JOURNAL of
MATERIALS and MECHATRONICS:A

e-ISSN 2717-8811
JournalMM, 2025, 6(1), 150-169
https://doi.org/10.55546/jmm.1660142

Araştırma Makalesi / Research Article

Comprehensive Comparative Analysis of GWO and Its Variants for Solving Mechanical Optimization Problems

Nermin ÖZCAN*

* Iskenderun Technical University, Faculty of Engineering and Natural Sciences, Department of Biomedical Engineering, Hatay, Türkiye
ORCID ID: https://orcid.org/0000-0001-5327-9090, nermin.ozcan@iste.edu.tr

Geliş/ Received: 18.03.2025; **Revize/Revised:** 22.04.2025 **Kabul / Accepted:** 06.05.2025

ABSTRACT: The intricacy of decision variables, multiple objectives, and nonlinear restrictions make it difficult to find suitable solutions for mechanical design problems. An alternative approach to these difficult challenges, the Grey Wolf Optimizer (GWO) is recognized for its ease of use, flexibility, scalability, and unique balance between exploration and exploitation. Like every stochastic approach, GWO has drawbacks, though, and numerous enhanced variants have been put up to overcome them. The GWO algorithm and its variants are examined in this investigation. It conducts an experimental comparison of the original approach and its two variations. It examines how the approaches behave with various combinations of parameters. Five mechanical design problems are used to test the algorithms' effectiveness utilizing statistical analysis and search performance. In the literature, the performance of alternative approaches is also contrasted with the ideal outcomes.

Keywords: Grey wolf optimizer, Engineering problem, Mechanical design, Meta-heuristic algorithm, Optimization

*Sorumlu yazar / Corresponding author: nermin.ozcan@iste.edu.tr
Bu makaleye atıf yapmak için /To cite this article

Özcan, N. (2025). Comprehensive Comparative Analysis of GWO and Its Variants for Solving Mechanical Optimization Problems. Journal of Materials and Mechatronics: A (JournalMM), 6(1), 150-169.

1. INTRODUCTION

Engineering design across disciplines such as machinery, mechatronics, and construction is a crucial research domain focused on attaining a precise equilibrium between technical specifications and cost efficiency. Issues in this domain encompass diverse complexities, including linear and nonlinear constraints stemming from geometric, kinematic, and material considerations, alongside challenges related to high dimensionality (Gupta et al., 2021). Traditional optimization techniques encounter challenges such as premature convergence, entrapment in local minima, and sluggish convergence rates (Ezugwu et al., 2022). The nonlinearity of the issues or constraints restricts the application of linear methods (Lee et al., 2025). These challenges hinder traditional methods from achieving optimal solutions, resulting in inadequacies in addressing real-world problems due to their restricted applicability. The growing integration of disciplines like operations research, drug discovery, and engineering design with machine learning and technological advancements heightens the significance of optimization methods and necessitates the development of more advanced techniques to address complex challenges (Özcan and Kuntalp, 2017; Çetinkaya and Taşkıran, 2022; Ayğahoğlu et al., 2023; Kababulut et al., 2023; Gürkan Kuntalp et al., 2024).

In view of the escalating intricacy of real-world optimization problems in engineering, researchers are increasingly adopting meta-heuristic algorithms sas a viable solution (Li et al., 2024). While these stochastically structured algorithms do not consistently ensure optimal solutions, they provide a resilient alternative to conventional methods for addressing complex problems marked by nonlinearity and high dimensionality (Debnath et al., 2024). Over the past thirty years, numerous meta-heuristic algorithms have been devised and utilized for optimization challenges in engineering disciplines such as mechanical precision engineering (Ransegnola et al., 2019; Cui et al., 2020), automotive sector (Millo et al., 2018; Sun et al., 2018; Xu et al., 2025), structural design optimization (Hamza et al., 2018; Jahangiri et al., 2020), and power system issues (Eke et al., 2021; Coban and Saka, 2024). Nonetheless, it is prevalent that even these sophisticated algorithms often succumb to local minima and fail to address every problem with robustness.

Traditional meta-heuristics, including genetic algorithms (GA) (Holland, 1992), particle swarm optimization (PSO) (Eberhart and Kennedy, 1995), differential evolution (DE) (Storn and Price, 2009), and ant colony optimization (ACO) (Socha and Dorigo, 2008), have been extensively utilized in the past. The NFL theorem (Wolpert and Macready, 1997) and the difficulty of addressing complex optimization problems have compelled researchers to develop novel methods, resulting in an increase of meta-heuristic algorithms to over 500 (Li et al., 2024). Recent methodologies established, including the grasshopper optimization algorithm (Saremi, Mirjalili and Lewis, 2017), salp swarm optimization (Mirjalili et al., 2017), whale optimization algorithm (Mirjalili and Lewis, 2016), pathfinder algorithm (Yapici and Cetinkaya, 2019), equilibrium optimization (Faramarzi et al., 2020), harris hawks optimization (Heidari et al., 2019), and student psychology-based optimization (Das et al., 2020), have been employed by numerous researchers and have attained contemporary popularity. Furthermore, recently proposed methodologies, including artificial circulatory system algorithm (Özcan et al., 2025), african vulture optimization algorithm (Abdollahzadeh et al., 2021), animated oat optimization algorithm (Wang et al., 2025) and enzyme action optimizer (Rodan et al., 2025), have garnered attention due to their competitive efficacy.

Exploration and exploitation constitute the two primary phases in the optimization process of meta-heuristic algorithms, and these phases directly influence the algorithm's efficacy in addressing optimization challenges (Gezici, 2023). The intricacy of the issue restricts algorithms' capacity to explore and exploit. Exploration is linked to the capacity to transcend local minima, allowing the algorithm to conduct a global search of the search space. Exploitation denotes the capacity to conduct localized searches, enhancing the quality of solutions within particular areas. Performance is linked to a judicious equilibrium between these two phases. Proposing novel meta-heuristic algorithms and refining established algorithms is a prevalent strategy to enhance exploration and exploitation capabilities.

Grey Wolf Optimization (GWO) is a metaheuristic algorithm inspired from the hunting behavior and social structure of grey wolves (Mirjalili et al., 2014). Since its introduction, GWO has garnered considerable attention owing to its simplicity, efficiency, and capacity to address complex optimization challenges. The algorithm's capacity to equilibrate exploration and exploitation enables it to adeptly traverse the search space, rendering it an invaluable asset for practitioners in pursuit of optimal solutions. Nonetheless, akin to numerous metaheuristics, GWO exhibits limitations including sluggish convergence rate, susceptibility to local optima, and an imbalance between exploration and exploitation. Numerous adaptations of GWO have been suggested, each presenting distinct strategies to tackle these challenges and enhance the algorithm's efficacy (Faris et al., 2018).

This paper examines GWO methodologies. The primary justifications for selecting this method are: (1) its popularity, ease of implementation, and algorithmic stability, and (2) its efficacy in addressing unconstrained and discrete optimization problems in preliminary assessments. The investigation offers an extensive summary of the algorithm and its modifications. It analyzes the enhancements, contributions, and applications of the GWO method. It also undertakes an experimental procedure to execute optimization tasks in the manufacturing processes of mechanical design issues. It seeks to achieve optimal solutions to problems through parameter optimization. It contrasts the outcomes derived from the GWO algorithm with its two modifications and the optimal solutions reported in the literature.

Section II provides a thorough literature review on the implementations, evolution, and current variations of the popular optimization algorithm, which serves as the theoretical foundation of the study. Section III presents the biological motivation and mathematical modeling of the GWO algorithm, as well as technical details of R-Walk and Improved GWO modifications. Section IV provides technical details on mathematical formulations of mechanical design problems, boundary conditions, and problem specifications. Section V details experimental methods, parameter optimization strategies, and findings, including quantitative and qualitative analyses, comparative algorithm performances, and statistical significance levels. Section VI critically discusses results, presents theoretical and practical implications, and presents limitations and suggestions for future research, integrating recent literature and academic rigor.

2. RELEATED WORKS

The GWO is a swarm intelligence algorithm created by Mirjalili et al. in 2014 and is widely regarded as one of the most prominent meta-heuristic algorithms among researchers (Mirjalili et al., 2014). The algorithm's efficacy has inspired other researchers to employ this method for addressing various optimization challenges. GWO has been utilized in machine learning for diverse applications, including feature selection (Emary et al., 2016), neural network training (Altay and Varol, 2023), and clustering tasks (Zhang and Zhou, 2015). It has also been utilized in image processing (Khairuzzaman and Chaudhury, 2017), bioinformatics applications (Jayapriya and Arock, 2015), and environmental prediction models (Song et al., 2015).

Other possible uses of GWO encompass a diverse array of engineering challenges. In control engineering, it has emerged as a commonly employed algorithm for tuning the parameters of controllers, including integral (I), proportional-integral (PI), and proportional-integral-derivative (PID) controllers, as well as addressing power distribution challenges related to optimal load distribution for resource operation and planning, robotics technologies, road planning, and wireless sensor network issues (Li and Wang, 2015; Sulaiman et al., 2015; Zhang et al., 2016; Saka, 2024). Research indicates that GWO markedly enhances the efficacy of the optimized components. Furthermore, GWO surpasses other optimization methods, including GA, PSO, and DE, regarding accuracy and efficiency. Nonetheless, certain researchers have identified limitations in the implementation of GWO owing to the intricate nature of real-world optimization challenges. The GWO algorithm has been redesigned to align with the search space of intricate domains.

Researchers seeking to enhance the efficacy of the GWO can be classified into four categories based on the nature of modifications they suggest for the GWO: (1) Research endeavors aimed at enhancing the equilibrium between exploration and exploitation processes concentrated on refining GWO mechanisms. Mittal et al. investigated the potential enhancement of the exploration process in GWO by reducing the value of a through an exponential decay function rather than employing a linear modification (Mittal et al., 2016). Malik et al. employed an alternative methodology for updating individual positions. Rather than employing a simple average of the best individuals, they utilized a weighted average of the positions of alpha, beta, and gamma wolves (Malik et al., 2015). Rodríguez et al. devised a methodology utilizing weighted averages and fuzzy logic to update the positions of omega wolves (Rodríguez et al., 2017). (2) Some researchers have concentrated on examining the enhancement of GWO performance through the incorporation of novel operators, such as crossover, or by employing a local search algorithm. Kishor et al. proposed a modified version of GWO to enhance population diversity by incorporating a straightforward crossover operator between two randomly selected distinct individuals. The transition operator's function is to enhance information exchange among individuals within the swarm (Kishor and Singh, 2016). Zhou et al. proposed the optimization of the parameters of the equivalent model for the small hydro generator swarm by integrating GWO with chaotic local search (Zhou et al., 2016).

(3) In a study (Luo et al., 2016), a variant of GWO was introduced wherein individuals possess distinct coding schemes. The authors employed a complex-valued coding approach rather than the conventional real-valued coding method. In this coding, the individual's genes consist of two primary components: an imaginary component and a real component. The authors contended that this technique can augment the information capacity of the individual and enhance the diversity of the population. (4) Another study employed a modified population structure and hierarchy (Yang *et al.*, 2017). In contrast to the four distinct wolf types in the traditional GWO, the population is segmented into two autonomous subpopulations: the first is designated as the cooperative hunting group, and the second as the random scout group. The objective of the scout group is to conduct extensive exploration, whereas the objective of the cooperative hunting group is to perform intensive exploitation. The alterations were not confined to this. Given that the GWO algorithm addresses single-objective problems, multi-objective variants of GWO have been introduced in the literature to tackle multi-objective challenges (Mirjalili et al., 2016). Moreover, certain researchers have suggested various hybrid approaches by integrating GWO to leverage the strengths and capabilities of alternative optimizers (Kamboj, 2016).

Despite a great deal of investigation on GWO and its many variations, certain gaps persist in the literature. The optimization of GWO parameters is inadequately explored in the literature.

Parameter tuning is essential for all optimization algorithms when addressing real-world problems. Moreover, GWO and its subsequent versions can be evaluated under equal experimental conditions on actual problems featuring intricate and varied constraints. This should be addressed to enhance comprehension of the current version of GWO and to evaluate its merits and drawbacks in relation to other variants of GWO. Consequently, our study has thoroughly examined the GWO algorithm and its two enhanced variants across five distinct mechanistic challenges. The experimental process encompasses the examination of mean performance, statistical evaluation, and the capacity to attain the optimal solution, as well as the influence of algorithmic parameters, including population structure and iteration count, on fitness landscapes. The number of GWO modifications was limited to two in order to be able to be analyzed in detail and to avoid complexity. Popular variants defined in the same library were preferred to avoid any superiority in the coding of the algorithms.

3. GREY WOLF OPTIMIZERS

3.1 Overview of the GWO

The primary inspiration for the GWO algorithm is the leadership structure and hunting tactics of grey wolves. The following sections elaborate on these essential components:

Leadership Hierarchy: The GWO follows to a rigid hierarchical framework, governed by wolves with distinct divisions of labor. Leaders, referred to as alphas, make critical decisions for the pack regarding activities such as hunting, selecting sleeping locations, and determining waking hours. Beta wolves are subordinate members of the pack who aid the alpha in decision-making and various activities. Delta wolves oversee territorial boundaries and alert the pack to potential threats. They safeguard and ensure the security of the pack, assisting the alphas and betas in hunting and procuring sustenance for the group. The omega wolves, the lowest-ranking members of the grey wolf hierarchy, monitor the other wolves and execute their directives. In the GWO algorithm, roles identified throughout the search process are assigned to solutions.

Hunting Mechanism: The algorithm emulates the encircling, hunting, and attacking behaviors of grey wolves during a hunt. This is accomplished via mathematical models that revise the locations of the search agents (wolves) within the solution space.

(1) Encircling prey - Wolves encircle prey by modifying their positions in relation to the optimal solution identified thus far. It employs the subsequent equations to mathematically represent the encircling behavior:

$$\boldsymbol{X}(t+1) = \boldsymbol{X}(t) - \boldsymbol{A}.\boldsymbol{D} \tag{1}$$

where **X**(t+1) represents the subsequent position of the wolf, **X**(t) denotes the current position, **A** is a coefficient matrix, and **D** is a vector contingent upon the prey's location (by **X**p), computed as follows:

$$\boldsymbol{D} = |\boldsymbol{C}.\boldsymbol{X}p(t) - \boldsymbol{X}(t)| \tag{2}$$

where,

$$\boldsymbol{C} = 2.\boldsymbol{r}_2 \tag{3}$$

The random components of the aforementioned equations replicate varying step lengths and velocities of grey wolves. The equations that delineate their values are as follows:

$$\boldsymbol{A} = 2\boldsymbol{a}.\boldsymbol{r}_1 - \boldsymbol{a} \tag{4}$$

where $\boldsymbol{a}$ is a vector whose values diminish linearly from 2 to 0 throughout the execution. $\mathbf{r_1}$ is a vector generated randomly from the interval [0,1].

(2) Hunting - Grey wolves possess the capability to detect and encircle their prey. The alpha typically directs the prey. In the mathematical simulation of grey wolf hunting behavior, the alpha is regarded as possessing superior knowledge regarding the probable locations of prey. Consequently, it retains the initial three optimal solutions acquired and adjusts the positions of the remaining wolves based on this data. In this context, the subsequent formulas are employed.

$$\boldsymbol{X}(t+1) = \frac{1}{3}\boldsymbol{X_1} + \frac{1}{3}\boldsymbol{X_2} + \frac{1}{3}\boldsymbol{X_3} \tag{5}$$

where $\mathbf{X_1}$ and $\mathbf{X_2}$ and $\mathbf{X_3}$ are calculated with Eq. 6.

$$\begin{aligned} \boldsymbol{X_1} &= \boldsymbol{X}_\alpha(t) + \boldsymbol{A_1}.\boldsymbol{D}_\alpha \\ \boldsymbol{X_2} &= \boldsymbol{X}_\beta(t) + \boldsymbol{A_2}.\boldsymbol{D}_\beta \\ \boldsymbol{X_3} &= \boldsymbol{X}_\delta(t) + \boldsymbol{A_3}.\boldsymbol{D}_\delta \end{aligned} \tag{6}$$

where $\mathbf{D_\alpha}$ and $\mathbf{D_\beta}$ and $\mathbf{D_\delta}$ are calculated using Eq. 7.

$$\begin{aligned} \boldsymbol{D}_\alpha &= |\boldsymbol{C_1}.\boldsymbol{X}_\alpha - \boldsymbol{X}| \\ \boldsymbol{D}_\beta &= |\boldsymbol{C_2}.\boldsymbol{X}_\beta - \boldsymbol{X}| \\ \boldsymbol{D}_\delta &= |\boldsymbol{C_3}.\boldsymbol{X}_\delta - \boldsymbol{X}| \end{aligned} \tag{7}$$

(3) Attacking the prey - As the search advances, the algorithm transitions from exploration to exploitation, and the wolves near their target. To mathematically model the prey's approach, we reduce **a**. The variable vector A within the interval [-2**a**, 2**a**] diminishes **a** from 2 to 0 across successive iterations.

The algorithm continues to iterate until a termination condition is satisfied, enhancing its solutions with each iteration and achieving the optimal solution.

3.2 Random Walk GWO

The Random Walk GWO algorithm is derived from the conventional GWO method, which is based on the hunting behavior and social hierarchy of grey wolves (Gupta and Deep, 2019). The primary distinction between this method and classical GWO lies in the incorporation of a random walk in the algorithm's exploration strategy, with the step size derived from the Cauchy distribution. The rationale for contemplating a random step size is the infinite variance of the Cauchy distribution. This concept posits that during periods of inactivity in the exploration of the search space, the dominant wolves are inclined to investigate potential optimal solutions by making significant leaps.

The algorithm is founded on the fundamental mathematical formulations of the original GWO. Nevertheless, it offers enhancement of the random walk through Eq. 8 for the modification of the random walk.

$$\boldsymbol{b} = 2 - 2\left(\frac{t}{\max no\ of\ iterations}\right)$$
$$\text{ɥ} = 2\mathbf{b}.\boldsymbol{r}_1 - \mathbf{b} \tag{8}$$

The wolves' expression around the prey is updated with Eq. 9.

$$\boldsymbol{X}(t+1) = \boldsymbol{X}(t) - \text{ɥ}\,.\boldsymbol{D} \tag{9}$$

3.3 Improved GWO

The Improved GWO is a modification of the traditional GWO algorithm designed to refine the optimization process (Kaveh and Zakian, 2018). It refines the optimization process by calibrating the parameter settings and seeks to enhance the outcomes through the implementation of novel techniques. Moreover, Enhanced GWO incorporates supplementary internal parameters that enhance flexibility and adaptability in complex problems, accelerating the optimization process and elevating solution quality relative to classical GWO.

In the Original GWO (as per Eq. 4), $\boldsymbol{a}$ uniform linear decreasing function is established for alpha, beta, and delta wolves. In Improved GWO, distinct functions are established for each scenario based on dominance principles to augment the exploration and application of the algorithm. In Eq. 10, alpha, beta, and delta exhibit the following exponentially decreasing functions for a single parameter:

$$\boldsymbol{a}_{\alpha}(i) = \boldsymbol{a}_{\max}\exp\left(\left(\frac{i}{\boldsymbol{i}_{\max}}\right)^{\text{ŋ}_{\alpha}} \ln\left(\frac{\boldsymbol{a}_{\min}}{\boldsymbol{a}_{\max}}\right)\right.$$
$$\boldsymbol{a}_{\delta}(i) = \boldsymbol{a}_{\max}\exp\left(\left(\frac{i}{\boldsymbol{i}_{\max}}\right)^{\text{ŋ}_{\delta}} \ln\left(\frac{\boldsymbol{a}_{\min}}{\boldsymbol{a}_{\max}}\right)\right.$$
$$\boldsymbol{a}_{\beta} = (\boldsymbol{a}_{\alpha}(i) + \boldsymbol{a}_{\delta}(i))/2 \tag{10}$$

where $\boldsymbol{a}_{\max}$, $\boldsymbol{a}_{\min}$, i, $\boldsymbol{i}_{\max}$, ŋ_{α} and ŋ_{δ} are the upper bound of $\boldsymbol{a}$, lower bound of $\boldsymbol{a}$, current iteration, maximum number of iteration, growth factor of alpha and growth factor of delta, respectively.

4. MECHANICAL DESIGN PROBLEMS

Mechanical design optimization problems encompass numerous nonlinear constraints and intricate variables associated with kinematics, geometric conditions, and material strength. Over the past three decades, optimization methods have been utilized to tackle numerous engineering problems and real-world challenges. This paper analyzes five prevalent problems to perform a comparative assessment of GWO variants and Table 1 delineates the critical informations regarding these problems.

Table 1. Summary of five mechanical optimization problems.

Problem Name	Abbr	Dimension	Constraints
Cantilever Beam Problem	CBP	5	1
Tubular Column Design	TCD	2	6
Piston Lever Design	PLD	4	4
Corrugated Bulkhead Problem	CBHD	4	6
Reinforced Concrete Beam	RCB	3	2

Figure 1 illustrates these problems graphically, with their definitions detailed in the subheadings. Various versions of the issues exist in the literature, and scholars have tailored the fitness function and limitations to align with their research objectives. In our research, we utilized the Enoppy library, which encompasses a standardized problem repository to facilitate comparisons and ensure the reproducibility of the study (Van Thieu, 2023). Mathematical expressions of the problems, including the fitness function, constraints and variable range, can be accessed from the Supplementary File.

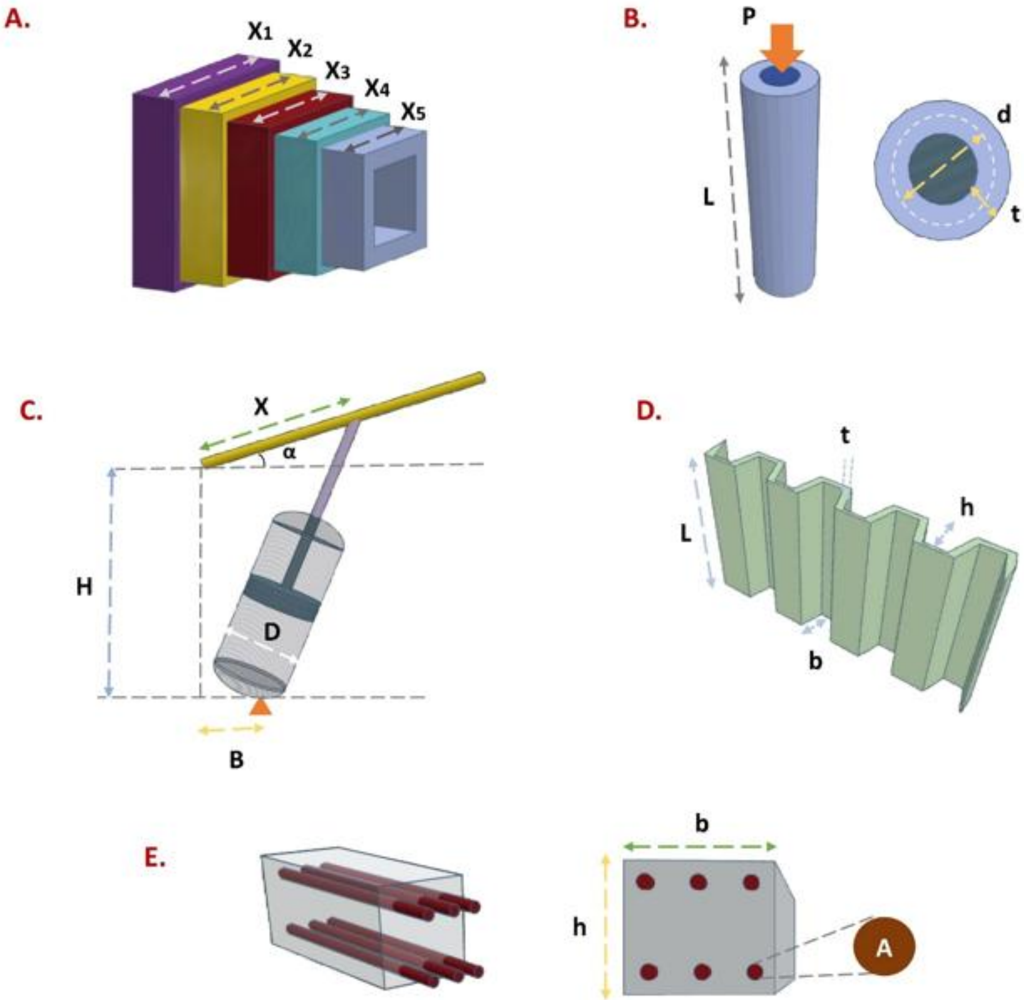

Figure 1. The demonstration of the mechanical design problems. (A) CBP, (B) TCD, (C) PLD, (D) CBHD, (E) RCB

4.1 The Cantilever Beam Design (CBP)

The cantilever is a design depicted in Figure 1.A comprises five hollow square blocks of uniform thickness. The dimensions of the blocks are represented by X_1, X_2, X_3, X_4, and X_5 for height and width. The objective of the problem is to minimize the weight of the cantilever beam while adhering to structural requirements and to ascertain the optimal block dimensions.

4.2 The Tubular Column Design (TCD)

The tubular column depicted in Figure 1.B is a structural component comprising a hollow cylinder constructed from metal, concrete, or alternative materials. It is frequently utilized in construction to reinforce beams and other structural components, as well as in bridges and various other edifices. Tubular columns are typically more robust and efficient than solid columns due to their ability to withstand torsional, bending, and shear forces. The goal of the problem is to optimize the construction cost of the column by utilizing the variables d, representing the average diameter of the column, and t, denoting the thickness of the column.

4.3 The Piston Lever Design (PLD)

The piston lever problem holds significant relevance in engineering applications, including the automotive industry, aerospace, and mechanical engineering. The primary aim of this problem is to optimally position the piston lever components H, B, D, and X by minimizing the oil volume as α in the piston lever is increased from 0° to 45° in the design illustrated in Figure 1.C.

4.4 The Corrugated Bulkhead Design (CBHD)

The corrugated bulkheads are commonly utilized on vessels owing to their benefits, including ease of maintenance and adaptability to thermal expansion and contraction. Reducing the weight of these mechanical designs is crucial due to the current high cost of materials and constitutes the primary objective of this problem. The structural component depicted in Figure 1.D possesses four design variables: width (b), depth (h), length (L), and thickness (t) of the plate.

4.5 The Reinforced Concrete Beam Design (RCB)

The design of reinforced concrete beams is a challenge faced in civil engineering. The issue pertains to a structure depicted in Figure 1.E. Concrete beams are fortified with steel bars to enhance their resistance to internal stresses. The process is a complex optimization involving three design variables: reinforcement area (A), beam width (b), and beam depth (h).

5. EXPERIMENTAL PROCEDURE, RESULTS AND DISCUSSION

This section presents an experimental comparison of the GWO, Improved GWO, and Random Walk GWO algorithms. To assess the efficacy of each algorithm, they were implemented on five distinct mechanical design challenges: CBD, TCD, PLD, CBHD, and RCB. All experiments were performed on a PC with an Intel Core(TM) i5-12400 (2.50 GHz) processor, 512 GB SSD, 16 GB RAM, and the Windows 11 Operating System. Furthermore, the Python programming language was employed for all computations, and the Mealpy (Van Thieu and Mirjalili, 2023) and Enoppy (Van Thieu, 2023) libraries were utilized alongside the fundamental libraries. In the optimization of the fundamental parameters of the algorithms, the iteration counts were established at 100, 500, 1000, and 5000, while the population sizes were designated as 20, 50, 100, 200, and 500, respectively. All case studies were executed under equal experimental conditions. Each algorithm was executed 25 times to assess the robustness of the comparative methods in solving the problem. The experimental methodologies and the resultant findings are elaborated upon in the subsequent subsections.

5.1 Average Efficacy

Figure 2 illustrates average values derived from the application of the three optimization models to five problems. The averages are computed based on the fitness results derived from 25 iterations across all iteration and population size parameters of the problems.

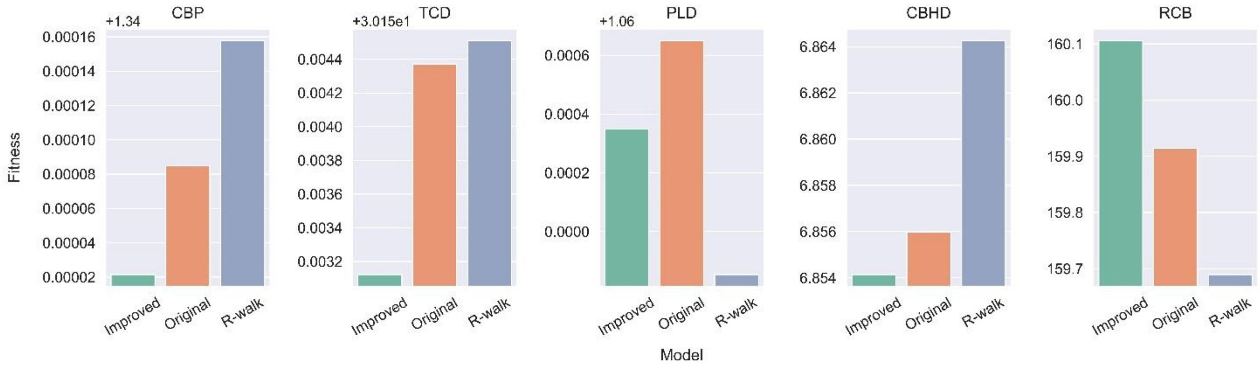

Figure 2. Average performance of optimization models in mechanical problems

Given that all optimization tasks are minimization problems, Improved GWO achieved the lowest average fitness value in addressing CBP, TCD, and CBHD problems. It demonstrates superior optimization efficacy relative to the Original method and Random Walk GWO. Conversely, in PLD and RCB issues, Random Walk GWO emerges as the most effective model. The enhanced GWO outperformed the original method in the PLD problem.

5.2 Statistical Assessments

The average performance graph offers a qualitative comparison of the methods, yet this is inadequate on its own. Statistical tests were conducted in the study to assess the superiority of the methods relative to one another and to determine if a statistically significant difference was achieved.

The results acquired for each parameter combination of the algorithms employed in the study were regarded as a single data. To ascertain the appropriate statistical test, the normality of the data distribution was initially assessed. The Shapiro-Wilk test was utilized for normality assessments owing to the limited sample size ($n<50$). The Shapiro-Wilk test results indicated that approximately 68.5% of the total data group satisfied the $p<0.05$ criterion and exhibited a non-normal distribution. The optimization method exhibiting the highest incidence of anomalies was R-walk GWO, while TCD was the most prevalent by problem type. The propensity for normal distribution heightened with an increase in population size.

In the second stage, a multiple comparison test was conducted to assess the statistical significance among the methods. ANOVA was conducted when $p >= 0.05$, while the Kruskal-Wallis test was utilized in other instances, as determined by the normality test. Analysis of the multiple comparison test results revealed that the methods satisfied the $p<0.05$ acceptance criterion in the majority of parameter combinations (77.7%), yielding statistically significant differences. Furthermore, 44.7% of the findings exhibited substantial significance ($p<0.001$). Systematic superiority was particularly evident in CBP and CBHD problems.

The results indicated systematic and quantifiable differences among the three methods. Nevertheless, comprehensive pairwise comparisons were conducted in the final stage to assess the nature of these differences among the methods. At this juncture, Dunn's test was employed due to the failure of the majority of normal distribution assumptions in data integrity. The average results derived from the data (across all problems) were Improved vs Original: 0.0092 ± 0.021, Improved vs

R-walk: 0.0004 ± 0.0021, and Original vs R-walk: 0.6821 ± 0.2974. The Improved GWO demonstrated considerable superiority ($p<0.01$) compared to the other two methods. No systematic difference exists between Original GWO and the R-walk variant ($p>0.05$). The statistical results align with the findings of Section 5.1.

5.3 Evaluation of Parameters

In optimization problems, the objective is to identify the optimal solutions with consistent stability. The average efficacy of an algorithm across a broad spectrum of problems appears to be a viable strategy; however, it is not invariably adequate. Achieving optimal solutions through efficient parameterization is essential. This section compares the results obtained from the GWO algorithm and its two variants with parameter modifications. Figure 3-7 displays the results for the CBP, TCD, PLD, CBHD, and RCB problems. Fitness results are normalised in graphical representations to ensure numerical traceability and to facilitate the observation of differences in comparisons.

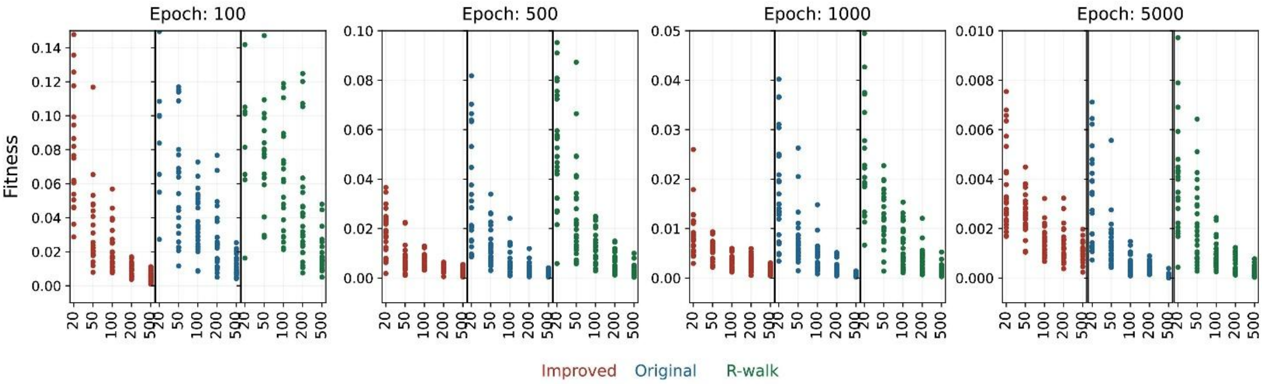

Figure 3. Fitness outcomes for all parameter combinations of GWOs on CBP

Figure 3 indicates that the improved GWO method on the CBP problem consistently yields consistent results across high iterations and population size combinations, despite minor fluctuations in performance with decreasing parameters. Stability is evident at medium to high population densities. The original model demonstrates highly stable behavior at an epoch value of 5000, sustaining competitive levels despite population size decreases. However, the R-walk variant experiences substantial performance declines when parameters drop below critical thresholds, leading to unregulated variations and discrepancies, especially at minimal population sizes.

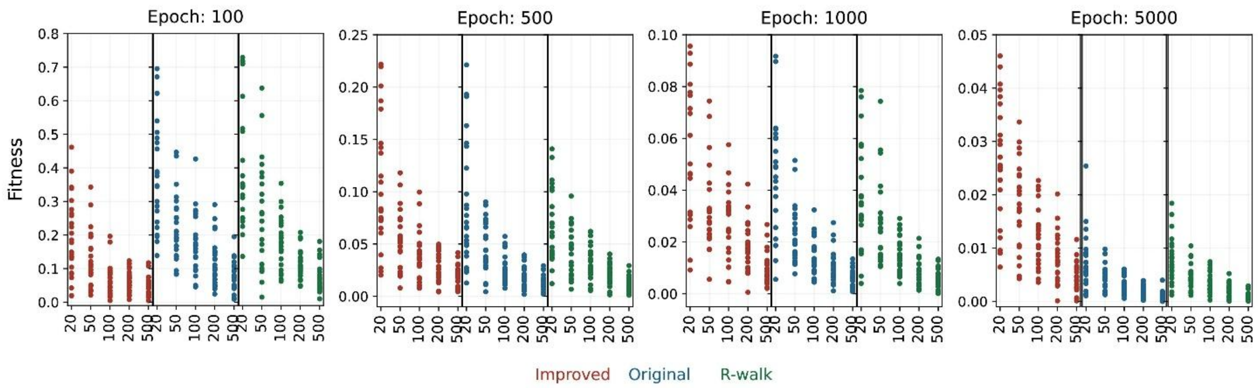

Figure 4. Fitness outcomes for all parameter combinations of GWOs on TCD

According to Figure 4, the TCD problem shows that the impact of epoch parameter is less pronounced than in the CBP problem. GWO and the R-walk variant show similar performance at elevated iteration and population sizes. The Original GWO yields the most consistent results with a population size of 500 and 5000 epochs. At 5000 iterations, they exhibit generally tolerant behavior, but minor performance declines occur as the population size diminishes. In situations with low populations, considerable fluctuations emerge, albeit in a more regulated manner than in the Improve model. The R-walk model demonstrates satisfactory performance only at elevated population and epoch values.

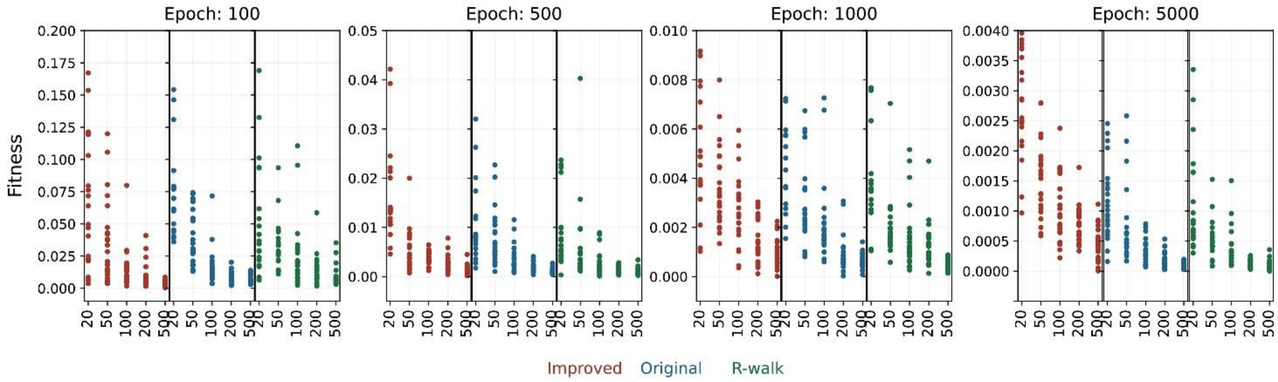

Figure 5. Fitness outcomes for all parameter combinations of GWOs on PLD

Figure 5 indicates that, generally, the performance of all models improves with population size and epochs, with the Original and R-walk models showing optimality. The R-walk model achieved lower minimum values, while the Original model had a limited spectrum of solutions, indicating greater stability reliability. The Improved model showed competitive performance at 100 and 500 epochs, but lagged behind other methods when epochs increased. The Original model's outcomes were concentrated on a limited spectrum, suggesting greater reliability.

Figure 6 illustrates that the Improved model offers optimal results for general applications, with minimal error and consistent outcomes at high epoch and population sizes. The Original model is particularly reliable in industrial-scale contexts, especially when maximum resources are used. R-walk, despite its theoretical ability to achieve minimal fitness values, is only suitable for resource-rich and regulated settings due to erratic deviations under low parameters. Prioritizing Improved or Original in resource-unrestricted contexts and incorporating additional validation measures in experimental or risk-tolerant situations is recommended.

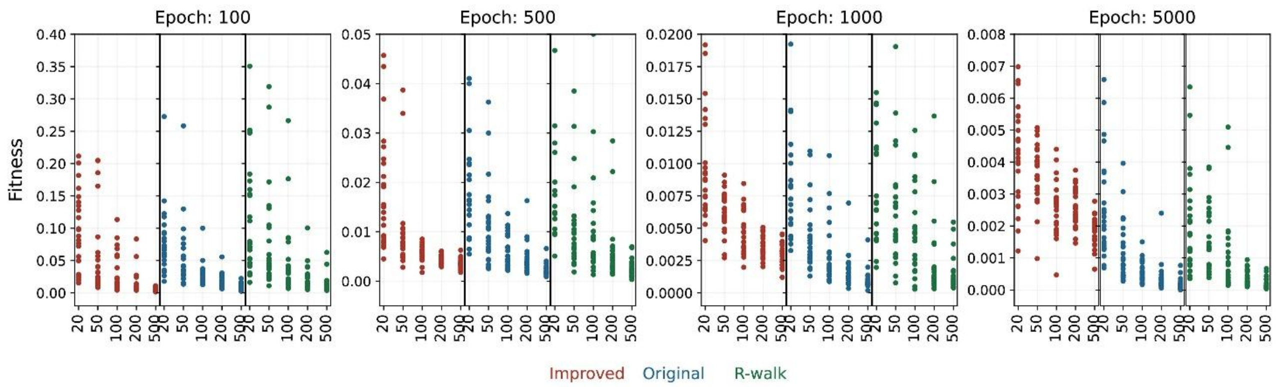

Figure 6. Fitness outcomes for all parameter combinations of GWOs on CBHD

Figure 7 demonstrates the performance of Improved, Original, and R-walk models in relation to epoch and pop_size parameters. All models yield low fitness and consistent results in high source scenarios. The Original model excels in industrial applications due to minimal variation, while the Improved model provides stability across parameters. R-walk achieves competitive measures in medium-scale configurations but poses a risk of inconsistency in low-source scenarios.

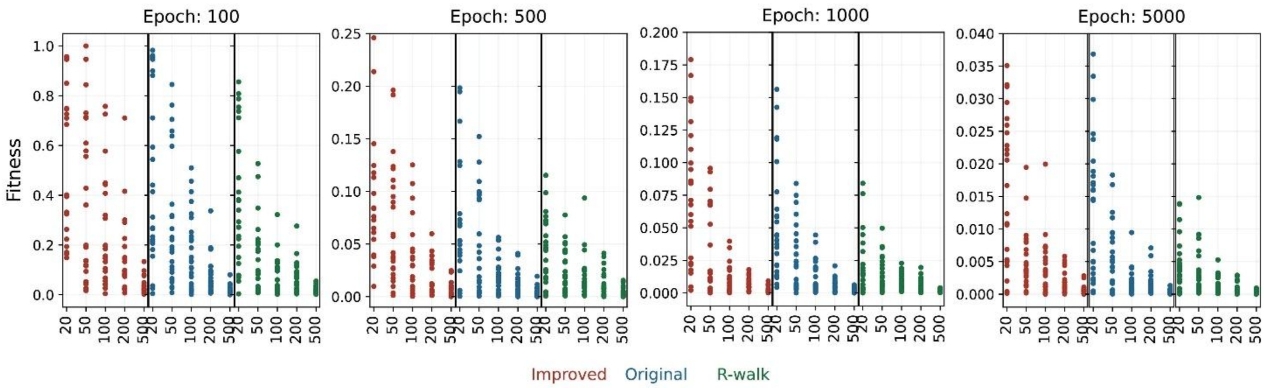

Figure 7. Fitness outcomes for all parameter combinations of GWOs on RCB

5.4 Optimal Performances and Literature Comparison

This section assesses the optimal fitness values attained by the algorithms. Table 2 presents the experimental outcomes for five engineering optimization challenges among GWOs. Furthermore, the outcomes of the top-performing models are juxtaposed with the advanced algorithms suggested in the literature to address the same issues. The results are presented in Tables 3 to 7.

Table 2. The minimum outcomes of algorithms on five mechanical problems

Problem	Improved	Original	R-walk
CBP	1.339958	1.339956	1.339957
TCD	30.149763	30.149755	30.149759
PLD	1.057401	1.057406	1.057400
CBHD	6.843375	6.843013	6.843038
RCB	159.360007	159.360037	159.360041

Table 2 illustrates notable disparities among the Improved, Original, and R-walk methodologies. The Original algorithm demonstrated better results in CBP, TCD, and CBHD problems, whereas the R-walk model scored in PLD. The enhanced algorithm demonstrated superiority in RCB. These findings indicate that the selection of algorithms tailored to specific problems is essential, with Improved being favored in particular contexts such as RCB.

Table 3. The optimal comparison of optimizers in CBP

Model	Parameters	Fitness
SRIME (Zhong et al., 2024)	Epoch:20000, Psize:100	1.3419
LLMOA (Zhong, Hussien, et al., 2025)	E:50000, Psize:100	1.3399
SHBA (Xu et al., 2024)	E:50000, Psize:100	1.3400
SNS (Bayzidi et al., 2021)	E:12000, Psize: Unknown	1.3399
L-SHACSO (Zhong, Wang, et al., 2025)	E:10000, Psize:100	1.3400
Original GWO (This Study)	E:5000, Psize:500	1.3399

Analysis of the comparisons reveals that the GWO methodologies employed in your study (Original GWO, R-walk, and Improved GWO) exhibit a notable performance. In the CBP problem, Original GWO proved its computational efficiency by achieving the same fitness value (1.3399) as LLMOA and SNS with 5 times fewer epochs (E:5000) and larger population.

Table 4. The optimal comparison of optimizers in TCD

Model	Parameters	Fitness
CCOA (Zhong, Zhang and Yu, 2024b)	E:20000, Psize:100	30.1670
SRIME (Zhong et al., 2024)	E:20000, Psize:100	30.1500
LLMOA (Zhong, Hussien, et al., 2025)	E:20000, Psize:100	30.1497
SHBA (Xu et al., 2024)	E:20000, Psize:100	30.1500
L-SHACSO (Zhong, Wang, et al., 2025)	E:10000, Psize:100	30.1488
Original GWO (This Study)	E:5000, Psize:500	30.1497

In TCD, although L-SHACSO achieves a superior result of 30.1488, Original GWO surpasses most methods in the literature (CCOA, SRIME) with a score of 30.1497, demonstrating a balanced performance.

Table 5. The optimal comparison of optimizers in PLD

Model	Parameters	Fitness
SRIME (Zhong et al., 2024)	E:40000, Psize:100	1.0574
SHBA (Xu et al., 2024)	E:40000, Psize:100	1.0570
L-SHACSO (Zhong, Wang, et al., 2025)	E:10000, Psize:100	1.0743
R-walk (This Study)	E:5000, Psize:500	1.0574

In PLD, R-walk yields an equivalent value to SRIME (1.0574) at one-eighth of the epoch cost, thereby demonstrating its adaptive search efficiency.

Table 6. The optimal comparison of optimizers in CBHD

Model	Parameters	Fitness
CVEGE (Zhong, Zhang and Yu, 2024a)	E:10000, Psize:100	6.8430
CCOA (Zhong, Zhang and Yu, 2024b)	E:20000, Psize:100	6.8485
SRIME (Zhong et al., 2024)	E:20000, Psize:100	6.8436
LLMOA (Zhong, Hussien, et al., 2025)	E:40000, Psize:100	6.8429
SNS (Bayzidi et al., 2021)	E:3125, Psize: Unknown	6.8429
L-SHACSO (Zhong, Wang, et al., 2025)	E:10000, Psize:100	6.8429
Original GWO (This Study)	E:5000, Psize:500	6.8430

Despite Original GWO in CBHD trailing LLMOA and SNS by a mere 0.0001, the fact that these methods utilize 4-8 times more epochs underscores GWO results are remarkable.

In RCB, the Improved GWO attains an equivalent fitness level as CCOA (159.3600) within one-quarter of an epoch, underscoring the algorithm's efficacy.

Table 7. The optimal comparison of optimizers in RCB

Model	Parameters	Fitness
CCOA (Zhong, Zhang and Yu, 2024b)	E:20000, Psize:100	159.3600
SRIME (Zhong et al., 2024)	E:20000, Psize:100	159.3700

Table 7. The optimal comparison of optimizers in RCB (continued)

Model	Parameters	Fitness
LLMOA (Zhong, Hussien, et al., 2025)	E:30000, Psize:100	159.4122
SHBA (Xu et al., 2024)	E:30000, Psize:100	160.3000
Improved GWO (This Study)	E:5000, Psize:100	159.3600

Overall, the parameter optimization in this study has yielded results that are competitive with existing methods in the literature, particularly regarding computational resource optimization using the low epoch-large population strategy. The slight advantage of certain methods, such as LLMOA and SNS in CBHD, necessitates a thorough examination of parameter adaptation mechanisms.

6. CONCLUSIONS

GWO is regarded as an effective algorithm for identifying the optimal solution to mechanical design problems. The intricacy of the issues, encompassing complexity, mixed variables with continuous and discrete elements, multiple objectives, and diverse nonlinear constraints associated with performance operations, manufacturing prerequisites, and kinematic conditions, prompted researchers to devise this efficient algorithm.

This article thoroughly examines the GWO algorithm and introduces various modifications of this widely-used algorithm. The present investigation not only reviews the GWO literature but also compares the original algorithm with its two variants under identical experimental conditions. The experiments encompass three models, twenty distinct combinations of fundamental parameters (four epochs, five population sizes) and five mechanical design challenges. The methods' performance is assessed based on their average efficacy, the statistically significant differences attained, stability under parameter variations, and the minimum fitness values achieved. The subsequent conclusions can be derived from the experimental analyses:

(1) The GWO modifications yielded distinct outcomes compared to the original algorithm, despite being based on the same methodology. This is statistically significant in the majority of instances.
(2) The original GWO exhibits strengths including consistency across various problem types and minimal parameter sensitivity. The substantial resource demand (5000 iterations/500 populations) constitutes a limitation of the Original GWO.
(3) In situations involving abundant resources and uncomplicated issues (e.g., RCB), the Enhanced model demonstrates effective performance. The absence of diversification in low populations increases the risk of local minima, representing a limitation of this method.
(4) The R-walk model demonstrates robust performance when employed by specialists in environments where parameters are meticulously regulated and substantial populations are feasible. Nonetheless, it may present risks when extensive and elevated parameter requirements are unmet.

These conclusions indicate that problem type, resource limitations, and performance consistency are interdependent factors in the selection of optimization algorithms. Given that energy efficiency and stability are paramount in industrial systems, even minor performance variances hold significant long-term implications. The Original model is evidently the more dependable choice regarding resource efficiency and robustness in comparison to alternative methods. The five problems examined in the investigations pertain solely to single-objective optimization. They have not undergone testing in real-time dynamic environments. These are the limitations of the study. Nonetheless, the comparative examination of the algorithms elucidates the merits and demerits of

GWO and its variations. The study can function as a reference for researchers to tackle issues across multiple engineering domains, including materials, machinery, automotive, and construction.

7. ACKNOWLEDGEMENTS

This study did not benefit from any support.

8. CONFLICT OF INTEREST

Author approves that to the best of their knowledge, there is not any conflict of interest or common interest with an institution/organization or a person that may affect the review process of the paper.

9. AUTHOR CONTRIBUTION

Nermin ÖZCAN has the full responsibility of the paper about determining the concept of the research, data collection, data analysis and interpretation of the results, preparation of the manuscript and critical analysis of the intellectual content with the final approval.

10. REFERENCES

Abdollahzadeh B., Gharehchopogh F. S., Mirjalili S., African Vultures Optimization Algorithm: A New Nature-Inspired Metaheuristic Algorithm for Global Optimization Problems, Computers and Industrial Engineering 158(5), 107408, 2021.

Altay O., Varol E., A Novel Hybrid Multilayer Perceptron Neural Network with Improved Grey Wolf Optimizer, Neural Computing and Applications, 35(1), 529–556, 2023.

Ayğahoğlu M. E., Gümüş M. S., Çakan, A., Kalyoncu M., Dimension Optimization of Polycentric Knee Mechanism using the Bees Algorithm And Genetic Algorithm, Journal of Materials and Mechatronics: A 4(1), 318–332, 2023.

Bayzidi H., Talatahari S., Saraee M., Lamarche, C. P., Social Network Search for Solving Engineering Optimization Problems, Computational Intelligence and Neuroscience 548639, 2021.

Çetinkaya M. B., Taşkıran K., Meta-Sezgisel Algoritmalara Dayalı Retinal Damar Bölütleme, Journal of Materials and Mechatronics: A 3(1), 79–90, 2022.

Coban M., Saka M., Directly Power System Harmonics Estimation using Equilibrium Optimizer, Electric Power Systems Research, 234(110565), 2024.

Cui D., Wang G., Lu Y., Sun K., Reliability Design and Optimization of The Planetary Gear by a GA Based on the DEM and Kriging Model, Reliability Engineering & System Safety 203,107074, 2020.

Das B., Mukherjee V., Das D., Student Psychology based Optimization Algorithm: A New Population based Optimization Algorithm for Solving Optimization Problems, Advances in Engineering Software 146(3), 102804, 2020.

Debnath S., Debbarma S., Nama S., Saha A. K., Dhar R., Yildiz A. R., Gandomi A. H., Centroid Opposition-Based Backtracking Search Algorithm For Global Optimization And Engineering Problems, Advances in Engineering Software 198, 103784, 2024.

Eberhart R., Kennedy J., New Optimizer using Particle Swarm Theory, Proceedings of the International Symposium on Micro Machine and Human Science 39–43, 1995.

Eke I., Saka M., Gozde H., Arya Y., Taplamacioglu M. C., Heuristic Optimization based Dynamic Weighted State Feedback Approach for 2DOF PI-Controller in Automatic Voltage Regulator, Engineering Science and Technology, an International Journal 24(4), 899–910, 2021.

Emary E., Zawbaa H. M., Hassanien A. E., Binary Grey Wolf Optimization Approaches for Feature Selection, Neurocomputing 172, 371–381, 2016.

Ezugwu A. E., Agushaka J. O., Abualigah L., Mirjalili S., Gandomi A. H., Prairie Dog Optimization Algorithm, Neural Computing and Applications 34(22), 2022.

Faramarzi A., Heidarinejad M., Stephens B., Mirjalili S., Equilibrium Optimizer: A Novel Optimization Algorithm, Knowledge-Based Systems 191, 105190, 2020.

Faris H., Aljarah I., Al-Betar M. A., Mirjalili S., Grey Wolf Optimizer: A Review ff Recent Variants and Applications, Neural Computing and Applications 30(2), 413–435, 2018.

Gezici H., Improved Tuna Swarm Optimization Algorithm for Engineering Design Problems, Journal of Materials and Mechatronics: A 4(2), 424–445, 2023.

Gupta S., Abderazek H., Yıldız B. S., Yildiz A. R., Mirjalili S., Sait, S. M., Comparison of Metaheuristic Optimization Algorithms for Solving Constrained Mechanical Design Optimization Problems, Expert Systems with Applications 183, 2021.

Gupta S., Deep K., A Novel Random Walk Grey Wolf Optimizer, Swarm and Evolutionary Computation 44, 101–112, 2019.

Gürkan Kuntalp D., Özcan N., Düzyel O., Kababulut F. Y., Kuntalp M., A Comparative Study of Metaheuristic Feature Selection Algorithms for Respiratory Disease Classification, Diagnostics 14(19), 2244, 2024.

Hamza F., Abderazek H., Lakhdar S., Ferhat D., Yıldız A. R., Optimum Design of Cam-Roller Follower Mechanism using a New Evolutionary Algorithm, The International Journal of Advanced Manufacturing Technology 99(5), 1267–1282, 2018.

Heidari A. A., Mirjalili S., Faris H., Aljarah I., Mafarja M., Chen H., Harris Hawks Optimization: Algorithm and Applications, Future Generation Computer Systems 97, 849–872, 2019.

Holland J. H., Genetic Algorithms, Scientific American 267(1), 66–72, 1992.

Jahangiri M., Hadianfard M. A., Najafgholipour M. A., Jahangiri M., Gerami M. R., Interactive Autodidactic School: A New Metaheuristic Optimization Algorithm for Solving Mathematical and Structural Design Optimization Problems, Computers & Structures 235, 2020.

Jayapriya J., Arock M., A Parallel GWO Technique for Aligning Multiple Molecular Sequences, International Conference on Advances in Computing, Communications and Informatics (ICACCI), India, 210–215, 2015.

Kababulut F. Y., Gürkan Kuntalp D., Düzyel O., Özcan N., Kuntalp M., A New Shapley-Based Feature Selection Method in a Clinical Decision Support System for the Identification of Lung Diseases, Diagnostics 13(23), 3558, 2023.

Kamboj V. K., A Novel Hybrid PSO–GWO Approach for Unit Commitment Problem, Neural Computing and Applications 27(6), 1643–1655, 2016.

Kaveh A., Zakian P., Improved GWO Algorithm for Optimal Design of Truss Structures, Engineering with Computers 34(4), 685–707, 2018.

Khairuzzaman A. K. M., Chaudhury S., Multilevel Thresholding using Grey Wolf Optimizer for Image Segmentation, Expert Systems with Applications 86, 64–76, 2017.

Kishor A., Singh P. K., Empirical Study of Grey Wolf Optimizer, Proceedings of Fifth International Conference on Soft Computing for Problem Solving, Singapore, 1037–1049, 2016.

Lee S. W., Haider A., Rahmani A. M., Arasteh B., Gharehchopogh F. S., Tang S., Liu Z., Aurangzeb K., Hosseinzadeh M., A Survey of Beluga Whale Optimization and Its Variants: Statistical Analysis, Advances, and Structural Reviewing, Computer Science Review 57, 2025.

Li G., Zhang T., Tsai C. Y., Yao L., Lu Y., Tang J., Review of the Metaheuristic Algorithms in Applications: Visual Analysis based on Bibliometrics, Expert Systems with Applications 255, 2024.

Li S. X., Wang J. S., Dynamic Modeling of Steam Condenser and Design of Pi Controller based on Grey Wolf Optimizer, Mathematical Problems in Engineering 120975, 2015.

Luo Q., Zhang S., Li Z., Zhou Y., A Novel Complex-Valued Encoding Grey Wolf Optimization Algorithm, Algorithms 9(1), 2016.

Malik M. R. S., Mohideen E. R., Ali L., Weighted Distance Grey Wolf Optimizer for Global Optimization Problems, IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), India, 1–6, 2015.

Millo F., Arya P. Mallamo F., Optimization of Automotive Diesel Engine Calibration using Genetic Algorithm Techniques, Energy 158, 807–819, 2018.

Mirjalili S., Saremi S., Mirjalili S. M., Coelho L. S., Multi-Objective Grey Wolf Optimizer: A Novel Algorithm for Multi-Criterion Optimization, Expert Systems with Applications 47, 106–119, 2016.

Mirjalili S., Lewis A., The Whale Optimization Algorithm, Advances in Engineering Software 95, 51–67, 2016.

Mirjalili S., Mirjalili S. M., Lewis A., Grey Wolf Optimizer, Advances in Engineering Software 69, 46–61, 2014.

Mirjalili S., Gandomi A. H., Mirjalili S. Z., Saremi S., Faris H., Mirjalili S. M., Salp Swarm Algorithm: A Bio-Inspired Optimizer for Engineering Design Problems, Advances in Engineering Software 114, 163–191, 2017.

Mittal N., Singh U., Sohi, B. S., Modified Grey Wolf Optimizer for Global Engineering Optimization, Applied Computational Intelligence and Soft Computing, 2016(1), 2016.

Özcan N., Kuntalp M., Determining Best HRV Indices for PAF Screening using Genetic Algorithm, 10th International Conference on Electrical and Electronics Engineering (ELECO), Bursa, 2018.

Özcan N., Utku S. Berber T., Artificial Circulation System Algorithm: A Novel Bio-Inspired Algorithm, CMES - Computer Modeling in Engineering and Sciences 142(1), 635–663, 2025.

Ransegnola T., Zhao X., Vacca A., A Comparison of Helical and Spur External Gear Machines for Fluid Power Applications: Design And Optimization, Mechanism and Machine Theory 142, 2019.

Rodan A., Al-Tamimi A. K., Al-Alnemer L., Mirjalili S., Tino P., Enzyme Action Optimizer: A Novel Bio-Inspired Optimization Algorithm, The Journal of Supercomputing 81(5), 686, 2025.

Rodríguez L., Castillo O., Soria J., Melin P., Valdez F., Gonzalez C. I., Martinez G. E., Soto J., A Fuzzy Hierarchical Operator in the Grey Wolf Optimizer Algorithm, Applied Soft Computing 57, 315–328, 2017.

Saka M., Novel HVsaGwo Algorithm for Non-Linear Dynamic Weighted State Feedback With 1DOF-PID based Controllers in AVR, Engineering Science and Technology, an International Journal 59, 2024.

Saremi S., Mirjalili S., Lewis, A., Grasshopper Optimisation Algorithm: Theory and Application, Advances in Engineering Software 105, 30–47, 2017.

Socha K., Dorigo M., Ant Colony Optimization for Continuous Domains, European Journal of Operational Research 185(3), 1155–1173, 2008.

Song X., Tang L., Zhao S., Zhang X., Li L., Huang J., Cai W., Grey Wolf Optimizer for Parameter Estimation in Surface Waves, Soil Dynamics and Earthquake Engineering 75, 147–157, 2015.

Storn R., Price K., Differential Evolution - A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces, Australasian Plant Pathology 38(3), 284–287, 2009.

Sulaiman M. H., Mustaffa Z., Mohamed M. R., Aliman O., Using the Gray Wolf Optimizer for Solving Optimal Reactive Power Dispatch Problem, Applied Soft Computing 32, 286–292, 2015.

Sun G., Tian J., Liu T., Yan X., Huang X., Crashworthiness Optimization of Automotive Parts with Tailor Rolled Blank, Engineering Structures 169, 201–215, 2018.

Van Thieu N, 2023., ENOPPY: A Python Library For Engineering Optimization Problems, https://github.com/thieu1995/enoppy (Accessed: 23.03.2025).

Van Thieu N., Mirjalili S., MEALPY: An Open-Source Library for Latest Meta-Heuristic Algorithms in Python, Journal of Systems Architecture 102871, 2023.

Wang R. B., Hu R. B., Geng F. D., Xu L., Chu S. C., Pan J. S., Meng Z. Y., Mirjalili S., The Animated Oat Optimization Algorithm: A Nature-Inspired Metaheuristic for Engineering Optimization and A Case Study On Wireless Sensor Networks, Knowledge-Based Systems, 113589, 2025.

Wolpert D. H., Macready W. G., No Free Lunch Theorems for Optimization, IEEE Transactions on Evolutionary Computation 1(1), 67–82, 1997.

Xu Y., Zhong R., Cao Y., Zhang C., Yu J., Symbiotic Mechanism-based Honey Badger Algorithm for Continuous Optimization, Cluster Computing 28(2), 2024.

Xu Y., Zhong R., Zhang C., Yu J., Crested Ibis Algorithm and Its Application in Human-Powered Aircraft Design, Knowledge-Based Systems 310, 2025.

Yang B., Zhang X., Yu T., Shu H., Fang Z., Grouped Grey Wolf Optimizer for Maximum Power Point Tracking of Doubly-Fed Induction Generator based Wind Turbine, Energy Conversion and Management 133, 427–443, 2017.

Yapici H., Cetinkaya N., A New Meta-Heuristic Optimizer: Pathfinder Algorithm, Applied Soft Computing Journal 78, 545–568, 2019.

Zhang S., Zhou Y., Li Z., Pan W., Grey Wolf Optimizer for Unmanned Combat Aerial Vehicle Path Planning, Advances in Engineering Software 99, 121–136, 2016.

Zhang S., Zhou Y., Grey Wolf Optimizer based on Powell Local Optimization Method for Clustering Analysis, Discrete Dynamics in Nature and Society 481360, 2015.

Zhong R., Yu J., Zhang C., Munetomo M., SRIME: A Strengthened RIME with Latin Hypercube Sampling and Embedded Distance-based Selection for Engineering Optimization Problems, Neural Computing and Applications 36(12), 2024.

Zhong R., Hussien A. G., Yu J., Munetomo M., LLMOA: A Novel Large Language Model Assisted Hyper-Heuristic Optimization Algorithm, Advanced Engineering Informatics 64, 2025.

Zhong R., Wang Z., Hussien A. G., Houssein E. H., Al-Shourbaji I., Elseify M. A., Yu J., Success History Adaptive Competitive Swarm Optimizer With Linear Population Reduction: Performance Benchmarking and Application in Eye Disease Detection, Computers in Biology and Medicine 186, 2025.

Zhong R., Zhang C., Yu J., Chaotic Vegetation Evolution: Leveraging Multiple Seeding Strategies and a Mutation Module for Global Optimization Problems, Evolutionary Intelligence 17(4), 2024.

Zhong R., Zhang C., Yu J., Cooperative Coati Optimization Algorithm with Transfer Functions for Feature Selection and Knapsack Problems, Knowledge and Information Systems, 66(11), 2024.

Zhou J., Zhu W., Zheng Y., Li C., Precise Equivalent Model of Small Hydro Generator Cluster and Its Parameter Identification using Improved Grey Wolf Optimiser, IET Generation, Transmission and Distribution 10(9), 2016.