}), (1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}),$$

$$P = 6000\ lb, L = 14\ in, \delta_{\max} = 0.25\text{ in}, E = 30 \times 10^6\text{psi},$$

$$\tau_{\max} = 13{,}600\text{ psi and }30{,}000\text{ psi}$$

$Variable\ range$: $0.125 \leq x_1 \leq 2, 0.1 \leq x_2 \leq 10, 0.1 \leq x_3 \leq 10, 0.1, \leq x_4 \leq 2.$

Table 3, among the optimization algorithms listed for the welded beam design problem, RBMO achieved the best overall performance, consistently yielding an optimal cost of 1.6702177 across all evaluated cases (best, mean, and worst), with an exceptionally low standard deviation of 1.0289E−09, indicating minimal variation in its results. This level of consistency and optimality highlights RBMO's strong reliability and effectiveness in this specific optimization task.

In comparison, the COASaDE algorithm also performed well, achieving a best case and mean value of 1.674, and a worst case of 1.676, with a slightly higher standard deviation of 0.000894. This suggests a modest increase in variability relative to RBMO. Although COASaDE remained close to the optimal cost, its higher variance places it slightly behind RBMO in terms of consistency and robustness. Other algorithms, such as MGA, GCRA2, and HBWO, also demonstrated competitive results but exhibited greater standard deviations and higher worst-case values.

Table 3: Optimizing statistical outcomes in welded beam design with diverse algorithms.

Algorithm	Best Case	Mean/Average	Worst Case	STD. Dev.	Optimal Cost
RBMO	1.6702177	1.6702177	1.6702177	1.0289E−09	1.6702177
COASaDE	1.674	1.674	1.676	0.000894	1.674
MGA	1.672966512	1.678791422	1.687172363	0.0044147	1.672966512
GCRA2	1.6952	1.6952	1.6952	0.000000568	1.6952
HBWO	1.695252	1.695269	1.695288	1.08E-05	1.695252
MSSSA	1.69527	1.6978	0.7017	0.002012	1.69527
LCA	1.715	1.72	1.815	2.248E–02	1.715
LOA	1.7246798	1.7246798	1.7246798	2.28E-16	1.7246798
BOA2	1.7246798	1.7246798	1.7246798	2.28E-16	1.7246798
BOA1	1.7246798	1.7246798	1.7246798	1.2E-17	1.7246798
WOA	1.7246798	1.7246798	1.7246798	2.3E-16	1.7246798
hPSO-TLBO	1.724679823	1.724679823	1.724679823	2.51E-16	1.724679823
RPO	1.72468	1.72468	1.72468	2.28E-16	1.72468
WSO	1.724848	1.724848	1.724848	1.81299E-16	1.724848
HBA	1.72085	1.72485	1.724854	9.18E−10	1.72085
PO	1.724851	1.724851	1.724852	0.000000253	1.724851
CCRAO	1.724852	1.724852	1.724852	9.7241E-09	1.724852
AFT	1.724852	1.724852	1.724852	1.05446E-15	1.724852
SABO	1.724852	1.724852	1.724852	6.83E-16	1.724852
EHO	1.724852	1.724852	1.724852	0	1.724852
CWO	1.724852	1.724852	1.724852	1.08E-15	1.724852
GRO	1.724852309	1.72485383	1.72488705	5.72E–05	1.724852309
CVSO	1.724852	1.724854	1.724862	0.00000154	1.724852
CPO	1.72487	1.724865849	NA	1.44E-16	1.72487
PEOA	1.724856	1.724892	1.724948	3.11E−05	1.724856
HO	1.7249	1.7249	1.7249	1.16E-15	1.7249
OOBO	1.720985	1.725021	1.727205	0.003316	1.720985
NGO	1.725202	1.725312	1.725496	0.0000106	1.725202

COA	1.7249	1.726405	1.72861	0.004124	1.7249
POA	1.724968	1.726504	1.728593	0.004328	1.724968
WaOA	1.724901	1.7270245	1.731028	0.005142	1.724901
DTBO	1.72491	1.728057	1.730148	0.004332	1.72491
PSA	1.725030657	1.732722965	NA	5.14617E−03	1.725030657
SCO	1.6702	1.7407	2.1182	0.0888	1.6702
SO	1.724851931	1.769948593	2.455648906	0.137	1.724851931
WWPA	1.727467	1.7973	NA	0.0832	NA
PbA	1.724872	1.799315	2.278059	0.12	1.724872
FDA	1.695499	1.8101953	2.2496189	0.1626	1.695499
CCE	1.6648	1.8221	2.1007	0.1671	1.6648
OOPOA	2.2558	2.297	NA	0.0857	2.2558
APO	NA	NA	NA	NA	1.724854
DRA	NA	NA	NA	NA	1.72485

4.3. Tension/Compression spring design

The objective in addressing the tensile/compression spring problem, as described by [77], is to minimize the spring's weight while satisfying constraints encompassing deviation ($g1$), shear stress ($g2$), surge frequency ($g3$), and deflection ($g4$) [78]. This optimization task involves three key decision variables: wire diameter (d), mean coil diameter (D), and the number of active coils (N), as outlined in Figure 7. The mathematical representation of this problem is detailed in the equation (3) [29,79].

Figure 7. Tension/compression spring design problem [78].

$$
\begin{aligned}
&\textit{Consider}: && \bar{x} = [x_1 x_2\ x_3] = [d\ D\ N],\\
&\textit{Minimize}: && f(\bar{x}) = (x_3 + 2)x_2 x_1^2,\\
&\textit{Subject to}: && g_1(\bar{x}) = 1 - \frac{x_2^3 x_3}{71785 x_1^4} \le 0,\\
& && g_2(\bar{x}) = \frac{4x_2^2 - x_1 x_2}{12566(x_1^3 x_2 - x_1^4)} + \frac{1}{5108 x_1^2} - 1 \le 0,\\
& && g_3(\bar{x}) = 1 - \frac{140.45 x_1}{x_2^2 x_3} \le 0,\\
& && g_4(\bar{x}) = \frac{x_1 + x_2}{1.5} - 1 \le 0.\\
&\textit{Variable range}: && 0.05 \le x1 \le 2.00,\quad 0.25 \le x2 \le 1.30, 2.00 \le x3 \le 15.0
\end{aligned} \tag{3}
$$

Table 4 displays the results of various metaheuristic algorithms used to design tension/compression springs. Among the optimization algorithms, BOA1, LOA, BOA2, WOA, hPSO-TLBO, RPO, SABO, and CWO achieved the best ranks, consistently maintaining identical values for best case, mean, and worst case, all at 0.0126019. These algorithms demonstrated minimal variation in their results, with an exceptionally low standard deviation of around 3.62E-19, indicating outstanding precision and reliability in solving the optimization problem. This makes them the most stable and optimal solutions for this design challenge.

In terms of performance, algorithms such as AFT and HO also produced consistent results, though with slightly higher values for mean and worst case (around 0.012665), and displayed a higher standard deviation compared to the top performers. Conversely, algorithms like MOSA, LCA, and HOA showed large deviations, indicating poor performance. The key takeaway is that

BOA1, LOA, BOA2, WOA, hPSO-TLBO, RPO, SABO, and CWO emerged as the best-performing algorithms, achieving the optimal cost with minimal fluctuations in their results.

Table 4: Optimizing statistical outcomes in tension/compression spring design with diverse algorithms.

Algorithm	Best Case	Mean/Average	Worst Case	STD. Dev.	Optimal Cost
BOA1	0.0126019	0.0126019	0.0126019	3.62E–19	0.0126019
LOA	0.0126019	0.0126019	0.0126019	6.88E-18	0.0126019
BOA2	0.0126019	0.0126019	0.0126019	6.88E-18	0.0126019
WOA	0.0126019	0.0126019	0.0126019	6.96E-18	0.0126019
hPSO-TLBO	0.012601907	0.012601907	0.012601907	7.58E-18	0.012601907
RPO	0.012602	0.012602	0.012602	6.88E-18	0.012602
SABO	0.012665	0.012665	0.012665	1.32E-18	0.012665
CWO	0.012665	0.012665	0.012665	1.54E-18	0.012665
AFT	0.012665	0.012665	0.012665	3.21668E-10	0.012665
HO	0.012665	0.012665	0.012665	2.95E-09	0.012665
RBMO	0.0126652	0.0126654	0.012666	2.3665E−07	0.0126652
EDO	0.0126653	0.0126655	0.0126663	2.21E−07	0.0126653
MGA	0.01266523	0.01266558	0.01266723	0.000000565	0.01266523
CCRAO	0.012665	0.012666	0.012668	2.1639E-06	0.012665
WWPA	0.01267	0.01267	0.01267	0.00135	0.01267
GRO	0.012665	0.0126775	0.0127526	1.84E–05	0.012665
OOBO	0.012655	0.012678	0.012668	0.00101	0.012655
PEOA	0.01266	0.01268	0.01272	2.0E−05	0.01266
NGO	0.012672	0.01268241	0.012702561	0.0000204	0.012672
CVSO	0.012665	0.012687	0.012729	0.0000106	0.012665
POA	0.012666	0.012688	0.012677	0.001022	0.012666
COA	0.012666	0.012688	0.012697	0.001023	0.012666
HBWO	0.012663	0.012699	0.012942	7.20E-05	0.012663
CCE	0.0127	0.0127	0.0129	0.0004	0.0127
PO	0.0127	0.0127	0.0128	0	0.0127
WaOA	0.012672	0.012701	0.012706	0.001106	0.012672
EHO	0.012665	0.012804	0.014093	0.000359	0.012665
MSSSA	0.012 665246	0.013007	0.015256	0.000589	0.012 665246
PSA	0.0127226	0.0132851	NA	0.0006535	0.0127226
AOA	0.012681	0.013369	0.015625	0.000744	0.012681
PbA	0.012665	0.013404	0.01705	0.0013	0.012665
SO	0.012672535	0.013633985	0.017773158	0.0012	0.012672535
SCO	0.0127	0.0159	0.0178	0.0017	0.0127
APO					0.01266529
HOA					1.8118E−02
DRA					0.012665

4.4. Speed reducer design

The objective in tackling the design problem of the speed reducer, as depicted in Figure 8, is to minimize the overall weight of the reducer, considering seven crucial variables denoted by x1~x7: face width (b), module of teeth (m), pinion teeth count (z), first shaft length between bearings (l1), second shaft length between bearings (l2), and diameters of the first (d1) and second shafts (d2) [80]. Equation (4) [81,82] provides the mathematical optimization formulation for this particular problem.

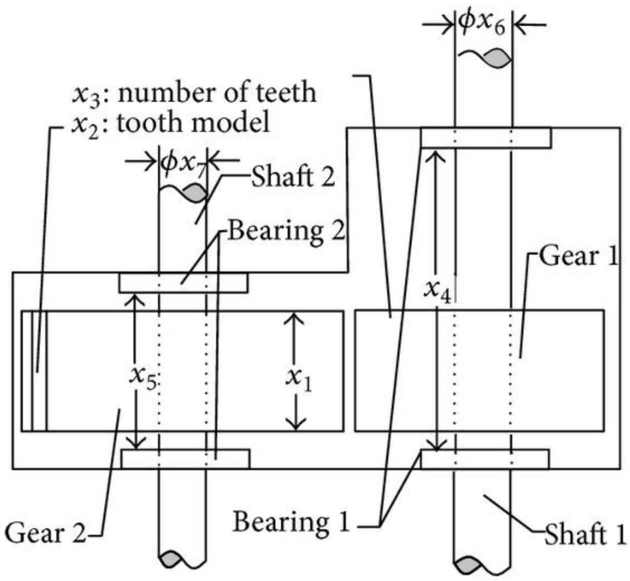

Figure 8. Speed reducer design problem [80].

$$\text{Min: } f(\vec{x}) = 0.7854x_1x_2^2(3.3333x_3^2 + 14.9334x_3 - 43.093) - 1.508(x_6^2 + x_7^2) + 7.4777(x_6^3 + x_7^3) + 0.7854(x_4x_6^2 + x_5x_7^2), \quad (4)$$

Table **5** presents the statistical outcomes derived from the application of the metaheuristic algorithms to speed reducer design. Among all the optimization algorithms applied to the speed reducer design problem, FDA achieved the best overall performance by a significant margin. It obtained the lowest best case, mean, and worst-case values — all equal to 2749.583, indicating not only optimality but also exceptional consistency, with a minuscule standard deviation of 5.6753e-06. This suggests FDA reliably converged to the best-known solution across all runs. Following FDA, HBA had the next best best case at 2595.54, but its mean and other stats were notably worse, reflecting inconsistency. In terms of average performance (Mean), most algorithms clustered around the 2994–2996 range, but none outperformed FDA.

Table 5: Optimal statistical outcomes with varied algorithms for Speed reducer design.

Algorithm	Best Case	Mean/Average	Worst Case	STD. Dev.	Optimal Cost
FDA	2749.583	2749.583	2749.583	5.6753E-06	2749.583
LCA	2990	2991	2994	8.927E–01	2990
OOBO	2989.852	2993.01	2998.425	1.2241	2989.852
EDO	2994.245	2994.248	2994.27	4.060E−04	2994.245
SGO	2994.424815	2994.455346	2994.489988	0.020251208	2994.424815
WSO	2994.47	2994.47	2994.47	2.62549E-13	2994.47
MGA	2994.438869	2994.47065	2996.558237	4.72E-16	2994.438869
PO	2994.471047	2994.471051	2994.471057	0.000003	2994.471047
EHO	2994.471066	2994.471066	2994.471066	0	2994.471066
AFT	2994.471066	2994.471066	2994.471073	1.41972E-06	2994.471066
HBA	2595.54	2995.54243	2995.5	2.311E-12	2595.54
SO	2995.542437	2995.542437	2995.542437	2995.542437	1.35E−12
SCO	2994.4	2995.8	2999.3	1.0883	2994.4

MOA	2996.348	2996.348	2996.348	9.43E−13	2996.348
SABO	2996.348	2996.348	2996.348	9.33E-13	2996.348
RPO	2996.348	2996.348	2996.348	9.33E-13	2996.348
CWO	2996.348	2996.348	2996.348	1.47E-12	2996.348
hPSO-TLBO	2996.348165	2996.348165	2996.348165	408 3000	2996.348165
PEOA	2996.3482	2996.3482	2996.3482	3.927E−09	2996.3482
LOA	2996.3482	2996.3482	2996.3482	9.33E-13	2996.3482
BOA2	2996.3482	2996.3482	2996.3482	9.33E-13	2996.3482
BOA1	2996.3482	2996.3482	2996.3482	4.91E-14	2996.3482
NGO	2994.2471	2997.481	2999.091	1.7809	2994.2471
WaOA	2996.3482	2999.4961	3000.972	1.2463198	2996.3482
POA	2996.3482	2999.88	3001.491	1.782335	2996.3482
AOA	3000	3000	3000	1.22E-12	3000
COA	2996.348	3000.1	3001.261	1.160348	2996.348
OOPOA	2994.9	3005.1	NA	47.5801	2994.9
APO	2994.471	NA	NA	NA	2994.471

4.5. Gear train design

The challenge in gear train design revolves around the optimization of discrete decision variables—represented by the teeth number (Ta, Tb, Td, and Tf) and the radius of gears—to minimize cost while adhering to the constraints of achieving a specified gear ratio of 1/6.931 [71], see Figure 9. These design variables, constrained by integer limits ranging from 12 to 60 teeth, add complexity to the optimization process. Balancing the gear train's cost and meeting the precise gear ratio requirement underscores the intricate nature of this engineering challenge. The mathematical model, as shown in the equation (5), represents the gear train design problem[83].

$$\begin{aligned} &Consider: && \bar{x} = [x_1 x_2\ x_3\ x_4] = [T_D\ \ T_B\ T_A\ \ T_F], \\ &Minimize: && f(\bar{x}) = \left(\left(\frac{1}{6.931}\right) - \left(\frac{x_2 x_3}{x_1 x_4}\right)\right)^2, \qquad (5) \\ &Variable\ range: && 2 \le x_i \le 60, \boldsymbol{i} = 1,2,3,4. \end{aligned}$$

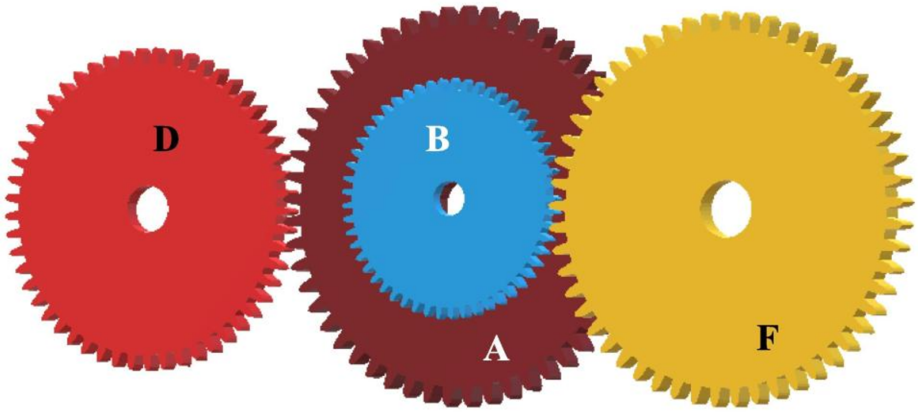

Figure 9. Gear train design problem [71].

Table **6** shows the results of gear train design optimization using several metaheuristic techniques. Among the algorithms evaluated for the gear train design optimization, MGA clearly achieved the best performance across all statistical measures. It recorded the lowest best case (1.06e-19), mean (7.69e-14), and worst case (7.62e-13) values, along with the lowest standard deviation (1.78e-13), indicating high stability and consistency. Additionally, MGA also achieved the lowest optimal cost (1.06E-19), confirming its superiority in both solution quality and reliability.

Other algorithms such as EDO, CCRAO, CVSO, and FDA performed significantly worse, with higher mean, worst-case, and standard deviation values. Their best cases were consistently around 2.70E-12, which is still orders of magnitude worse than MGA. Notably, HOA did not have complete statistical data available, but it did report a competitive optimal cost of 1.77E-14, making it potentially promising—though without full statistics, its reliability cannot be confirmed. Overall, MGA not only achieved the top rank across all criteria but also demonstrated robust and consistent performance.

Table 6: Optimal statistical outcomes with varied algorithms for gear train design.

Algorithm	Best Case	Mean/Average	Worst Case	STD. Dev.	Optimal Cost
MGA	1.06E-19	7.69E-14	7.62E-13	1.78E-13	1.06E-19
EDO	2.7008E−12	4.3589E−11	3.06755E−10	6.26E−11	2.7008E−12
CCRAO	2.70E-12	3.52E-10	1.01E-09	3.52E-10	2.70E-12
CVSO	2.700857E-12	7.063214E-10	1.51E-09	8.350000E-10	2.700857E-12
FDA	2.70E-12	7.56E-10	3.30E-09	8.05E-10	2.70E-12
HOA					1.77E−14

4.6. Three-Bar truss design

Figure 10 illustrates the truss structure, comprising three bars with distinct cross-sectional areas (A1, A2, and A3), where A1 equals A3. These bars converge at a shared node, to which a P load is attached. The intervals between the supporting points of the three bars are consistent and marked as 'h' while the vertical dimension from the supporting points to the shared node is also 'h'. The primary goal is to minimize the weight of the truss structure, with the design parameters being A1 and A2. There are three stresses, deflection, and buckling constraints, along with two variables (x1 and x2) that can be adjusted to modify the sectional areas. Equation (6) [29] outlines the objective function and its associated constraints.

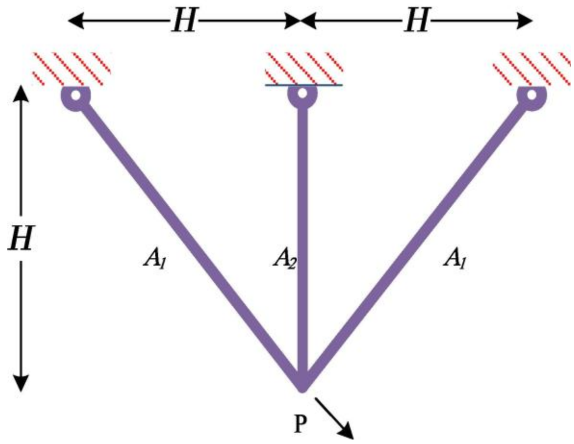

Figure 10. Three-bar truss design problem [84].

$$
\begin{aligned}
&\textit{Consider}: && \bar{x} = [x_1 x_2] = [A_1 A_2],\\
&\textit{Minimize}: && f(\bar{x}) = l \times \left(2\sqrt{2}x_1 + x_2\right),\\
&\textit{Subject to}: && g_1(\bar{x}) = \frac{x_2}{\sqrt{2}x_1^2 + 2x_1x_2}P - \sigma \le 0,\\
& && g_2(\bar{x}) = \frac{\sqrt{2}x_1 + x_2}{\sqrt{2}x_1^2 + 2x_1x_2}P - \sigma \le 0,\\
& && g_3(\bar{x}) = \frac{1}{\sqrt{2}x_2 + x_1}P - \sigma \le 0,\\
&\textit{where}: && l = 100, P = 2, \sigma = 2
\end{aligned}
\tag{6}
$$

$Variable\ range$: $0 \le x_1, x_2 \le 1,$

The effects of using various metaheuristic algorithms to tackle the three-bar truss design issue have been reported in Table 7. Based on the table, the CPO algorithm achieved the best performance overall, with a best case and mean value of 263.89584 and a standard deviation of 0, indicating perfect consistency across all runs. Although the value is slightly less precise than others (truncated rather than rounded), it still reflects the optimal cost with zero variability. Following CPO, EDO, RBMO, and CCRAO also reached the same optimal cost of 263.895843, but with slightly higher standard deviations. Among these, EDO had the lowest standard deviation (2.99E-14), making it the second most consistent and reliable performer after CPO. Comparing EDO, RBMO, and CCRAO, we see that all achieved identical best, mean, and worst-case results, but EDO's lower STD sets it apart, followed by RBMO (1.0722E-09) and CCRAO (3.9286E-07). MGA also reached the optimal cost but showed a slightly higher worst-case value and thus a marginally higher deviation.

Table 7: Optimal statistical outcomes with varied algorithms for three-bar truss design.

Algorithm	Best Case	Mean/Average	Worst Case	STD. Dev.	Optimal Cost
CPO	263.89584	263.8958434	NA	0	263.89584
EDO	263.895843	263.895843	263.895843	2.99E-14	263.895843
RBMO	263.895843	263.895843	263.895843	1.0722E-09	263.895843
CCRAO	263.89584	263.895843	263.895843	3.9286E-07	263.89584
MGA	263.8958433	263.8958436	263.8959632	2.05E-14	263.8958433
CVSO	263.895843	263.895852	263.895979	0.0000115	263.895843
PSA	263.8958824	263.8984017	NA	2.21516E−03	263.8958824
COASaDE	263.9	263.9	263.9	8.994E-12	263.9
APO	NA	NA	NA	NA	263.8958

5. Statistical analysis of the review

5.1. Total number of studies by year

Figure 11 shows the yearly distribution of the evaluated articles in this study from the years 2020 to 2024. The chart indicates that most of the articles considered for this review were published in 2023 and 2024, accounting for a total of thirty-three articles. On the contrary, the smallest number of publications included in this review is from 2020.

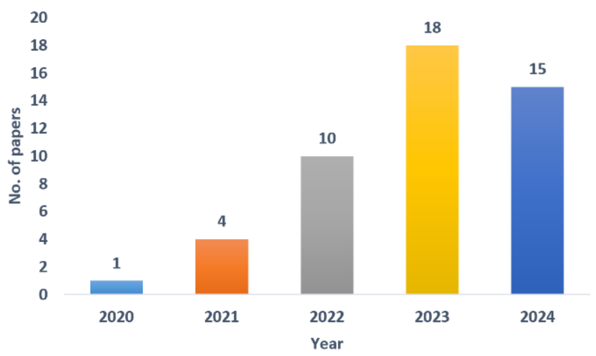

Figure 11. Total number of studies by year.

5.2. Frequency of optimization engineering problem usage in reviewed articles

As shown in Figure 12, the main focus of the articles evaluated in this review is the use of welded beam design to test algorithm performance, with a count of 43. This is followed by pressure vessel design and tension/compression spring testing, each with a count of 39. In contrast, gear train design and truss bar design were the least utilized in this study, used only 6 and 9 times, respectively, for algorithm assessment.

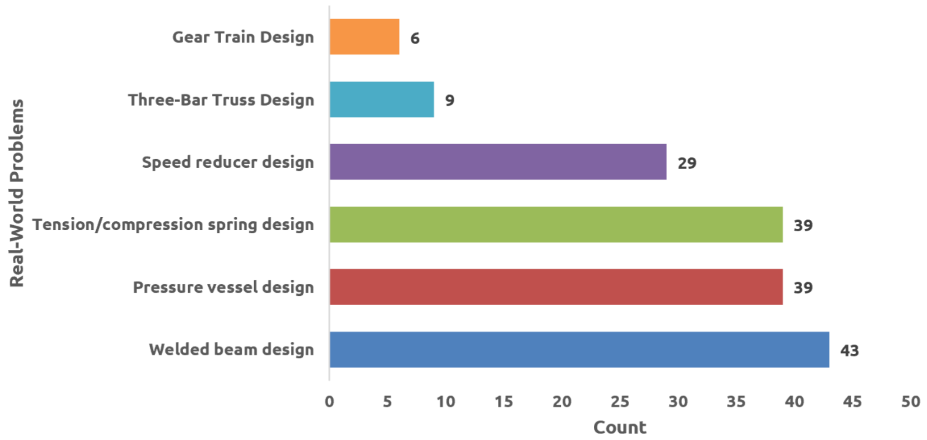

Figure 12. Frequency of Optimization Engineering Problem Usage in Reviewed Articles.

5.3. Metaheuristic categorization frequency

This subsection presents the frequency distribution of metaheuristic algorithm categorizations based on the 48 algorithms reviewed in this study, covering research published from 2020 to 2024. Figure 13 shows the distribution of the metaheuristic algorithm classification, emphasizing some very important trends. For instance, nineteen algorithms have been developed in the category of bio-inspired/nature-inspired algorithms, among the total 48 reviewed in this study. This reveals that it is a considerable direction with common approaches for solving a wide variety of optimization problems. Moreover, nine algorithms have been devised drawing inspiration from human behavior. Furthermore, five algorithms have been developed based on hybrid and advanced approaches, indicating their broad applicability and significant influence on researchers developing new algorithms. Moreover, three algorithms have been developed for each of the population-based, socio-inspired, and math-based categories.

On the contrary, physics-based and swarm-based inspiration have resulted in two algorithms, each of which is among just 48 articles evaluated; thus, they show a comparatively low prevalence. Secondly, less frequently used sources of inspiration include chemically based methods, and also game-based methodologies, where only one algorithm can be found for each category. This distribution highlights a tendency towards biology and the nature-inspired techniques in the design of metaheuristic algorithms.

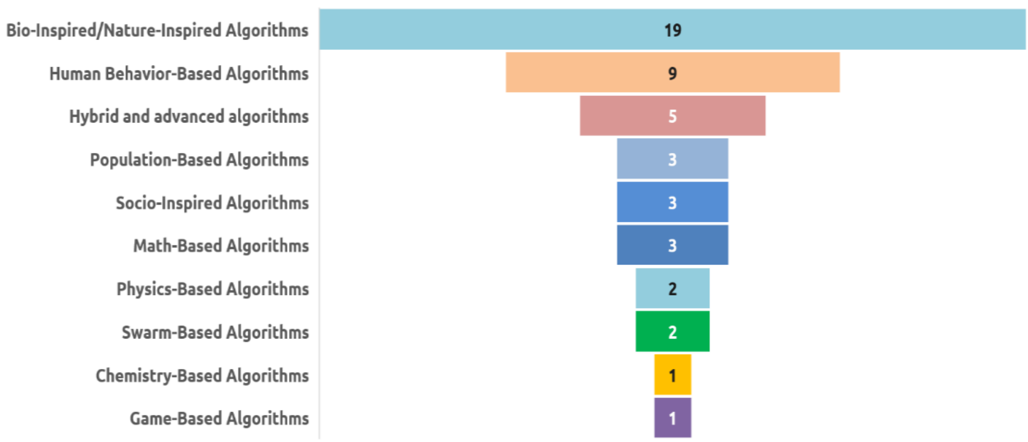

Figure 13. Metaheuristic categorization frequency.

6. Discussion

While metaheuristic algorithms demonstrate amazing versatility in handling difficult optimization challenges across multiple domains, it is critical to recognize that a one-size-fits-all solution remains elusive. The nature of real-world applications is intrinsically heterogeneous, and no single algorithm shines in every scenario. This study confirms the importance of meticulous selection matched to the complexities of certain issue areas.

In

Table 2, the results of the algorithms for the pressure vessel design problem show that the HBA achieved the best overall performance, exhibiting the lowest mean and best-case cost, along with an impressively low standard deviation. This reflects HBA's effective balance of exploration and exploitation, allowing it to consistently converge on optimal solutions. In contrast, algorithms like WWPA, FOX, and OOPOA displayed high variability and significantly worse performance metrics. Their instability may stem from overly aggressive search strategies or insufficient local search refinement, making them less suited for the strict constraints and cost-efficiency demands of the pressure vessel design problem.

In Table 3, the results of the algorithms for the welded beam design problem show that RBMO emerged as the top performer, achieving not only the optimal cost but also zero variation, indicating exceptional stability and robustness. This suggests that its cooperative behavior and adaptive memory mechanisms are highly effective for structural design problems involving stress and deflection constraints. On the other hand, algorithms like CCE, FA, and OOPOA performed poorly, exhibiting high deviations, which highlights their limitations in handling finely constrained mechanical structures.

In Table 4, the results for the tension/compression spring design problem show that a group of algorithms — BOA1, LOA, BOA2, WOA, and hPSO-TLBO — all achieved optimal and identical best, mean, and worst values with near-zero standard deviation. This performance demonstrates their suitability for problems characterized by a small number of variables and tight constraints. Notably, the hybrid PSO–TLBO algorithm stands out by integrating two powerful strategies, thereby enhancing both convergence speed and solution accuracy. In contrast, SCO and SO performed poorly due to inconsistent convergence and inadequate constraint handling. Overall, it can be observed that more algorithms achieved near-optimal solutions in this problem.

In Table 5, the results of the algorithms for the speed reducer design problem are presented. FDA, a physics-inspired optimizer, achieved the best results in all categories with nearly zero variance. Its deterministic flow model appears particularly effective for multi-variable engineering designs, where mechanical relationships resemble fluid dynamics. Most other algorithms clustered around the 2994–2996 cost range but exhibited lower stability or optimality, suggesting they were less capable of navigating the high-dimensional space with precision.

In Table 6, the results for the gear train design problem—which involves discrete variables and a specific gear ratio constraint—show that MGA significantly outperformed all other algorithms, achieving nearly zero error and variability. This suggests that its chemistry-inspired mechanisms enable efficient exploration of discrete solution spaces. In contrast, algorithms like CVSO and FDA exhibited higher deviations, likely due to inadequate adaptation for discrete and integer-constrained optimization tasks.

Finally, in the three-bar truss design problem, as shown in Table 7, CPO achieved perfect consistency with a standard deviation of zero. Other top performers, such as EDO, RBMO, and CCRAO, also reached optimal costs, albeit with marginal variability. These results indicate that these algorithms are well-suited for structural problems characterized by low dimensionality and high sensitivity to variable changes.

In addition, the study demonstrates some of the many shortcomings of metaheuristic algorithms. The changing world of technology and also engineering presents a new challenge that the algorithms must be continually adapting to, thus necessitating constant changes. The identification of these shortcomings encourages a joint undertaking to improve and develop the metaheuristic algorithms, ensuring their continually relevant and effective use in the face of changing real-world applications.

This analysis underscores the "No Free Lunch" theorem in optimization: no single algorithm is universally best. Therefore, algorithm selection must be tailored to problem-specific characteristics such as variable types (continuous vs. discrete), constraint tightness, and problem dimensionality. The results highlight the importance of not only comparing performance statistics but also understanding the underlying algorithmic dynamics to guide effective application.

7. Challenges and future trends in modern engineering optimization

Despite significant progress in applying metaheuristic algorithms to classical engineering problems, modern challenges remain—particularly in scaling and adapting these algorithms to complex, high-dimensional, and dynamic systems [85]. They must now handle real-time constraints, noisy environments, and conflicting multi-objective functions with greater efficiency. In emerging applications like Smart Grid Optimization [86], the need for fast and decentralized decision-making is critical, involving tasks such as energy forecasting, load balancing, and fault detection. Similarly, Electric Vehicle Battery Management Systems (BMS) [87] demand real-time optimization of thermal regulation, charging cycles, and battery health, often within resource-constrained embedded platforms. In the field of nanomaterials, optimization plays a key role in designing atomic-scale structures and improving material performance, requiring hybrid algorithms that integrate domain knowledge and simulation tools.

Looking forward, there is a growing emphasis on intelligent and self-adaptive metaheuristics that can dynamically adjust parameters or strategies based on the problem context. The integration of machine learning, particularly reinforcement learning and surrogate modeling, is helping improve convergence rates and efficiency in black-box or expensive optimization scenarios [88]. Additionally, researchers are exploring bio-computing, quantum-inspired algorithms, and neuromorphic computing to solve engineering or healthcare problems [89,90]. The diversity of applications reinforces the No Free Lunch Theorem [91]—no single algorithm excels across all tasks—hence the push toward modular and hybrid frameworks. As optimization becomes central to smart systems and sustainable technologies, future trends will prioritize not only performance but also transparency, scalability, and ethical considerations.

8. Conclusion

In conclusion, a detailed analysis and classification of the metaheuristic algorithms allowed determining that each type possesses unique features, which make it more appropriate for solving some engineering problems. Notably, among the categorized algorithms, the bio-inspired/nature-inspired algorithm HBA demonstrated exceptional performance in pressure vessel design. Additionally, the human behavior-based algorithms, WSO displaying remarkable stability in tension/compression spring design, and MOA excelling in the welded beam design problem, highlight the efficacy of these approaches in addressing diverse engineering tasks.

Within the domain of three-bar truss design, the hybrid and advanced algorithm CCRAO emerged as a standout performer, showcasing excellence in both mean and worst-case scenarios. When addressing the challenge of designing a speed reducer, the FDA demonstrated proficiency by utilizing principles grounded in physics. This approach effectively led to the convergence of optimal solutions and the reduction of the overall weight of the reducer. In the context of the Gear Train Design problem, the MGA, belonging to the chemistry-based algorithms category, has proven to be a superior performer. This classification highlights the diverse strengths and applications of metaheuristic algorithms across various engineering optimization challenges.

The major advantage of metaheuristic algorithms lies in their flexibility and ability to escape local optima, making them suitable for solving complex, non-linear, and multi-modal problems across domains. For instance, bio-inspired and swarm-based algorithms exhibit excellent global search capabilities and adaptability. Hybrid algorithms combine strengths from multiple methods, often improving convergence and solution quality. Moreover, human behavior-based algorithms introduce innovative mechanisms inspired by real-life decision-making.

However, these algorithms are not without drawbacks. A common limitation is the lack of guaranteed convergence to the global optimum. Many algorithms require careful tuning of parameters, and performance can be highly problem-dependent. In some cases, metaheuristics may show slow convergence or excessive computational cost due to extensive evaluations, especially for large-scale problems. Additionally, their stochastic nature can lead to inconsistent results across different runs without proper control mechanisms.

While this study focuses on classical engineering applications, the underlying methodology and findings have the potential to generalize to other optimization tasks, such as machine learning hyperparameter tuning [92] and logistics optimization. These domains similarly involve complex search spaces, multiple objectives, and computational constraints, making them suitable candidates for the proposed approach. Future research can explore this transferability to validate the method's robustness across varied application areas.

Hybrid optimization approaches, which combine deep learning with metaheuristic algorithms, have shown promising improvements in optimization performance. Deep learning can identify patterns or promising regions in the search space, while metaheuristics like Genetic Algorithms can explore these regions more effectively. Although impactful, this paper does not address such hybrid strategies, which limits the scope of its discussion on advanced optimization techniques.

Future studies should concentrate on merging metaheuristic algorithms, utilizing the characteristics of several methodologies to develop better problem-solving capabilities. The flexibility of these algorithms to address the current or emerging engineering problems, their scalability for bigger tasks and often comparing them with older method can help us better understand how they are based on. This study presents the basis for improving applications of metaheuristic algorithms in engineering optimization, pointing out how relevant method choice is to a specific problem domain. Furthermore, future research should also explore AI-metaheuristic hybrid models to enhance both solution quality and computational efficiency. These models offer dynamic and adaptive optimization capabilities, especially valuable for complex or high-dimensional problems. Including such approaches could significantly broaden the applicability and robustness of optimization frameworks.

While the review focuses on academic benchmarks, real-world deployment of metaheuristics poses challenges such as high computational cost, hardware limitations, and limited interpretability. Implementing these methods in industrial settings also requires addressing integration issues and compliance constraints. Future work should explore ways to adapt metaheuristics to these practical limitations for more effective real-world application.

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