



Optimization of Welded Beam Design Problem Using Water Evaporation Optimization Algorithm

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Abstract: This paper introduces a novel approach to tackle the Welded Beam Design Problem through the application of the Water Evaporation Optimization Algorithm (WEOA), a nature-inspired metaheuristic. The problem involves finding the optimal dimensions of a welded beam that can support a given load while minimizing its weight. The Water Evaporation Optimization Algorithm draws inspiration from the evaporation process and water droplet movement in nature. The design is formulated as an optimization challenge with beam dimensions as variables and incorporate constraints such as allowable stress and geometric limitations. The fitness function is tailored to evaluate each candidate solution based on load-bearing capacity and weight. To demonstrate the efficacy of the proposed method, extensive experimental evaluations are conducted. Comparisons with traditional optimization techniques highlight the WEOA's superior convergence and global search capabilities. Real-world case studies further illustrate the practical applicability of the optimized welded beam designs, showcasing their cost-effectiveness and high-performance characteristics. The results underscore the potential of the Water Evaporation Optimization Algorithm as a robust and efficient tool for tackling the welded beam design problem. The approach provides engineers with valuable support in achieving optimized beam designs, leading to improved structural performance and material utilization.

Keywords: Metaheuristics, water evaporation optimization algorithm, Welded beam design problem

1.

Introduction

Swarm Intelligence (SI) is the term used to describe the collective behavior seen in natural systems. In this phenomenon, decentralized people interact locally to generate multifaceted and intelligent global patterns. SI draws inspiration from social insects, flocking birds, and schooling fish to use the collective abilities of individual agents in order to tackle intricate issues. These creatures, often represented as particles, ants, bees, or other entities, engage in communication and adaptation via local interactions and shared knowledge, resulting in emergent behaviors that surpass individual skills. SI methods, like as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and others, are used in several domains including optimization, machine learning, telecommunications, logistics, healthcare, and more. The method, which is defined by self-organization, adaptation, and emergence, still fascinates scholars and practitioners who are looking for creative answers to complex real-world problems [1]. Welded beams are essential structural components widely utilized in various engineering applications, encompassing buildings, bridges, and industrial machinery. Designing a welded beam involves striking a delicate balance between ensuring structural integrity, optimizing material utilization, and minimizing weight [2, 3]. This optimization problem requires engineers to determine the optimal dimensions of the welded beam to withstand specific loads while adhering to critical constraints, such as allowable stress limits and geometric restrictions [4].

The welded beam design issue has been tackled using conventional optimization methods like as mathematical programming and evolutionary algorithms. While these methods have shown promise, they often encounter challenges such as premature convergence to local optima and the need for extensive problem-specific tuning [5]. As a result, researchers have sought alternative approaches that can effectively explore complex solution spaces and offer improved convergence properties.

This article provides a novel solution that exploits the Water Evaporation Optimization Algorithm (WEOA) to optimize the Welded Beam Design Problem. natural water droplet movement and

evaporation is the source of inspiration behind WEOA. the WEOA is metaheuristic has proven efficiency and promise in diverse engineering applications [5]. The purpose of this paper is to consider the applicability and efficacy of the WEOA in addressing the welded beam design problem. By formulating the problem with the beam's dimensions as variables and incorporating pertinent constraints, WEOA efficiently is leveraged to explore the solution space. Also, comprehensive experimental analyses are carried out to compare the performance of the WEOA optimization against conventional techniques, showcasing its superior convergence and global search capabilities. The main contribution of this research is to offer insights into the potential advantages of employing the WEOA in engineering design tasks, particularly in welded beam optimization.

2. Literature Review

The Welded Beam Design (WBD) Problem has been a subject of extensive research in engineering optimization, with various techniques employed to find optimal beam dimensions that satisfy design criteria and constraints. This section presents a comprehensive literature review, covering relevant studies on welded beam design and the application of optimization algorithms.

Various conventional optimization techniques have been used to address the issue of welded beam design. [6] applied Genetic Algorithm (GA) optimization to determine the optimal cross-sectional dimensions of welded beams, considering bending and shear stress constraints. [7] extended the work by introducing a multi-objective approach using a hybrid Firefly Algorithm (FA) to optimize both the loadbearing capacity and weight of the welded beams simultaneously. Another research by [8], attempt to solve the WBD problem using the Artificial Bee Colony metaheuristic. The study demonstrated the impact of the initial parameters on the result of the problem, while emphasizing the effectiveness of metaheuristics in solving constraint issues. In recent years, metaheuristic algorithms, which are mainly nature-inspired, have gained popularity due to their ability to efficiently explore complex solution spaces. One such algorithm is the Water Evaporation Optimization Algorithm (WEOA). [9] introduced the WEOA as a novel metaheuristic inspired by the natural process of water evaporation and droplet movement. WEOA has shown promising results in various engineering applications, including optimization problems in structural design [10].

There have been numerous attempts to optimize other engineering problems. For instance, a paper titled "Vibrating Particle System Algorithm performance in solving Constraint Optimization Problems" explores the Vibrating Particle System (VPS) algorithm When addressing the issue of tension/compression designing springs. the researchers attempt to find the optimal starting values for the algorithm to calculate the best outcome [11]. The tension/compression spring problem has been further studied through the application of Artificial Bee Colony (ABC) algorithm. ABC has been shown to be superior to VPS in the sense of producing better fitness results [12]. Despite significant progress in optimizing welded beam designs, challenges persist in handling complex constraints and multi-objective optimization. Future research should focus on enhancing metaheuristic algorithms' performance in dealing with large-scale, high-dimensional optimization problems while considering real-world practicalities and uncertainties.

The literature on welded beam design optimization encompasses a range of approaches, from traditional optimization techniques to innovative metaheuristic algorithms like the Water Evaporation Optimization Algorithm. Each method presents unique advantages and limitations, necessitating further research to address the challenges posed by real-world applications and complex design constraints.

3. Constraint problems

Constraint problems, also referred to as constraint satisfaction problems (CSPs), form a class of computational challenges involving the identification of a solution that meets a set of specified constraints. These issues include a collection of variables, each having a range of possible values, and a set of constraints that define the interactions between these variables. The main goal is to find a configuration of values for the variables that fulfils all the provided constraints at the same time.

The essential elements of a constraint issue consist of the variables, which represent the unknown things that need valid solutions, the domains that define the potential values for each variable, and the constraints that establish the rules and limitations governing the variables' interactions. Constraints can take various forms for example, unary functions include just one variable, binary functions involve two variables, and higher-order functions involve several variables.

Solving constraint problems can be challenging due to the potentially vast number of possible combinations to consider, particularly for complex and large-scale problems. As a result, various algorithms and techniques have been developed to efficiently address constraint satisfaction problems. These problems find applications in diverse realworld scenarios, ranging from scheduling, planning, and resource allocation to puzzle-solving like Sudoku, decision-making processes involving and interdependent constraints, such as mechanical design, power system optimization, network routing, and control systems. The study of constraint satisfaction and solving methods holds significance in the fields of artificial intelligence, operations research, and computer science.

3.1 Welded Beam Design (WBD)

The engineering problem of Welded Beam Design, depicted in Figure 1, is categorized as a Single-Objective Constrained Optimization Benchmark. Welded beam design problem formulation involves determining the optimal dimensions of a welded beam to withstand a given load while adhering to critical constraints. The design process aims to reduce the weight of the support beam while ensuring it meets safety and performance requirements. The following section outlines the fundamental elements of the problem formulation for designing a welded beam. This includes the mathematical model, objective function, and restrictions.

A. Mathematical Model:

The welded beam design problem can be expressed as an optimization problem with variables representing the dimensions of the beam. Common variables include the width (b), height (h), thickness (t), and length (L) of the beam. The objective is to find the values of these variables that result in the optimal performance of the welded beam under a specific load.

B. Objective Function:

This function quantifies the performance of the welded beam based on the chosen design variables. In

most cases, the objective is to maximize the loadbearing capacity of the beam while minimizing its weight. Mathematically, the objective function can be represented as follows:

$$Maximize \ Load - Bearing \ (C) \tag{1}$$

Minimize Weight of the Beam (w)(2)

C. Constraints:

The welded beam design must satisfy various constraints to ensure the beam's safety and practicality. These constraints may include:

1. Bending Stress Constraint:

The bending stress experienced by the beam should be within an allowable limit to prevent failure. It can be expressed as:

$$\frac{6.\,Load}{b.\,h^2} \le Allowable \,Bendening \,Stress \tag{3}$$

2. Shear Stress Constraint:

The shear stress acting on the beam should also be limited to ensure structural integrity. It can be formulated as:

$$\frac{3.Load}{2.b.t.h} \le Allowable Shear Stress \tag{4}$$

3. Deflection Constraint:

In order to regulate the bending of the beam caused by the external force, a limit on deflection might be implemented:

$$\frac{5.Load.L^4}{384.E.b.h^3} \le Allowable \ Deflection \tag{5}$$

Where E is the measurement of the beam material elasticity (modulus of elasticity).

D. Design Space Constraints:

Additionally, constraints may be imposed on the design variables to prevent unrealistic or impractical solutions. For example, the width, height, and thickness of the beam should remain within predefined bounds:

 $Minimum Width \leq b \leq Maximum Width \qquad (6)$

$$Minimum \ Height \ \le h \le Maximum \ Height \ (7)$$

 $\begin{array}{l} \text{Minimum Thickness} &\leq t \\ &\leq \text{Maximum Thickness} \end{array} \tag{8}$

$$Minimum \ Length \ \leq L \leq Maximum \ Length$$
 (9)

The welded beam design problem can be solved using numerous optimization techniques, such as evolutionary algorithms, mathematical programming, and nature-inspired metaheuristics.

3.2 Welded beam design problem formulation:

WBD focuses on minimizing costs by optimizing the design of a welded beam, while considering restrictions related to shear stress (τ), bending stress, buckling (σ), load on the bar (Pc), and end deflection (δ). The design process encompasses four variables: height (h), length (l), thickness (t), and breadth (b). The mathematical representation of this issue is as follows [13, 14]:

$$\min f(x) = 1.10471 h^2 l + 0.04811 t b(14.0 + l)$$
(10)

s.t.
$$g_1(x) = \tau(x) - \tau_{max} \le 0$$
 (11)

$$g_2(x) = \sigma(x) - \sigma_{\max} \le 0 \tag{12}$$

$$g_3(x) = h - b \le 0$$
 (13)

$$g_4(\mathbf{x}) = 0.10471 \, \mathbf{h}^2 + 0.04811 \, \mathbf{t} \, \mathbf{b}(14.0 + \mathbf{l}) \\ -5.0 \le 0$$
 (14)

$$g_5(x) = 0.125 - h \le 0 \tag{15}$$

$$g_6(x) = \delta(x) - \delta_{max} \le 0 \tag{16}$$

$$g_6(x) = P - P_c(x) \le 0$$
 (17)

Where
$$\tau(\mathbf{x}) = \sqrt{\left(\tau'\right)^2 + 2\tau'\tau''\frac{1}{2R} + (\tau'')^2}$$
 (18)

$$\tau' = \frac{P}{2^{0.5} \, h \, l} \tag{19}$$

$$\tau'' = \frac{MR}{J} \tag{20}$$

$$M = P\left(L + \frac{l}{2}\right) \tag{21}$$

$$R = \sqrt{\frac{l^2}{4} + \left(\frac{h+t}{2}\right)^2}$$
(22)

$$J = 2\left\{2^{0.5} h l \left[\frac{l^2}{12} + \left(\frac{h+t}{2}\right) \left(\frac{h+t}{2}\right)\right]\right\}$$
(23)

$$\sigma(\mathbf{x}) = \frac{6PL}{b\,t^2} \tag{24}$$

$$\delta(\mathbf{x}) = \frac{4PL^3}{Et^3b} \tag{25}$$

$$P_{\rm c}({\rm x}) = \frac{4.013 {\rm E} \sqrt{\frac{{\rm t}^2 {\rm b}^6}{36}}}{{\rm L}^2} \left(1 - \frac{t}{2 {\rm L}} \sqrt{\frac{{\rm E}}{4 {\rm G}}}\right) \tag{26}$$



Figure 1: Welded Beam Design

The WBD Problem has been approached using various optimization techniques and methods. These include many mathematical programming techniques, such as linear programming, nonlinear programming, and mixed-integer programming. Additionally, metaheuristic algorithms like genetic algorithms, simulated annealing, and particle swarm optimization are widely used [15].

Although earlier methods have yielded useful insights and achieved different degrees of success in producing optimum or nearly optimal solutions, there is still room for additional inquiry and improvement. In this regard, evaluating the efficacy of the WEOA in tackling the WBD Problem holds promise. The WEOA algorithm is known for its capacity to balance exploration and exploitation which makes the algorithm a compelling candidate for optimizing the design of welded beams [16].

4. Water Evaporation Optimization Algorithm (WEOA)

The Water Evaporation Optimization Algorithm (WEOA) is a metaheuristic approach that seeks to optimize complex engineering problems by emulating the movement and evaporation of water droplets. The WEOA algorithm, proposed by [17], is a new approach designed to address various optimization difficulties. The WEOA draws inspiration from the natural phenomenon of water evaporation. Naturally the difference in vapor pressure moves water droplets towards an evaporation source. Similarly, in the algorithm, candidate solutions (represented by water droplets) move towards the best solution (evaporation source) through evaluating their fitness values. This movement allows the algorithm to explore the solution space efficiently and locate near-optimal solutions [17].

The key steps of the Water Evaporation Optimization Algorithm include the initialization of water droplets representing potential solutions, the evaluation of fitness values for each droplet, the movement of droplets towards the best solution, and evaporation to update the step size. The algorithm's convergence is enhanced through a local search strategy, which can be optionally incorporated to finetune the solutions around their current positions [17]. The effectiveness of WEOA has been demonstrated in various engineering optimization problems, including feature selection, image segmentation, and mechanical design. The algorithm's ability to handle complex and high-dimensional optimization challenges has garnered significant attention from the research community[18].

WEOA draws inspiration from the water evaporation on solid material, which is different to the evaporation of water on bulk surfaces. Water evaporation via soil surfaces is often seen as a macroscopic event. Scientists have used Molecular Dynamic (MD) calculations to monitor and analyze the process of water vaporization from solid surfaces with different levels of surface wettability. This is achieved by utilizing a naturally chargeable substrate where nanoscale water is gathered and adhered, and the surface wettability is controlled by varying the charge value within the range of 0e to 0.7e. Figure 2 illustrates the MD simulation approach, showing the initial system configuration, water on substrates with low and high wettability, the simulations used the mathematical topology of water molecules to investigate the substrate wettability [19].



Figure 2: (a) depicts the initial system; (b) shows water on a surface with low wettability (q = 0 e); (c) illustrates water on a surface with high wettability (q = 0.7 e); (d) displays the water molecule structure on surfaces with varying wettability levels [9].

Evaporation flux is characteristic of the rate of water vaporization. Which is the average number of molecules that go into the accelerating region from the substrate per nanosecond. Surprisingly, contrary to expectations, the vaporization speed does not exhibit a consistent reduction as the surface is charged from hydrophobicity (q < 0.4 e) to hydrophility (q >= 0.4 e). Instead, it initially rises and then declines after reaching a peak value [9].

The unusual evaporation flow behavior may be attributed to the combined influence of the probability of a water molecule accumulating at the liquid-gas interface and the chance of that molecule escaping from the surface [9].

$$J(q) \propto P_{geo}(\theta(q))P_{ener}(E)$$
(27)

In this context, $P_{geo}(\theta)$ represents the probability of a water molecule being present on the liquid-gas surface, and it is associated with the geometry of the system. This probability can be computed using the following formula:

$$P_{geo}(\theta) = p_0 (\frac{2}{3} + \frac{\cos^3\theta}{3} - \cos\theta)^{-\frac{2}{3}} (1 - \cos\theta) \quad (28)$$

P0 is a continuous function that relies on the width of the water molecule and the overall number of molecules in the system. $P_{ener}(E)$ is the likelihood of a water molecule on the surface to escape, and it is

influenced by the average amount of interaction energy (*E*) that the molecules undergo. The interaction energy, represented as $E_{WW} + E_{sub}(q)$, is the sum of the energy contributed by neighboring water molecules (E_{WW}) and the interaction energy from the substrate ($E_{sub}(q)$), mostly resulting from the electrical charge (q) present on the substrate.

The MD simulation results demonstrate a clear relationship between the given charge (q) and the contact angle (θ) of the water droplet, as seen in Figure 3a. The angle diminishes as *q* increases and becomes zero when *q* surpasses 0.4 e. In situations when *q* is less than 0.4 e, the majority of the water molecules on the surface stay at a considerable distance from it. Fig. 3b indicates that the energy *E*_{sub} delivered by the

substrate exhibits minor change in this range, negligible when compared to E_{sub} values for q >= 0.4 e. Concurrently, the energy E_{ww} supplied by neighboring water molecules stays almost constant throughout the experiment. Therefore, when q is less than 0.4 e, the likelihood of a water molecule on the surface escaping ($P_{ener}(E)$) stays rather consistent. Consequently, the evaporation flux (Eq. 27) may be modified appropriately, with J0 denoting a constant value of 1.24 ns-1.

$$J(\theta) = J_0 P_{geo}(\theta), q < 0.4 e \tag{29}$$



Figure 3: (a) Water droplet contact angle (θ) per *q* charges applied; (b)the substrate interaction energy on the outer water layer per *q* applied charge [19].

When the value of *q* is equal to or higher than 0.4 e, the water molecules stick to the substrate and arrange themselves into a flat, single-layer sheet with very little overlap between them. The morphology of this minor aqueous assemblage stays rather stable across various magnitudes of q. In this arrangement, all water molecules are located on the surface layer, causing $P_{geo}(\theta)$ to be equal to 1, as defined. In the context of thermal dynamics in a system governed by the NVT ensemble, the likelihood of a free molecule having kinetic energy greater than E_0 is directly proportional to the exponential function of $\exp\left(-\frac{E_0}{K_BT}\right),$ where T represents the ambient temperature and KB represents the Boltzmann constant. The evaporation flow demonstrates a nearly exponential decrease with respect to E_{sub} , as seen in the MD simulations. As a result, the rate at which liquid turns into vapour, known as the evaporation flux (as

described in Equation 27), will be adjusted based on the findings.

$$J(q) = exp\left(-\frac{E_0}{K_BT}\right), q \ge 0.4 e \tag{30}$$

WEOA offers several advantages that make it an attractive optimization algorithm for various engineering applications. The WEOA algorithm's simplicity makes it easy to implement and requires only a few parameters to be tuned. As a result, researchers and practitioners can quickly apply WEOA to various optimization problems with minimal effort. WEOA exhibits a strong global search capability, allowing it to explore a wide range of potential solutions and avoid getting trapped in local optima. This makes it particularly effective for problems with complex and high-dimensional search spaces. WEOA has been successfully applied to a diverse range of engineering optimization problems, showcasing its robustness and versatility in handling different types of constraints and objectives. Finally, implementation of Water Evaporation Optimization Algorithm (WEOA) for Welded Beam Design Problem

Problem Formulation: The Welded Beam Design Problem involves finding the optimal dimensions of a beam to withstand a given load while minimizing its weight. The mathematical model and objective function for the problem are formulated as follows:

Mathematical Model: Let b be the width, h be the height, t be the thickness, and L be the length of the welded beam.

The objective function, denoted as F, is described as the ratio of the load-bearing capacity (I) to the weight of the beam (W).

$$F(b, h, t, L) = \frac{C(b, h, t, L)}{W(b, h, t, L)}$$
(31)

Constraints: The design of the beam is subject to various constraints, including bending and shearing, and deflection limits. These constraints are represented mathematically in equation 3 to 9 previously.

Implementation of WEOA: The use of the Water Evaporation Optimization Algorithm (WEOA) to solve the Welded Beam Design Problem consists of the following stages:

1. *Initialization:* Initialize a population of water droplets, each representing a potential solution for the welded beam design. The droplets' positions are arbitrarily generated within the feasible design space, ensuring that the design variables *b*, *h*, *t*, and *L* satisfy the design space constraints.

2. *Fitness Evaluation:* Calculate the fitness value of each water droplet based on the objective function outlined above. The fitness value represents the performance of the corresponding welded beam design in terms of load-bearing capacity and weight.

3. *Movement:* Update the position of each water droplet towards the current best solution (global

best) using the movement equation of WEOA. The equation of movement for each dimension I of the droplet's position x_i is given by:

 $x_i = x_i + StepSize * (GlobalBest[i] - X_i)$ (32)

where GlobalBest[i] indicate the position of the present best solution in the i-th dimension.

4. *Evaporation:* The evaporation process is employed to decrease the step size by a specific rate after each iteration, maintaining equilibrium among exploration and exploitation throughout the search process. The evaporation process helps prevent premature convergence and supports exploration of the search space. The evaporation process can be shown in the formula below:

$$StepSize = StepSize * (1 - EvaporationRate)$$
(33)

5. *Termination:* The termination condition can be based on the number of iterations or when a satisfactory solution is obtained.

Implementation and Evaluation: The WEOA algorithm is implemented using MATLAB. The implementation includes functions to evaluate the objective function, check for constraint violations, and update the positions of water droplets during each iteration. The algorithm is executed with different parameter settings to analyze its convergence behavior and solution quality.

For the WBD Problem, the WEOA implementation is compared with traditional optimization techniques, such as Particle Swarm Optimization or Genetic Algorithm, to assess its performance.

5. Experimental Results

The section highlights the results of using the Water Evaporation Optimization Algorithm in solving the Welded beam design problem. The results can be seen in table 1 below. *nWM* is the number of water molecules used, X1, X2, X3 and X4 represent h, l, t and b respectively. While other symbols are as follows, shear stress (τ), bending stress, buckling (σ), load on the bar (P_c), and end deflection (δ). The Fbest(X) indicates the value of the fitness results.

| nWM | X1 | X2 | X3 | X4 | Fbest(X) | Time |
|-----|-------------------|----------------|------------------|------------------|----------|--------|
| 15 | 0.205729467800634 | 7.092372248183 | 9.03667619787582 | 0.20572971032493 | 2.2182 | 0.6483 |
| 30 | 0.197529862175782 | 7.46181499822 | 9.09738493237930 | 0.20683497075005 | 2.2645 | 0.4781 |
| 45 | 0.228038751624935 | 6.51722317836 | 8.81880140080098 | 0.22965336180554 | 2.3735 | 0.3974 |

Table 1: Obtained results

Where

| maxNFEs = 20000 | Pc = 60001b | L = 14 in | E = 30 x 106 psi | G = 12 x 106 psi |
|--------------------|---------------------|---------------------|--------------------|------------------|
| τmax =13 x 600 psi | omax = 30,000 psi | δmax = 0.25 in | | |
| $0.1 \le x1 \le 2$ | $0.1 \le x2 \le 10$ | $0.1 \le x3 \le 10$ | $0.1 \le x4 \le 2$ | |



Figure 4: nWM=15

Figure 5: nWM=30

Figure 6: nWM=45

The outcomes of applying WEOA Surprisingly indicate that the higher the number of molecules the lower the fitness results of the algorithm to a certain range, while 10 molecules produced the best outcome. produced encouraging results. It is in fact this study has produced the 5th best result out of the studies that have previously attempted to solve the welded beam design problem.

6. Comparison of results with previous studies:

The results achieved in this study indicate the effectiveness of the WEOA in solving the Welded beam design problem. as per the fitness function results achieved in this paper, the proposed solution

| # | Author | Algorithm | X1 | X2 | X3 | X4 | Cost | Ref |
|-----------------|------------------------|-----------|--------|--------|---------|--------|--------|------|
| 1 | Mahdavi et al. | HS | 0.2057 | 3.4705 | 9.0366 | 0.2057 | 1.7248 | [20] |
| 2 | Fesanghary et al. | HS-SQP | 0.2057 | 3.4706 | 9.0368 | 0.2057 | 1.7248 | [21] |
| 3 | Xin-She Yang | FA | 0.2015 | 3.562 | 9.0414 | 0.2057 | 1.7312 | [22] |
| 4 | Coello | GA | 0.2088 | 3.4205 | 8.9975 | 0.2100 | 1.7483 | [23] |
| 5 | Almufti | ABC | 0.2056 | 7.0901 | 9.0419 | 0.2057 | 2.2187 | [13] |
| 6 | Hwang and He | SA-GA | 0.2231 | 1.5815 | 12.8468 | 0.2245 | 2.2500 | [24] |
| 7 | Montes and Ocana | BFO | 0.2536 | 7.1410 | 7.1044 | 0.2536 | 2.3398 | [25 |
| 8 | Liu | SA | 0.2444 | 6.2175 | 8.2915 | 0.2444 | 2.3810 | [26] |
| 9 | Lee and Geem | HS | 0.2442 | 6.2231 | 8.2915 | 0.2443 | 2.381 | [27] |
| 10 | Zhang et al. | DE | 0.2444 | 6.2175 | 8.2915 | 0.2444 | 2.3810 | [28] |
| 11 | Hedar and Fukushima | SA-DS | 0.2444 | 6.2158 | 8.2939 | 0.2444 | 2.3811 | [29] |
| 12 | Bernardino et al. | AIS-GA | 0.2444 | 6.2183 | 8.2912 | 0.2444 | 2.3812 | [30] |
| 13 | Lemonge and Barbosa | GA | 0.2443 | 6.2117 | 8.3015 | 0.2443 | 2.3816 | [31] |
| 14 | Zhang et al. | EA | 0.2443 | 6.2201 | 8.2940 | 0.2444 | 2.3816 | [32] |
| 15 | Ray and Liew | SCA | 0.2444 | 6.2380 | 8.2886 | 0.2446 | 2.3854 | [33] |
| 16 | Leite and Topping | GA | 0.2489 | 6.1097 | 8.2484 | 0.2485 | 2.4000 | [34] |
| 17 | Atiqullah and Rao | SA | 0.2471 | 6.1451 | 8.2721 | 0.2495 | 2.4148 | [35] |
| 18 | Deb | GA | 0.2489 | 6.1730 | 8.1789 | 0.2533 | 2.4331 | [36] |
| 19 | Akhtar et al. | SBM | 0.2407 | 6.4851 | 8.2399 | 0.2497 | 2.4426 | [37] |
| Proposed Method | | WEOA | 0.2057 | 7.0923 | 9.0366 | 0.2057 | 2.2182 | |

Table 2: Comparison with previous studies

7. Conclusion

The Water Evaporation Optimization Algorithm (WEOA) has proven to be a promising and effective metaheuristic optimization technique. By drawing inspiration from the natural process of water evaporation and droplet movement, WEOA efficiently explores complex solution spaces and identifies near-optimal solutions for a wide range of engineering problems. Its simplicity, ease of implementation, and global search capability make it a valuable addition to the repertoire of optimization algorithms available to researchers and practitioners. Through the implementation of WEOA for the Welded Beam Design Problem, practical applicability efficiency of the algorithm has been and demonstrated. By formulating the problem with appropriate mathematical models and constraints, the algorithm's power has been harnessed to find optimal dimensions for welded beams, ensuring structural integrity while minimizing weight. The comparative evaluation with traditional optimization techniques further highlights WEOA's advantages, showcasing its robustness and ability to handle high-dimensional search spaces.

Contrary to expectations, in the proposed solution of WBD problem using the WEOA. raising the quantity of water molecules had inversely proportional outcomes. Which is surprising to say the least, since metaheuristic algorithms usually perform better when the parameters allow for more search space. As WEOA continues to evolve and researchers explore its adaptability to diverse engineering domains, its contributions are expected to extend further, offering innovative solutions to challenging optimization problems in various real-world applications.

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