IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received January 7, 2022, accepted January 23, 2022, date of publication January 27, 2022, date of current version February 14, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3146374

Dynamic Arithmetic Optimization Algorithm for Truss Optimization Under Natural Frequency Constraints

NIMA KHODADADI[1], (Member, IEEE), VACLAV SNASEL[2], (Senior Member, IEEE), AND SEYEDALI MIRJALILI[3,4], (Senior Member, IEEE)

[1]Department of Civil Engineering, Iran University of Science and Technology, Narmak, Tehran 13114-16846, Iran
[2]Department of Computer Science, Faculty of Electrical Engineering and Computer Science, VŠB—Technical University of Ostrava, 708 00 Ostrava, Czech Republic
[3]Centre for Artificial Intelligence Research and Optimization, Torrens University Australia, Adelaide, SA 5000, Australia
[4]Yonsei Frontier Laboratory, Yonsei University, Seoul 03722, South Korea

Corresponding author: Seyedali Mirjalili (ali.mirjalili@gmail.com)

ABSTRACT Metaheuristic algorithms have successfully been used to solve any type of optimization problem in the field of structural engineering. The newly proposed Arithmetic Optimization Algorithm (AOA) has recently been presented for mathematical problems. The AOA is a metaheuristic that uses the main arithmetic operators' distribution behavior, such as multiplication, division, subtraction, and addition in mathematics. In this paper, a dynamic version of the arithmetic optimization algorithm (DAOA) is presented. During an optimization process, a new candidate solution change to regulate exploration and exploitation in a dynamic version in each iteration. The most remarkable attribute of DAOA is that it does not need to make any effort to preliminary fine-tuning parameters relative to the most present metaheuristic. Also, the new accelerator functions are added for a better search phase. To evaluate the performance of both the AOA and its dynamic version, minimizing the weight of several truss structures under frequency bound is tested. These algorithms ' efficiency is obtained by five classical engineering problems and optimizing different truss structures under various loading conditions and limitations.

INDEX TERMS Dynamic arithmetic optimization algorithm; DAOA, frequency constraints, optimal design, truss structures, optimization, benchmark.

I. INTRODUCTION

Various metaheuristic optimization techniques for almost any engineering problem have been created in the past few decades. These algorithms discover the search area in a pseudo-random method complying with some motivating principles and without demanding gradient. Metaheuristic algorithms have lately been popular in a variety of fields because they are more efficient, need less computing capacity, and take less time to implement than deterministic algorithms. To get the best outcomes, simple principles are needed, and transplants are carried out in a multitude of areas. Local optimality can be avoided by using random elements in meta-heuristic algorithms, which allow the algorithm to search for the best solution inside the search area, thus preventing it from becoming optimal locally. Specific gradient descent algorithms are more useful in using gradient information than stochastic algorithms in direct and straightforward problems. Indeed, the convergence rate of metaheuristic algorithms will be far below the gradient descent algorithms and may be considered a disadvantage [1].

Meta-heuristic algorithms, which are used to find better answers for optimization problems, are typically based on human, natural, physical, and art phenomena. Under actual circumstances, the solution space of many issues is endless or usually unlimited. By traversing the solution space in the current situation, it might be impossible to discover optimal solutions. Metaheuristic algorithms detect the almost optimum solution of the problem by randomly detecting the significant solution area in one method to identify or create much better solutions for the problem of optimization under minimal circumstances or computational capacity [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Gustavo Olague.

Genetic Algorithm (GA) [3], Particle Swarm Optimization (PSO) [4], Ant Colony Optimization (ACO) [5], Imperialist Competitive Algorithm (ICA) [6], Grey Wolf Optimizer (GWO) [7], Whale Optimization Algorithm (WOA) [8], Krill Herd Algorithm (KH) [9], Bat Algorithm (BA) [10], Human Mental Search (HMS) [11] and Teaching-Learning Based Optimization (TLBO) [12] are some of the well-formulated metaheuristic optimization algorithms based on the social behavior of animals or human features alongside the application of these algorithms in different fields [13]–[17].

Gravitational Search Algorithm (GSA) [18], Charged System Search (CSS) [19], Big-Bang Big Crunch (BB-BC) [20], Stochastic Paint Optimizer (SPO) [21], Simulated Annealing (SA) [22], Harmony Search (HS) [23] and Colliding Bodies Optimization (CBO) [24] are inspired by art, physical and natural phenomena.

The optimization of trusses has been a difficult subject in structural engineering in the last few decades. There were a number of meta-heuristic techniques tested for optimizing the structures' size and layout: Genetic algorithm (GA) [25], Particle Swarm Optimization (PSO) [26], School-Based Optimization (SBO) [27], Symbiotic Bodies Optimization (SBO) [28], Dynamic Water Strider Algorithm (DWSA) [29], Hybrid Invasive Weed Optimization-Shuffled Frog-leaping Algorithm (IWO-SFLA) [30], Cuckoo Search Algorithm (CS) [31].

Natural frequency is a critical criterion provided based on knowledge of structural dynamics. The natural frequencies of a structure have a significant impact on its performance. The optimal design of trusses based on dynamic behavior is a demanding research area. In other words, natural frequencies give vital information on the dynamic behavior of structures. In addition, optimization of trusses based on frequency constraints has seen many factors to consider in the past ten years. An important practical concern is to increase the truss's dynamic behavior by considering its natural frequencies. This criterion must be controlled to prevent the resonance phenomenon and improve the structural performance. Lightweight structures are very important in engineering. When it comes to optimizing trusses, mass minimization conflicts with frequency constraints and also increases the complexity of the problem. As a result, an effective optimization technique is required for the design of trusses based on primary frequency constraints, and academics are taking proactive steps to improve their understanding of this element.

Bellagamba and Yang [32] investigated the truss optimization with frequency constraints for the first time, and then many researchers examined this research area. A bi-factor algorithm was developed for these structures by Lin *et al.* [33]. Wei *et al.* [34] presented a parallel genetic algorithm. Kaveh and Zolghadr suggested charged system search and enhanced CSS [35], democratic particle swarm optimization (DPSO) [36], and tug of war optimization (TWO) [37]. Pholdee and Bureerat [38] tested various metaheuristic algorithms. Tejani *et al.* [28] improved symbiotic organisms search (ISOS) for truss structures with frequency bound. Multi-class teaching learning-based algorithm [39] was applied for truss structures subjected to frequency constraints.

All these researches confirmed stochastic optimization algorithms' efficiency in managing many problems when solving structure design troubles. In the optimization field, there is no technique to solve all optimization problems, according to the no free lunch (NFL) theorem [40]. As a result, a new algorithm that has been modified will be able to handle a particular set of problems better than the existing algorithms. At the same time, they still carry out equal, taking into consideration all optimization problems. This motivated our attempts to boost the efficiency of the recently suggested arithmetic optimization algorithm (AOA) [41] and adjust it much better for structure design problems.

Laith Abualigah *et al.* [41] recently developed an arithmetic optimization algorithm for constraint and unconstrained optimization problems based on the mathematical model. Arithmetic is the mathematics branch that deals with numerical study with various operations. Adding, subtraction, multiplication, and division are the basic mathematical operations.

The Dynamic Arithmetic Optimization Algorithm (DAOA), a recently developed population-based meta-heuristic, is applied to structural design problems in this study. The motivation for this research is to use the AOA and DAOA for the optimal weight design of truss structures with frequency limitations for the first time in the literature. Two dynamic features have been successfully introduced in the basic version of AOA in order to increase its performance. Since no prior fine-tuning of parameters in connection to the most recent meta-heuristic is required, DAOA offers an advantage over other optimization algorithms.

This new algorithm provides a proper equilibrium between exploration and exploitation strategies that generate excellent accuracy along with swift convergence. All the results of optimizing distinct architectures are thoroughly analyzed and evaluated in detail. The structural weight with frequency constraints is used as an objective function to solve these challenges, and distinct and continuous areas are considered design variables.

The paper is arranged as follows: Section II presents the formulation of truss structures optimization. Section III and IV provide an extensive explanation of the arithmetic optimization algorithm (AOA) and its dynamic version (DAOA), respectively. Section V identifies the problem and discusses numerical findings. Finally, section VI provides the final observations.

II. FORMULATION OF TRUSS STRUCTURES OPTIMIZATION

Several natural frequency constraints are included in this section's formulation of truss structure optimization. Figure 1 depicts the flow chart for solving the truss optimization problem. Optimization of the truss structures suggests

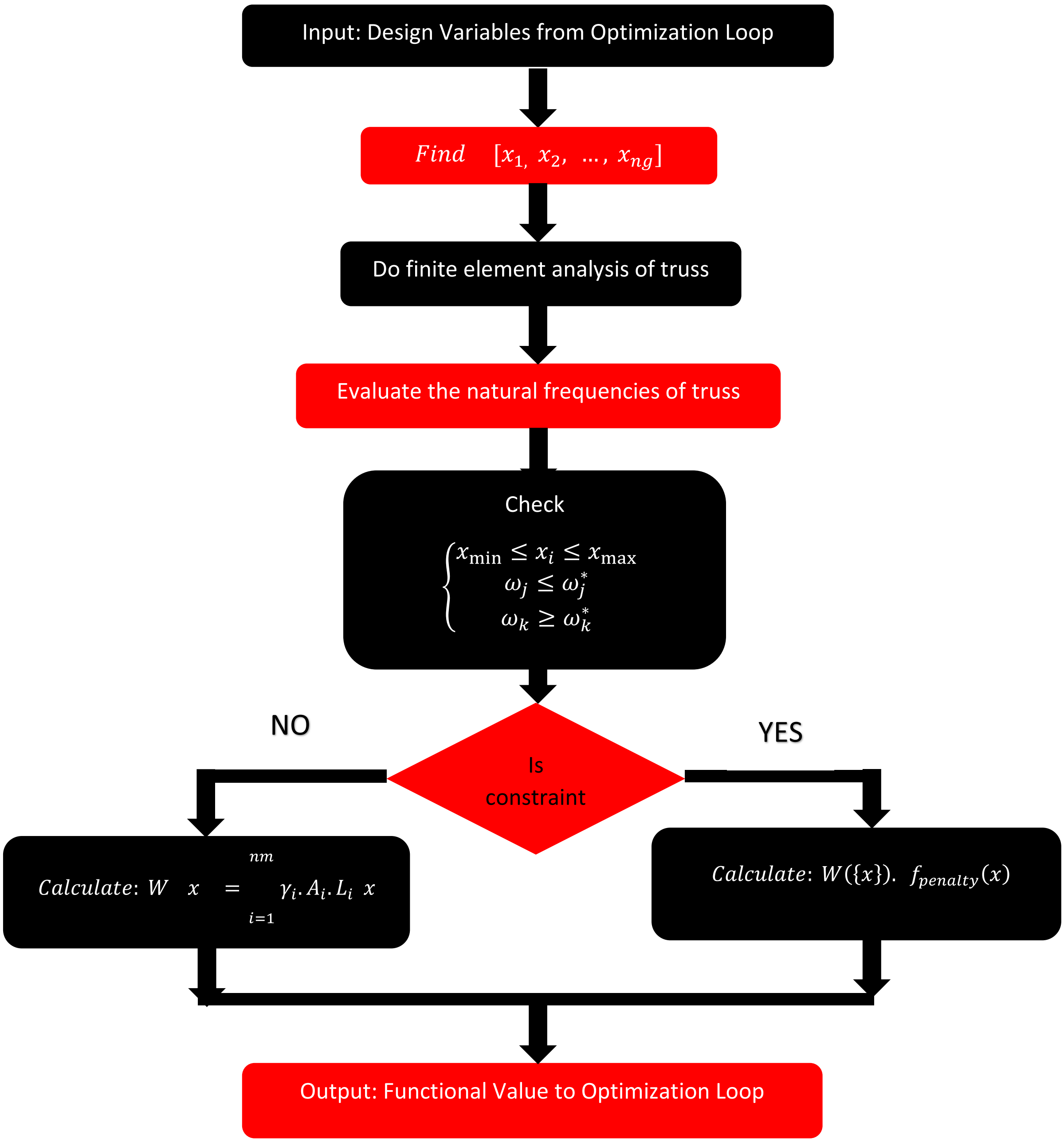

FIGURE 1. The flowchart of the truss optimization problem.

achieving the best possible cross-sectional (A_i) values, which reduce the weight (W) of construction. This minimum design has to satisfy the following requirements [36] additionally:

$$Find\ [x_1, x_2, \ldots, x_{ng}] \tag{1}$$

$$Minimize\ W(\{x\}) = \sum_{i=1}^{nm} \gamma_i.A_i.L_i(x) \tag{2}$$

$$Subjected\ to\ \begin{cases} x_{\min} \le x_i \le x_{\max} \\ \omega_j \le \omega_j^* \\ \omega_k \ge \omega_k^* \end{cases} \tag{3}$$

where $\{x\}$ presents the design variables, the number of design variables is defined by ng defines the variety of design variables, the structure weight is introduced by $W(\{x\})$ and the variety of structural members is specified by nm. In addition, the material density, member's length, the member's cross-sectional area for all components is shown as γ_i, L_i and x_i, respectively. The jth and kth natural frequency of the truss are defined by ω_j (ω_j^* is upper bound) and ω_k (ω_k^* is lower bound). The popular appropriate function for dealing with the restrictions as a result of the fundamental principle and also simplicity of application is revealed as follows:

$$f_{penalty}(x) = (1 + \varepsilon_1.\nu)^{\varepsilon_2},$$

$$\nu = \sum_{i=1}^{n} \max(0, \nu_i) \tag{4}$$

where ν is the total amount of the constraints violated and constants ε_1 and ε_2 are selected considering the exploration and the exploitation rate of the search space. In this case, ε_1 is set to 1, ε_2 is chosen to minimize penalties and to reduce cross-sections. ε_2 is initially set to 1.5 and then increased to 3 as the search progresses [42].

III. ARITHMETIC OPTIMIZATION ALGORITHM (AOA)

This algorithm was proposed in 2020 by Abualigah [41] using several mathematical equations and operators. Just like other metaheuristics, the AOA algorithm starts with a population of random solutions. In each iteration, the objective value of each solution gets calculated. There are two controlling parameters in this algorithm called MOA and MOP that should be updated prior to updating the position of solutions as follows:

$$MOA\,(t) = Min + t \times \left(\frac{Max - Min}{T}\right) \tag{5}$$

MOA(t) is the value of the function at tth iteration, t is the current iteration, T shows the maximum iteration, and *Max/Min* is the maximum and minimum values to bound MOA.

$$MOP\,(t) = 1 - \left(\frac{t}{T}\right)^{\frac{1}{\alpha}} \tag{6}$$

where math optimizer probability (MOP) is a coefficient, MOP(t) is the value of the function at tth iteration, T is the maximum number of iterations, t is the current iteration and α shows a controlling parameter.

After updating MOA and MOP, a random number is generated called r1 to switch between exploration and exploitation. For exploration, the following equation is used:

$$x_{i,j}\,(t+1) = \begin{cases} \dfrac{best\,(x_j)}{MOP + \epsilon} \cdot \left(UB_j - LB_j\right) .\mu + LB_j & if\ r2 < 0.5 \\ best\,(x_j) \times MOP \times \left(UB_j - LB_j\right) \times \mu + LB_j & if\ r2 \geq 0.5 \end{cases} \tag{7}$$

where t is the current iteration, μ is a controlling parameter, ϵ is a small number to avoid division by 0, and *r2* is a random number in [0,1].

For exploitation, the following equation is used:

$$x_{i,j}\,(t+1) = \begin{cases} best\,(x_j) - MOP \times \left(UB_j - LB_j\right) \times \mu + LB_j & if\ r3 < 0.5 \\ best\,(x_j) + MOP \times \left(UB_j - LB_j\right) \times \mu + LB_j & if\ r3 \geq 0.5 \end{cases} \tag{8}$$

where $x_i\,(t+1)$ indicates the ith solution in the next iteration, $x_{i,j}(t)$ indicates the jth position of the ith solution at the current iteration, and best(x_j) is the jth position in the best-obtained solution so far, t is the current iteration, μ is a controlling parameter, ϵ is a small number to avoid division by 0, and *r3* is a random number in [0,1]. In addition, the upper bound value and lower bound value of the jth position are described by UB_j and LB_j, respectively.

IV. DYNAMIC ARITHMETIC OPTIMIZATION ALGORITHM (DAOA)

Two dynamic characteristics with a new accelerator function are implemented in the basic arithmetic optimization algorithm version to improve this performance. The dynamic version, which controls the exploration and exploitation behavior, changes the candidate solutions and search phase during the optimization process. The most remarkable attribute of DAOA is that it does not need to make any effort to preliminary fine-tuning parameters relative to the most present metaheuristic. Algorithm. 1 shows the DAOA pseudo-code. These new dynamic features are discussed in the following section.

Algorithm 1 Pseudo-Code of DAOA

```
procedure Dynamic Arithmetic Optimization Algorithm
  Initial the Algorithm Parameters α, μ
  Create random values for initial positions
  while (t < maximum number of iterations) Do
  Evaluate fitness values for given solutions
  Find the best solution
  Update the DAF value using Eq. (9)
  Update the DCS value using Eq. (12)
  for i = 1: number of solutions Do
    for j = 1: number of positions Do
      Create random values between 0 and 1 for r1, r2, r3
        if r1 > DAF then exploration phase
          if r2 > 0.5 then update the solutions' positions
            Using first rule in Eq. (10)
          else
            Using second rule in Eq. (10)
          end if
        if r1 < DAF then exploitation phase
          if r3 > 0.5 then update the solutions' positions
            Using first rule in Eq. (11)
          else
            Using second rule in Eq. (11)
          end if
        end if
      end for
    end for
      t = t + 1
    end while
  Return best solution
end procedure
```

A. DYNAMIC ACCELERATED FUNCTION FOR DAOA

Dynamic accelerated function (DAF) in the arithmetic optimization algorithm dynamic plays a pivotal role in the search phase. In the AOA, one needs to adjust the Min and Max initial values of the accelerated function. It is better to have an algorithm without adjustable internal parameters since DAF is replaced with a new downward function. In the optimization algorithm, this modification factor is presented as follow:

$$DAF = \left(\frac{Iter_{max}}{Iter}\right)^{\alpha} \tag{9}$$

where $Iter$ describes the current number of iterations, $Iter_{max}$ is the maximum number of iterations, and α has the constant value. This function is decreased during every iteration in the algorithm.

B. DYNAMIC CANDIDATE SOLUTION FOR DAOA

In this section, the following dynamic features for candidate solutions in DAOA are introduced. The two main phases of metaheuristic algorithms are exploration and exploitation, which has a good balance between them is essential for the algorithm. In the proposed dynamic version to emphasize the exploration and exploitation, each solution renews its positions dynamically from the best-obtained solution during the optimization process. Dynamic candidate solution (DCS) function is added to Eq (10) and Eq (11) instead of Eq (7) and Eq (8) in the basic version, respectively:

$$x_{i,j}\left(C_{Iter}+1\right) = \begin{cases} best\left(x_j\right) \div (DCS+\epsilon) \times ((UB_j - LB_j) \times \mu + LB_j)), & r2 < 0.5 \\ best\left(x_j\right) \times DCS \times ((UB_j - LB_j) \times \mu + LB_j)), & Otherwise \end{cases} \tag{10}$$

$$x_{i,j}\left(C_{Iter}+1\right) = \begin{cases} best\left(x_j\right) - DCS \times ((UB_j - LB_j) \times \mu + LB_j)), & r3 < 0.5 \\ best\left(x_j\right) + DCS \times ((UB_j - LB_j) \times \mu + LB_j)), & Otherwise \end{cases} \tag{11}$$

where dynamic candidate solution (DCS) function is introduced due to the effect of the decreasing percentage in candidate solution and during every iteration, its value was decreased as follow:

$$DCS(0) = 1 - \sqrt{\frac{Iter}{Iter_{Max}}} \tag{12}$$

$$DCS\,(t+1) = DCS\,(t) \times 0.99 \tag{13}$$

Numerous search agents and iterations showed that using candidate solutions in DAOA considerably increased the speed of AOA convergence. As a result of these enhancements, solution quality is also improved. An algorithm's ability to operate with no parameters is generally seen as an advantage for metaheuristic algorithms. The distinction between DAOA and AOA is that DAOA employs dynamic functions, while the remaining approach is identical to the AOA algorithm described in the previous section. The DAOA algorithm benefits from adaptive parameters, so the number of parameters that should be tuned is at the minimum (population size and maximum iteration). This is opposed to the rival algorithms, which require parameter tunings for different problems. As one of the drawbacks of this algorithm, we can mention the adaptive mechanism based on the iteration counter and not fitness improvement.

V. NUMERICAL EXAMPLES

A. NUMERICAL EXAMPLES

The optimization technique is performed using the DAOA and AOA algorithms and assessed with four optimization instances of classical engineering problems and truss structures to satisfy this aim. The maximum number of function evaluations was also employed as the final condition in order to establish a fair comparison. Each problem is solved separately 20 times, and DAOA is used in the same number of analyses and representatives to compete fairly. In addition, the stated references provided the other control parameters for the comparative algorithms. The DAOA and its standard version are used in the same range of evaluations and representatives to compete fairly.

1) TENSION/COMPRESSION SPRING

One of the most common optimization problems is presented in Fig. 2 by Belegundu [43] and Arora [44]. The goal is to make the tension/compression spring as light as possible. There are other constraints (shear stress, frequency, and minimum deflection.) that must be met in order for this reduction to be successful.

$$\begin{aligned}
&\textbf{Consider } \vec{X} = [x_1, x_2, x_3] = [d, D, N] \\
&\textbf{Minimize } f_{cost}(\vec{X}) = (2 + x_3) \times x_2 x_1^2 \\
&\textbf{Subject to } g_1\left(\vec{X}\right) = 1 - \frac{x_3 x_2^3}{71785 x_1^4} \le 0 \\
&\quad g_2\left(\vec{X}\right) = \frac{4x_2^2 + x_2 x_1}{12566(x_2 x_1^3 - x_1^4)} + \frac{1}{5108 x_1^2} - 1 \le 0 \\
&\quad g_3\left(\vec{X}\right) = 1 - \frac{140.45 x_1}{x_2^2 x_3} \le 0 \\
&\quad g_4\left(\vec{X}\right) = \frac{x_1 + x_2}{1.5} - 1 \le 0 \\
&\quad g_6(\vec{X}) = \delta(\vec{X}) - \delta_{max} \\
&\quad g_7(\vec{X}) = P - P_c(\vec{X}) \le 0 \\
&\textbf{Variable Range } 0.05 \le x_1 \le 2, \quad 0.25 \le x_1 \le 1.3, \\
&\qquad 2 \le x_1 \le 15
\end{aligned} \tag{14}$$

FIGURE 2. Tension/compression spring.

TABLE 1. Statistical results of different algorithms for tension/compression spring.

Algorithm	Optimal values for variables			Optimal cost
	x_1=d	x_2=D	x_3=N	
DAOA	0.051689	0.35663	11.294103	0.012665
WCA [45]	0.05168	0.356522	11.30041	0.012665
BA [46]	0.05169	0.35673	11.2885	0.012665
DELC [47]	0.051689	0.356717	11.288965	0.012665
GWO [7]	0.05169	0.356737	11.28885	0.012666
HS [48]	0.051154	0.349871	12.076432	0.012670
PSO [49]	0.051728	0.357644	11.244543	0.012674
GA [50]	0.05148	0.351661	11.632201	0.012704
Belegundu [43]	0.053396	0.39918	14.25	0.012730
Arora [44]	0.05	0.3159	9.1854	0.012833
AOA	0.05000	0.310436	15.0000	0.013194

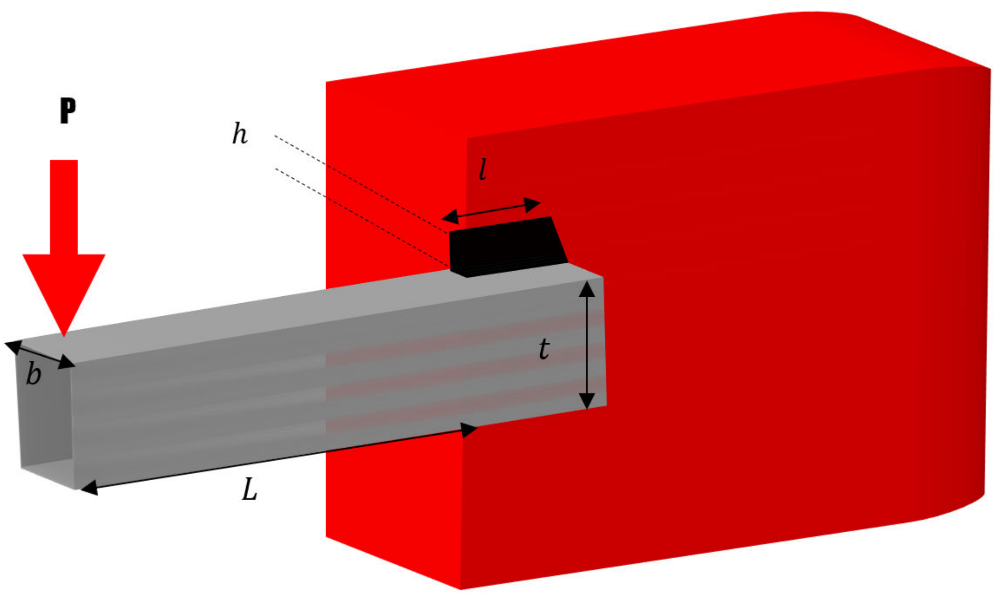

FIGURE 3. Welded beam.

The best result gained by DAOA is 4% lighter than that of AOA, and its solution obtained the 1st rank in terms of the best solution. In addition, the result and best variable values for different algorithms such as WCA [45], BA [46], DELC [47], GWO [7], HS [48], PSO [49], GA [50], Belegundu [43] and Arora [44] are shown in Table 1.

2) WELDED BEAM

Coello [50] suggested this benchmark design issue, and several researchers discussed it. The vertical force of the beam is shown in Fig. 3. The goal is to achieve a design that will have the minimum objective function. Seven stress, deflection, welding, and geometry constraints are present in the problem.

The formulation of this problem is given below:

$$\textbf{Consider } \vec{X} = [x_1, x_2, x_3, x_4] = [h, l, t, b]$$
$$\textbf{Minimize } f_{\text{cost}}(\vec{X}) = 1.10471x_1^2x_2 + 0.04811x_3x_4 (14.0 + x_2)$$
$$\textbf{Subjectto } g_1(\vec{X}) = \tau(\vec{X}) - \tau_{max}$$
$$g_2(\vec{X}) = \sigma(\vec{X}) - \sigma_{max}$$
$$g_3(\vec{X}) = x_1 - x_4 \leq 0$$
$$g_4(\vec{X}) = 0.10471x_1^2 + 0.04811x_3x_4(14.0 + x_2) - 5.0 \leq 0$$
$$g_6(\vec{X}) = \delta(\vec{X}) - \delta_{max}$$
$$g_7(\vec{X}) = P - P_c(\vec{X}) \leq 0$$

TABLE 2. Comparison of the best design for welded beam.

Algorithm	Optimal values for variables				Optimal cost
	$x_1 = h$	$x_2 = l$	$x_3 = t$	$x_4 = b$	
DAOA	0.20573	3.470489	9.036624	0.20573	1.724852
WSA [52]	0.20573	3.470489	9.036624	0.20573	1.724852
MFO [53]	0.20573	3.470489	9.036624	0.20573	1.724852
CSS [19]	0.20582	3.468109	9.038024	0.205723	1.724866
GWO [7]	0.205676	3.478377	9.03681	0.205778	1.72624
CDE [49]	0.203137	3.542998	9.033498	0.206179	1.733462
GA [50]	0.220448	3.282171	8.750954	0.219381	1.778087
PSO [49]	0.219292	3.430416	8.433559	0.236204	1.85272
AOA	0.1847551	3.710272	10.0000	0.204171	1.87950
HS [48]	0.2442	6.2231	8.2915	0.2443	2.3807
APPROX [51]	0.2444	6.2189	8.2915	0.2444	2.3815
Random [51]	0.4575	4.7313	5.0853	0.66	4.1185

$$\textbf{Where } \tau(\vec{X}) = \sqrt{(\tau')^2 + 2\tau'\tau''\frac{x_2}{2R} + (\tau'')^2},$$
$$\tau' = \frac{P}{\sqrt{2}\,x_1x_2}, \quad \tau'' = \frac{MR}{J}$$
$$M = P(L + \frac{x_2}{2}), \quad R = \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1+x_3}{2}\right)^2}$$
$$J = 2\left\{\sqrt{2}\,x_1x_2\left[\frac{x_2^2}{12} + \left(\frac{x_1+x_3}{2}\right)^2\right]\right\}$$
$$P_c(\vec{X}) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right)$$
$$\sigma(\vec{X}) = \frac{6PL}{x_4x_3^2}, \quad \delta(\vec{X}) = \frac{4PL^3}{Ex_3^3x_4}$$
$$P = 6000lb, \quad L = 14in, \ E = 30 \times 10^6psi,$$
$$G = 12 \times 10^6psi$$
$$\textbf{Variable Range } 0.1 \le x_1, \quad x_4 \le 2, \ 0.1 \le x_2, \ x_3 \le 10 \tag{15}$$

Table 2 contains the result of DAOA and AOA in comparison with other algorithms. As seen here, DAOA finds the better variables for this problem than CSS [19], GWO [7], CDE [49], GA [50], PSO [49], AOA, HS [48], APPROX [51], and Random [51]. The results of the DAOA for this problem are compared to several other optimization algorithms published in the literature. The DAOA algorithm provides very competitive results, and its best solution obtained is ranked second to none, the same as WSA [52] and MFO [53]. In comparison to well-known optimization approaches, DAOA is a competitive algorithm, according to this study.

3) THREE BAR-TRUSS

The following example is designing a three-bar truss to reduce weight. As shown in Fig. 4, there are three bar components of the truss structure with symmetric configuration. The objective function is fundamental, but the problem is extremely limited. There is a wide range of constraints to structural design problems, such as stress, deflection, and buckling constraints. This problem is mathematically

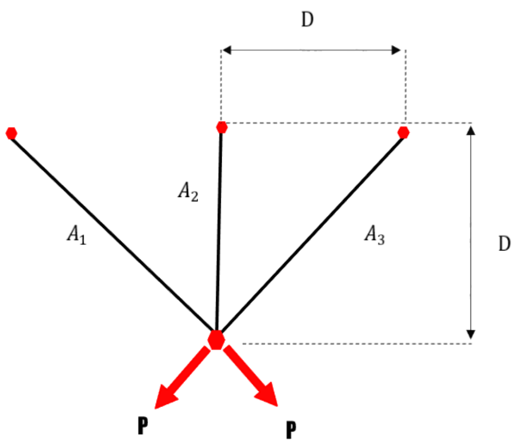

FIGURE 4. Three bar truss.

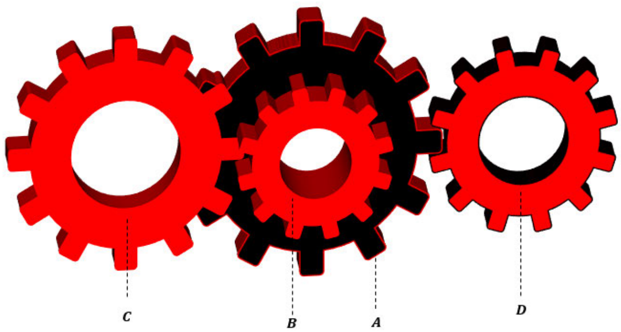

FIGURE 5. Compound gear.

TABLE 3. The best designs obtained for three-bar truss.

Algorithm	Optimal values for variables x_1	x_2	Optimal cost
DAOA	0.788683	0.408265	263.895843
WSA [52]	0.788683	0.408227	263.895843
PSO [49]	0.788669	0.408265	263.895843
ALO [56]	0.788662	0.408283	263.895843
MFO [53]	0.788601	0.408458	263.895847
MVO [59]	0.788603	0.408453	263.89585
GA [50]	0.788915	0.407569	263.895886
GWO [7]	0.788648	0.408325	263.896006
AOA	0.79369	0.39426	263.9154
CS [54]	0.78867	0.40902	263.9716
Ray and Sain [60]	0.795	0.395	264.3
Tsai [61]	0.788	0.408	265.6245

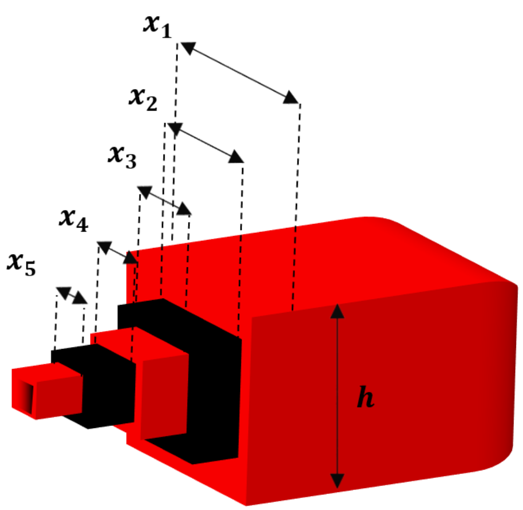

FIGURE 6. Cantilever beam.

formulated as follows:

$$\begin{aligned}
&\textit{Consider } \vec{X} = [x_1, x_2] = [A_1, A_2] \\
&\textit{Minimize } f_{cost}(\vec{X}) = (2\sqrt{2}\, X_1 + X_2) \times l \\
&\textit{Subject to } g_1\left(\vec{X}\right) = \frac{\sqrt{2}\, x_1 + x_2}{\sqrt{2}\, x_1^2 + 2x_1x_2} P - \sigma \le 0 \\
&\qquad g_2\left(\vec{X}\right) = \frac{\sqrt{2}\, x_1 + x_2}{\sqrt{2}\, x_1^2 + 2x_1x_2} P - \sigma \le 0 \\
&\qquad g_3\left(\vec{X}\right) = \frac{x_2}{\sqrt{2}\, x_1^2 + 2x_1x_2} P - \sigma \le 0 \\
&\qquad g_4\left(\vec{X}\right) = \frac{1}{\sqrt{2}\, x_2 + x_1} P - \sigma \le 0 \\
&\textit{Where } l = 100cm, \quad P = 2KN/cm^3, \ \sigma = 2KN/cm^3 \\
&\textit{Variable Range } 0 \le x_1, \quad x_2 \le 1 \qquad (16)
\end{aligned}$$

TABLE 4. Comparison of the best designs for compound gear.

Algorithm	Optimal values for variables x_1	x_2	x_3	x_4	Optimal cost
DAOA	49	16	19	43	2.70E-12
CS [54]	43	16	19	49	2.70E-12
WSA [52]	43	16	19	49	2.70E-12
MBA [55]	43	16	19	49	2.70E-12
GA [50]	49	19	16	43	2.70E-12
ALO [56]	49	19	16	43	2.70E-12
SCA [57]	43	16	19	49	2.70E-12
SSA [58]	49	16	19	43	2.70E-12
GWO [7]	49	19	16	43	2.70E-12
PSO [49]	34	13	20	53	2.31E-11
MFO [53]	51	30	13	53	2.31E-11
AOA	54	12	37	57	8.88E-10

Ten well-known algorithms are chosen for comparison with DAOA. The comparison results of best values are provided in Table 3. DAOA finds a design, which is the lowest among all other methods. Table 3 shows the best optimum designs. The DAOA algorithm produces excellent results, and its optimal solution is unrivaled.

4) COMPOUND GEAR

In mechanical engineering, this example is a discrete design issue. It is intended to reduce the gear ratio as defined by the ratio of the output shaft's angular speed to the angular velocity of the input shaft. As shown in Fig. 5, The number of gears

TABLE 5. The best designs for cantilever beam problem.

Algorithm	Optimal values for variables					Optimal cost
	x_1	x_2	x_3	x_4	x_5	
DAOA	5.977432	4.874808	4.469891	3.478552	2.138456	1.303252
WSA [52]	5.975921	4.880778	4.465427	3.477822	2.139194	1.303252
GWO [7]	5.971406	4.881808	4.473385	3.476943	2.135661	1.303256
MFO [53]	5.997765	4.874964	4.454762	3.483629	2.128316	1.30327
GA [50]	6.005599	4.851472	4.457484	3.482148	2.143109	1.303294
SCA [57]	6.147025	4.652444	4.498136	3.624997	2.107317	1.308902
CS [54]	6.0089	5.3049	4.5023	3.5077	2.1504	1.33996
GCA II [62]	6.01	5.3	4.49	2.15	2.15	1.33999
MMA [62]	6.01	5.3	4.49	2.15	2.15	1.34
GCA I [62]	6.01	5.3	4.49	2.15	2.15	1.34
SOS [66]	6.01878	5.30344	4.49587	3.49896	2.15564	1.34
AOA	6.007493	6.0287397	3.683363	3.8246820	2.567173	1.3762

TABLE 6. Design Parameters for various optimization problems.

Test Problem	Modulus of Elasticity $E\ (N/m^2)$	Material Density $\rho\ (Kg/m^3)$	Cross-Sectional $A\ (cm^2)$	Natural Frequency Constraints $\omega\ (Hz)$
37-bar planer bridge	2.1×10^{11}	7800	$1 \leq A$	$\omega_1 \geq 20, \omega_2 \geq 40, \omega_3 \geq 60$
72-bar space truss	6.98×10^{11}	2770	$0.645 \leq A$	$\omega_1 = 4, \omega_3 \geq 6$
120 bar dome truss	2.1×10^{11}	7971.810	$1 \leq A \leq 129.3$	$\omega_1 \geq 9, \omega_2 \geq 11$
200-bar planer truss	2.1×10^{11}	2860	$0.1 \leq A$	$\omega_1 \geq 5, \omega_2 \geq 10, \omega_3 \geq 15$

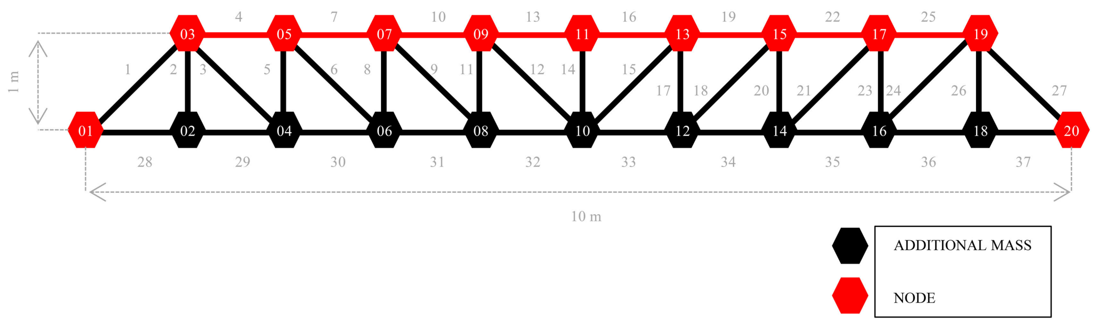

FIGURE 7. The 37- bar planar bridge.

teeth is known to be a discrete variable. The following is the mathematical formula:

$$\textbf{Consider } \vec{X} = [x_1, x_2, x_3, x_4] = [n_A, n_B, n_C, n_D]$$
$$\textbf{Minimize } f_{cost}\left(\vec{X}\right) = \left(\frac{1}{6.931} - \frac{x_3 x_2}{x_1 x_4}\right)^2$$
$$\textbf{Discerte Variable Range } 12 \leq x_1, \quad x_2, \ x_3, \ x_4 \leq 60 \quad (17)$$

The best number of teeth were found by the DAOA, CS [54], WSA [52], MBA [55], GA [50], ALO [56], SCA [57], SSA [58] and GWO [7]. Table 4 displays DAOA's optimal findings, which is clear that DAOA can outperform other approaches, amongst others, by obtaining the lowest total cost. Overall, the results of this research demonstrate the efficiency and effectiveness of DAOA in solving this problem.

5) CANTILEVER BEAM

Chickermane and Gea [62] have taken up the cantilever beam issue. The beam is rigidly supported, and at the free end of the cantilever, the vertical force acts, as shown in Fig. 6. The challenge is reducing the weight of the beam. The beam consists of five hollow square blocks with constant thickness,

TABLE 7. Comparison of optimized 37- bar planar bridge obtained through AOA and DAOA with other algorithms.

Member group	PSO [36]	HS [37]	FA [37]	TLBO [63]	VPS [64]	SBO [63]	SOS [28]	CBO [65]	AOA	DAOA
(Y_3-Y_{19}) m^2	0.9637	0.8415	0.9392	0.9639	0.9042	0.9551	0.9598	0.9562	1.2654	0.9363
(Y_5-A_{17}) m^2	1.3978	1.2409	1.3270	1.3551	1.2850	1.3289	1.3867	1.3236	1.7951	1.3616
(Y_7-A_{15}) m^2	1.5929	1.4464	1.5063	1.5338	1.5017	1.5273	1.5693	1.5037	1.9831	1.5496
(Y_9-Y_{13}) m^2	1.8812	1.5334	1.6086	1.6367	1.6509	1.6727	1.6687	1.6318	1.9691	1.7010
(Y_{11}) m^2	2.0856	1.5971	1.6679	1.7052	1.7277	1.7509	1.7203	1.6987	2.2851	1.7404
(A_1-A_{27}) cm^2	2.6797	3.2031	2.9838	2.9055	3.1306	2.9219	2.9038	2.7472	3.5121	3.6294
(A_2-A_{26}) cm^2	1.1568	1.1107	1.1098	1.0012	1.0023	1.0007	1.0163	1.0132	1.0000	0.9042
(A_3-A_{24}) cm^2	2.3476	1.1871	1.0091	1.0001	1.0001	1.0005	1.0033	1.0052	1.0000	0.8121
(A_4-A_{25}) cm^2	1.7182	3.3281	2.5955	3.5598	2.5883	2.6633	3.1940	2.5054	2.8833	2.6849
(A_5-A_{23}) cm^2	1.2751	1.4057	1.2610	1.2523	8.1226	1.2387	1.0109	1.1809	1.6015	1.2206
(A_6-A_{21}) cm^2	1.4819	1.0883	1.1975	1.2141	1.1119	1.2030	1.5877	1.2603	1.0000	1.2513
(A_7-A_{22}) cm^2	4.6850	2.1881	2.4264	2.3851	2.6743	2.4843	2.4104	2.709	3.5554	2.2377
(A_8-A_{20}) cm^2	1.1246	1.2223	1.3588	1.3881	1.2961	1.3706	1.3864	1.4023	1.8527	1.6491
(A_9-A_{18}) cm^2	2.1214	1.7033	1.4771	1.5235	1.5036	1.4618	1.6276	1.4661	1.6695	1.2881
(A_{10}-A_{19}) cm^2	3.8600	3.1885	2.5648	2.6065	2.4441	2.4432	2.3594	2.6107	1.2654	2.0686
(A_{11}-A_{17}) cm^2	2.9817	1.0100	1.1295	1.1378	1.2977	1.2758	1.0293	1.1764	1.0000	1.3162
(A_{12}-A_{15}) cm^2	1.2021	1.4074	1.3199	1.3078	1.3619	1.3491	1.3721	1.3767	2.5408	1.2831
(A_{13}-A_{16}) cm^2	1.2563	2.8499	2.9217	2.6205	2.3500	2.3831	2.0673	2.6809	2.4424	2.4432
(A_{14}-A_{16}) cm^2	3.3276	1.0269	1.0004	1.0003	1.0000	1.0000	1.0000	1.0064	2.9145	0.4000
Best weight	377.20	361.50	360.05	359.88	359.94	359.883	360.865	359.923	378.2591	359.5617
Average weight	381.2	361.04	330.37	360.803	360.23	360.23	364.582	360.446	397.3923	362.044
Standard deviation	4.26	0.52	0.26	0.63	0.22	0.47	2.965	0.356	11.43	0.9882
No. analyses	12500	20000	5000	12000	30000	12000	4000	6000	2300	9800

TABLE 8. Comparison of Natural frequencies (Hz) for the best design of 37- bar planer bridge.

No. Frequency	PSO	HS	FA	TLBO	VPS	SBO	SOS	CBO	AOA	DAOA
f_1	20.0001	20.0037	20.0024	20.0001	20.0002	20.0001	20.0366	20.0031	20.0001	20.0001
f_2	40.0003	40.0050	40.0019	40.0005	40.0005	40.0000	40.0007	40.0060	40.0003	40.0003
f_3	60.0001	60.0082	60.0043	60.0066	60.0000	60.0000	60.0138	60.0033	60.0001	60.0001

whose height decision. The classic principle of the beam develops the problem as follows:

$$\begin{aligned}
&\textbf{\textit{Consider}}\ \vec{X} = [x_1, x_2, x_3, x_4, x_5] = [h_1, h_2, h_3, h_4, h_5] \\
&\textbf{\textit{Minimize}}\ f_{cost}\left(\vec{X}\right) = 0.06224\,(x_1 + x_2 + x_3 + x_4 + x_5) \\
&\textbf{\textit{Subject to}}\ g\left(\vec{X}\right) = \frac{61}{x_1^3} + \frac{27}{x_2^3} + \frac{19}{x_3^3} + \frac{7}{x_4^3} + \frac{1}{x_5^3} - 1 \le 0 \\
&\textbf{\textit{Variable Range}}\ 0.01 \le x_1,\quad x_2,\ x_3,\ x_4,\ x_5 \le 100
\end{aligned} \tag{18}$$

Table 5 displays DAOA's optimal findings and their comparison to those of other approaches. It should be mentioned DAOA and WSA obtained the 1th rank in terms of best values. According to Table 5, the solution superior to any other approach has been obtained by DAOA and WSA [52].

B. STRUCTURAL EXAMPLES

In order to demonstrate the effectiveness of DAOA, various common structural optimum design problems are investigated in this section. Material properties, cross-sectional area, and natural frequency constraints applied for a 37-bar planer bridge, a 72-bar space truss, a 120-bar dome truss, and a 200-bar planer truss are summarized in Table 6. In order to provide a point of comparison, the results of a few other optimization algorithms are also presented.

In MATLAB 2021b, the algorithm was made. SAP2000 v14.1 solves the trusses with a direct stiffness method, and also the API is used to make changes during the optimization

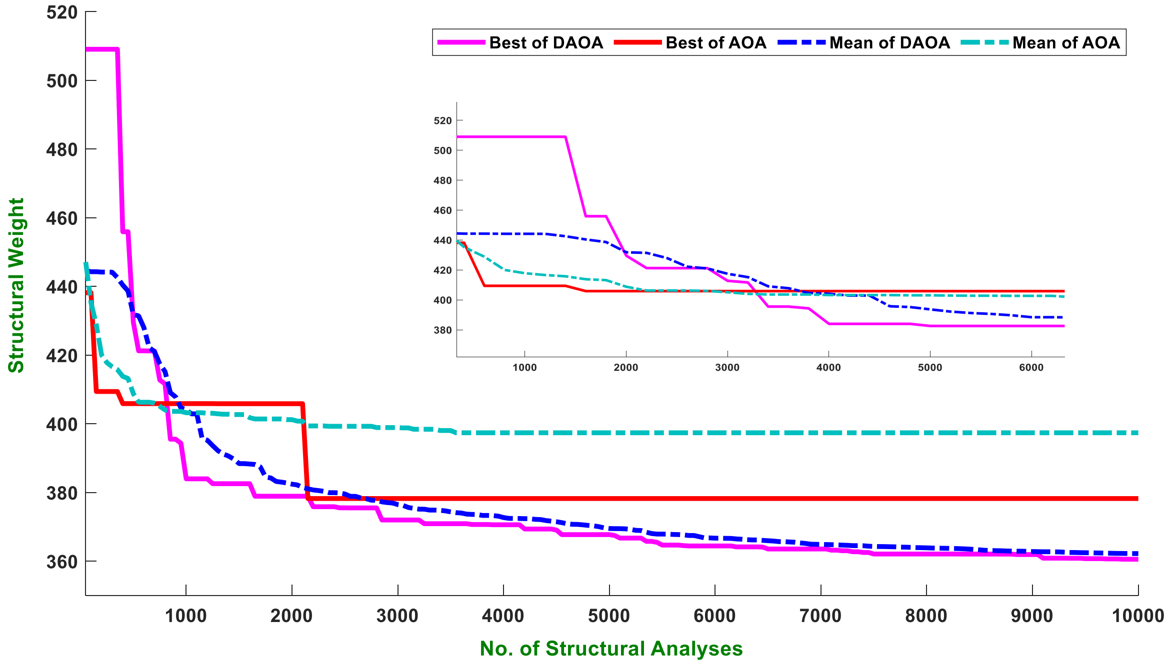

FIGURE 8. Best and average convergence curve obtained by AOA and DAOA for the 37-bar planer bridge.

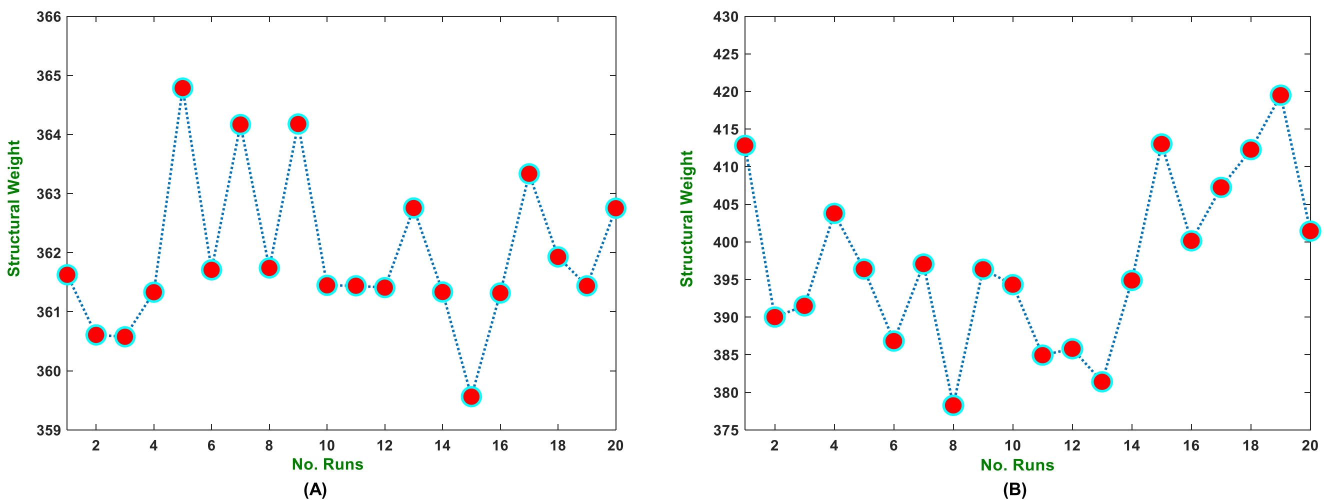

FIGURE 9. Twenty independent runs were obtained by (A) DAOA and (B) AOA for the 37-bar planer bridge.

process. The computer's current work is done with the help of these features: 2.3 GHz CPU, 16 GB 2400 MHz DDR4 RAM, and a Macintosh platform (macOS Big Sur).

1) 37-BAR PLANER TRUSS

The first instance is the weight reduction of the planar 37-bar truss structure depicted in Fig 7. Wang *et al.* [34] initially explored this example, and a large number of scholars later investigated it. For this problem, the design properties are shown in Table 6. The problem consists of fourteen sizes and five design variables. Each lower chord free node has a concentrated mass of $10Kg$. The cross-sectional areas of the lower chord bars are $0.4\,cm^2$ while the remaining bars are supposed to have a cross-section area of $1\,cm^2$. All nodes of the upper chord can be moved along the y-way while maintaining the structure's symmetry. This structure had been optimized previously with different metaheuristic algorithms. In this section, 37- bar planer bridge under natural frequency constraints is investigated by AOA and DAOA by considering population size 50 and function number evaluations as 10000. The best and average convergence curves obtained by AOA and DAOA for the 72-bar planer bridge are depicted in Fig 8. As seen in Fig. 8, the best design of AOA and DAOA is $359.5617\,Kg$ *and* $378.2591\,Kg$, which have been located at 2300 and 9000 analyses respectively. The results presented above clearly show the high convergence

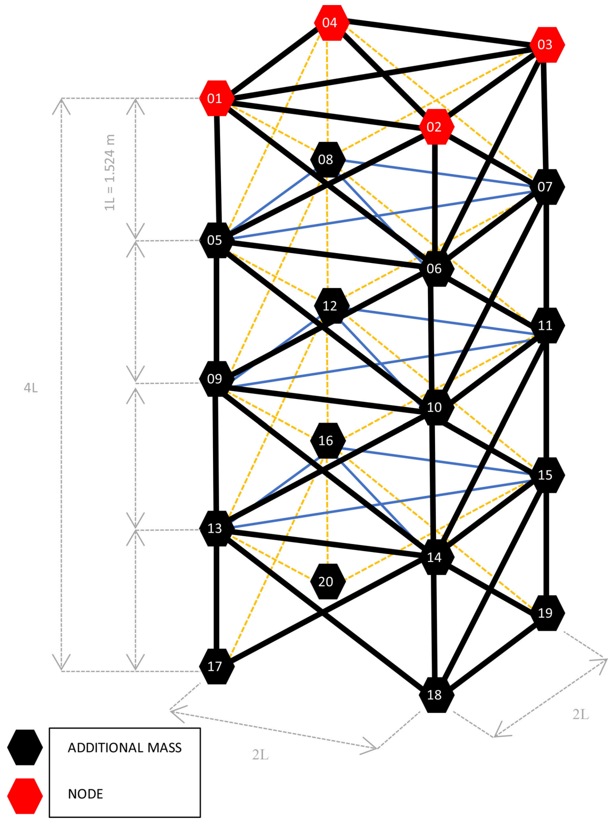

FIGURE 10. The 72-bar space truss structure.

capability of the dynamic version of AOA. The design found by DAOA is 4.94% lighter than that found by AOA. Tables 7 and 8 show optimization results and the first three natural frequencies obtained by DAOA, AOA in comparison with other referenced algorithms using particle swarm optimization (PSO) [36], harmony Search (HS) [37], firefly algorithm (FA) [37], teaching- learning-based optimization (TLBO) [63], vibrating particles system (VPS) [64], school-based optimization (SBO) [63], symbiotic organisms search (SOS) [28] and colliding-bodies optimization (CBO) [65].

Obviously, DAOA gained the lightest structure overall and strictly satisfied all constraints, while some algorithms violated these constraints. The standard deviation and average of results for DAOA are better than AOA. It should be noted that DAOA is more reliable than AOA and has better performance. Fig 9. shows the 20 independent runs for both AOA and DAOA. It is clear that the final results of DAOA are close to the value of average weight.

2) 72-BAR SPACE TRUSS

The second instance for weight minimization of the structure is a spatial truss of 72 bar, as shown in Fig 10. This example was divided into 16 groups because of structural symmetry; therefore, this problem has 16 sizing variables. Four non-structural masses of 10 *Kg* have been added at nodes 1-4. This example demonstrates material properties and constraints in Table 6. Both AOA and DAOA are evaluated for 72- space truss with natural frequencies.

Optimization outcomes for DAOA are compared with other methods by considering population size 50 and function number evaluations as 10000. Table 9 highlights size variables, best weight, average weight, standard deviation (STD) of weight, and a number of function evaluations gained for

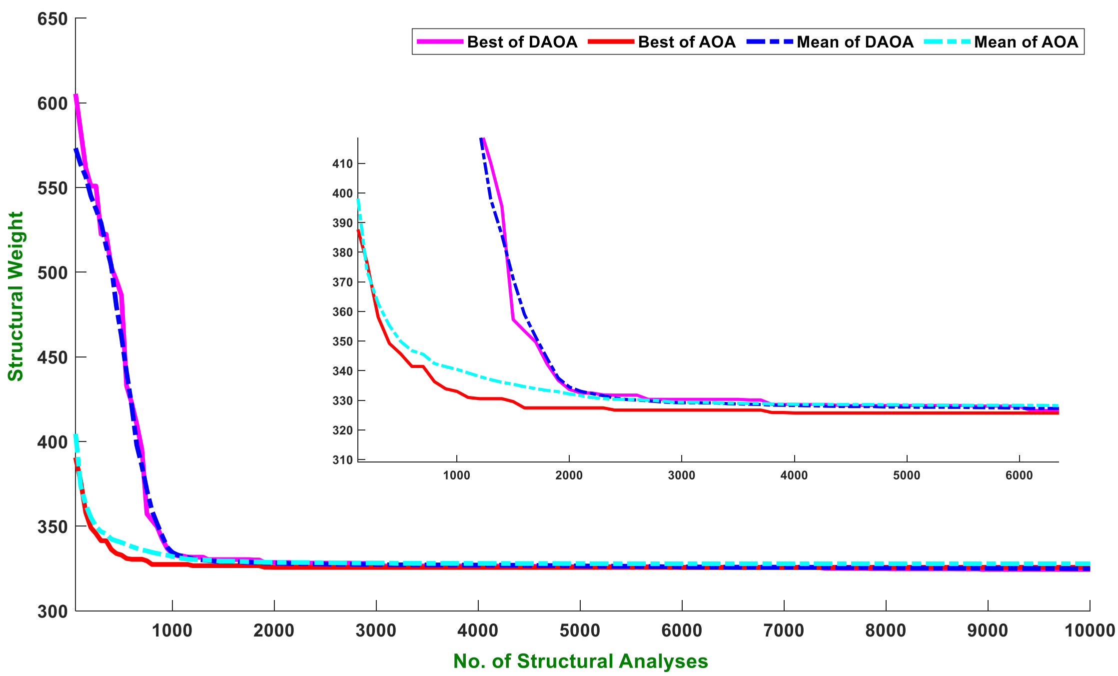

FIGURE 11. Best and average convergence curve obtained by AOA and DAOA for the 72-bar spatial truss.

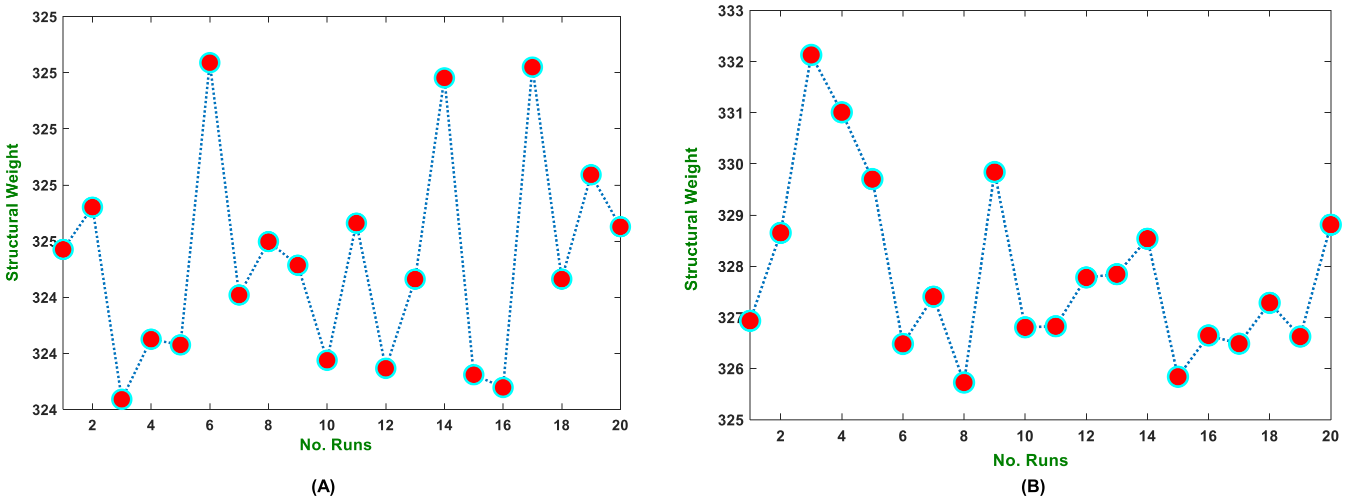

FIGURE 12. Twenty independent runs were obtained by (a) DAOA and (b) AOA for the 72-bar spatial truss.

TABLE 9. Comparison of optimized the 72-bar spatial truss obtained through AOA and DAOA with other algorithms.

Member group	FA [37]	PSO [36]	TWO [67]	CSS [35]	TLBO [39]	SBO [63]	SOS [28]	CBO [65]	AOA	DAOA
1 (A_1-A_4)	3.3411	2.9870	3.3800	2.5280	3.5491	3.4917	3.6957	3.3699	3.3981	3.5030
2 (A_5-A_{12})	7.7587	7.8490	8.0860	8.7040	7.9676	7.9414	7.1779	7.3428	8.3201	7.7526
3 (A_{13}-A_{16})	0.6450	0.6450	0.6470	0.6450	0.6450	0.6450	0.6450	0.6468	0.6450	0.6450
4 (A_{17}-A_{18})	0.6450	0.6450	0.6460	0.6450	0.6450	0.6450	0.6569	0.6458	0.6450	0.6450
5 (A_{19}-A_{22})	9.0202	8.7650	8.8900	8.2830	8.1532	8.1154	7.7017	8.0056	8.2371	8.2378
6 (A_{23}-A_{30})	8.2567	8.1530	8.1360	7.8880	7.9667	8.0533	7.9509	8.0185	7.8459	8.0970
7 (A_{31}-A_{34})	0.6450	0.6450	0.6540	0.6450	0.6450	0.6450	0.6450	0.6458	0.6450	0.6450
8 (A_{35}-A_{36})	0.6450	0.6450	0.6470	0.6450	0.6450	0.6450	0.6450	0.6457	0.6450	0.6450
9 (A_{37}-A_{40})	12.045	13.450	13.097	14.660	12.927	12.856	12.399	12.458	13.974	11.9516
10 (A_{41}-A_{48})	8.0401	8.0730	8.1010	6.7930	8.1226	8.0425	8.6121	8.121	8.0347	7.8948
11 (A_{49}-A_{52})	0.6450	0.6450	0.6630	0.6450	0.6452	0.6451	0.6450	0.6460	0.6450	0.6450
12 (A_{53}-A_{54})	0.6450	0.6450	0.6460	0.6450	0.6450	0.6450	0.6450	0.6459	0.6450	0.6450
13 (A_{55}-A_{58})	17.380	16.684	16.483	16.4600	17.052	17.213	17.482	17.363	15.7319	17.5769
14 (A_{59}-A_{66})	8.0561	8.0561	7.8730	8.8090	8.0618	8.0804	8.1502	8.3371	7.71608	8.0254
15 (A_{67}-A_{70})	0.6450	0.6450	0.6510	0.6450	0.6450	0.6450	0.6740	0.6460	0.6450	0.6450
16 (A_{71}-A_{72})	0.6450	0.6450	0.6570	0.6450	0.6450	0.6450	0.6550	0.6476	0.6450	0.6450
Best weight	327.691	328.81	328.83	328.814	327.568	327.55	325.558	324.755	325.726	324.4786
Average weight	329.89	332.24	336.1	337.70	328.684	327.68	331.122	330.415	329.343	324.9286
Standard deviation	2.59	4.23	5.80	5.42	0.73	0.07	4.227	7.706	4.454	0.3731
No. analyses	10000	42840	N/A	4000	15000	15000	4000	6000	10000	3800

TABLE 10. Comparison of Natural frequencies (Hz) for the best design of a 72-bar spatial truss.

No. Frequency	FA	PSO	TWO	CSS	TLBO	SBO	SOS	CBO	AOA	DAOA
f_1	4.0000	3.9999	4.0000	4.0000	4.0000	4.0000	4.0023	4.0000	4.0000	4.0002
f_2	4.0000	3.9999	4.0000	4.0000	4.0000	4.0000	4.0023	4.0000	4.0001	4.0004
f_3	6.0000	6.0080	6.0000	6.0040	6.0000	6.0000	6.0020	6.0000	6.0108	6.0000
f_4	6.2468	6.1900	6.2491	6.1550	6.2515	6.2460	6.2926	6.2541	6.2840	6.2695
f_5	9.0380	8.2410	8.9726	8.3900	9.0799	9.0719	9.0631	9.0433	9.1341	9.0985

TABLE 11. Comparison of optimized the 120-bar dome truss obtained through AOA and DAOA with other algorithms.

Member group	PSO [36]	CSS [35]	DPSO [36]	VPS [64]	AOA	DAOA
1	23.494	21.71	19.607	19.6836	21.2745	20.1113
2	32.976	40.862	41.29	40.9581	47.4293	39.4442
3	11.492	9.048	11.136	11.3325	9.8291	10.8334
4	24.839	19.673	21.025	21.5387	22.6812	21.6426
5	9.964	8.336	10.06	9.8867	10.5738	10.1433
6	12.039	16.12	12.758	12.7116	26.5688	13.3953
7	14.249	18.976	15.414	14.9330	16.8293	14.9580
Best weight	9171.93	9204.51	8890.48	8888.74	10180.737	8890.044
Average weight	9251.84	N/A	8895.99	8896.04	11380.768	9042.086
Standard deviation	89.38	N/A	4.26	6.65	98.33	85.496
No. analyses	6000	10000	6000	30000	10000	2400

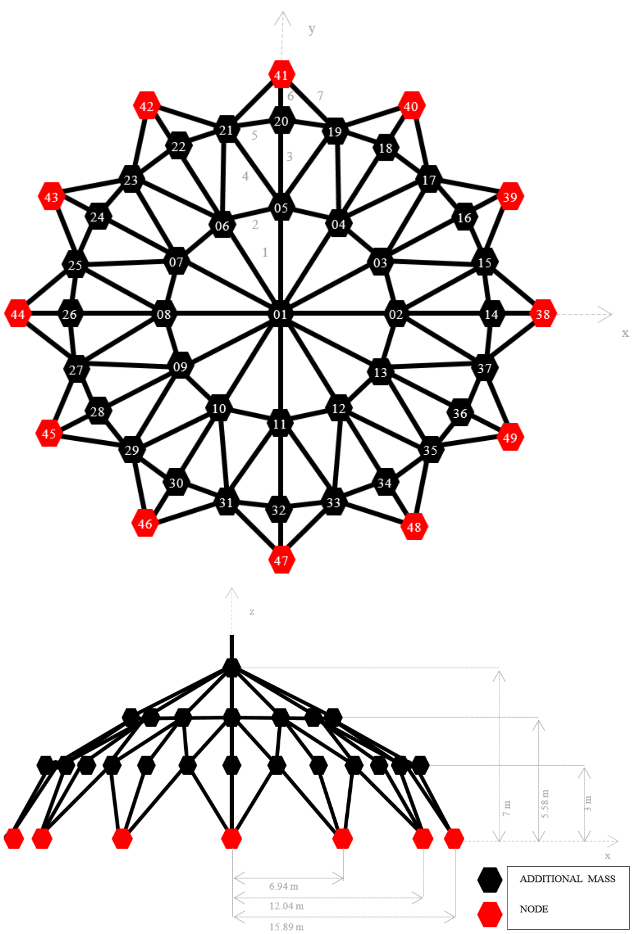

FIGURE 13. The 120-bar dome truss structure.

20 runs. The best results of the AOA and DAOA approach are 325.726 *Kg* and 324.4786 *Kg*, while it is 327.691 *Kg*, 328.81 *Kg*, 328.83 *Kg*, 328.814*Kg*, 327.568 *Kg*, 327.55 *Kg*, 325.558 *Kg* and 324.755 *Kg* for the such as FA [37], PSO [36], TWO [67], CSS [35], TLBO [39], SBO [63], SOS [28] and CBO [65] algorithms, respectively (see Table 9). According to Table 10, the natural frequency constraints of the presented method are strictly satisfied all bound.

Fig 11. demonstrates that DAOA needs 3800 number analyses to obtain a feasible solution and ranked first among all other algorithms in this paper in terms of a number of function evaluations. Moreover, DAOA gives the best average weight among the mentioned algorithms. The twenty independent runs for 72- spatial bar truss for AOA and DAOA are shown in Fig 12. As depicted in Table 4, the average weight of the DAOA and AOA approaches are 324.9286 *Kg*and 329.343 *Kg*, while it is 329.89 *Kg*, 332.24 *Kg*, 331.6 *Kg*, 337.70 *Kg*, 328.684 *Kg*, 327.68 *Kg*, 331.122*Kg* and 330.415 *Kg* for the such as FA [37], PSO [36], TWO [67], CSS [35], TLBO [39], SBO [63], SOS [28]and CBO [65] algorithms, respectively. The standard deviation of DAOA is 0.3731, which ranked second among its competitors. These results show that DAOA is more reliable and superior than the other results reported in the literature. Moreover, it is found from the results that DAOA is more efficient than AOA.

3) 120-BAR DOME TRUSS

The 3rd benchmark is presented in Fig 13. Initially, the 120-bar 3-D dome truss was optimized for size optimization by Kaveh and Zolghadr [68]. Table 6 shows the design considerations. There are non-structural masses added as 3000 *Kg* at node 1, 500 *Kg* at nodes 2 to 13 and 100 *Kg* at the rest of the free nodes. The elements are classified into seven groups by assuming symmetry about the z-axis. The minimum and maximum cross-sectional area are 1 and 129.3cm^2, respectively. This example is solved with various algorithms such as PSO [36], CSS [35], DPSO [36], and VPS [64] by considering population size 50 and function number evaluations as 10000. Table 11 reveals size variables, best weight, average weight, standard deviation (STD) of

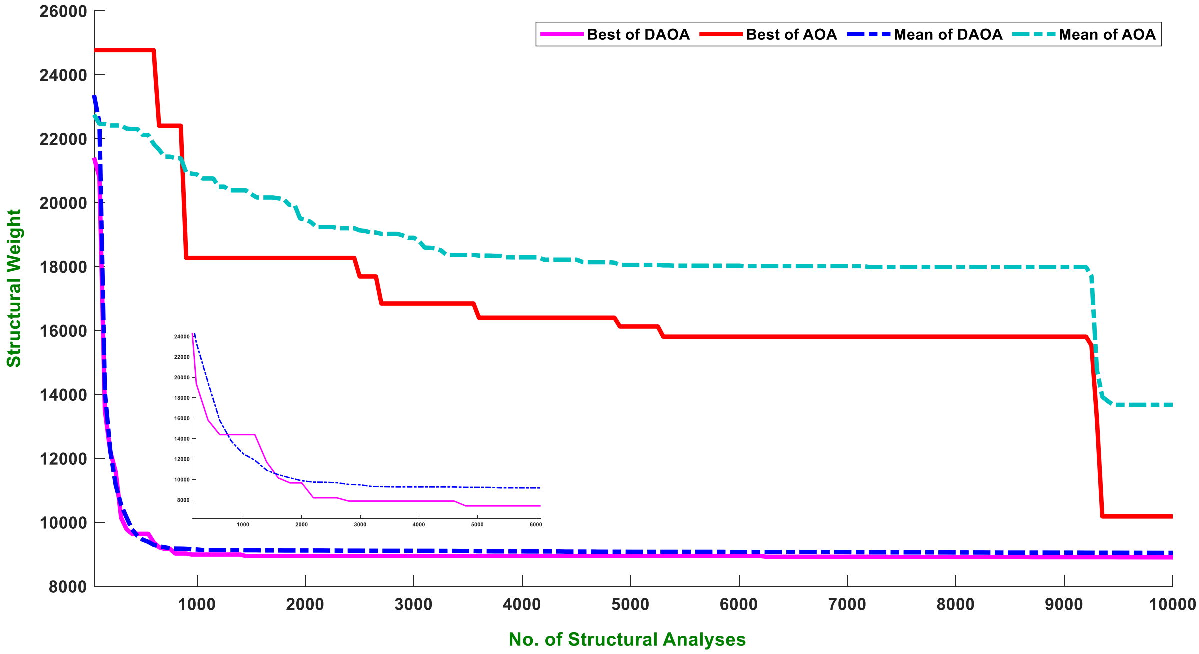

FIGURE 14. Best and average convergence curve obtained by AOA and DAOA for the 120-bar dome structure.

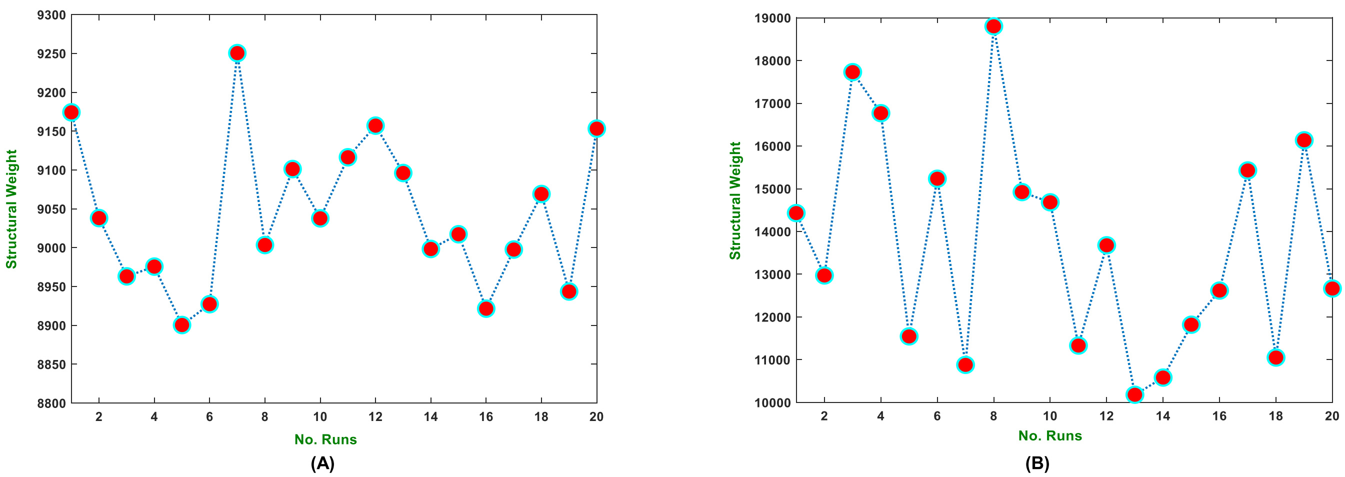

FIGURE 15. Twenty independent runs were obtained by (a) DAOA and (b) AOA for the 120-bar dome structure.

TABLE 12. Comparison of Natural frequencies (Hz) for the best design of a 120-bar dome truss.

No. Frequency	PSO	CSS	DPSO	VPS	AOA	DAOA
f_1	9.0000	9.002	9.0001	9.0000	9.3499	9.0001
f_2	11.0000	11.002	11.0007	11.0000	11.1904	11.0000
f_3	11.0052	11.006	11.0053	11.003	11.2367	11.0000
f_4	11.0134	11.015	11.0129	11.010	11.2766	11.0097
f_5	11.0428	11.045	11.0471	11.052	11.2873	11.0507

weight, and a number of function evaluations. As shown in Table 11, VPS [64] and DAOA ranked first and second, respectively, regarding the best optimization weight. Furthermore, DAOA finished the search process within 2400 function evaluations, the lightest number of function evaluations (see Fig 14.). AOA results show that this method found infeasible optimized designs with the highest weight of structures and could not escape from the local

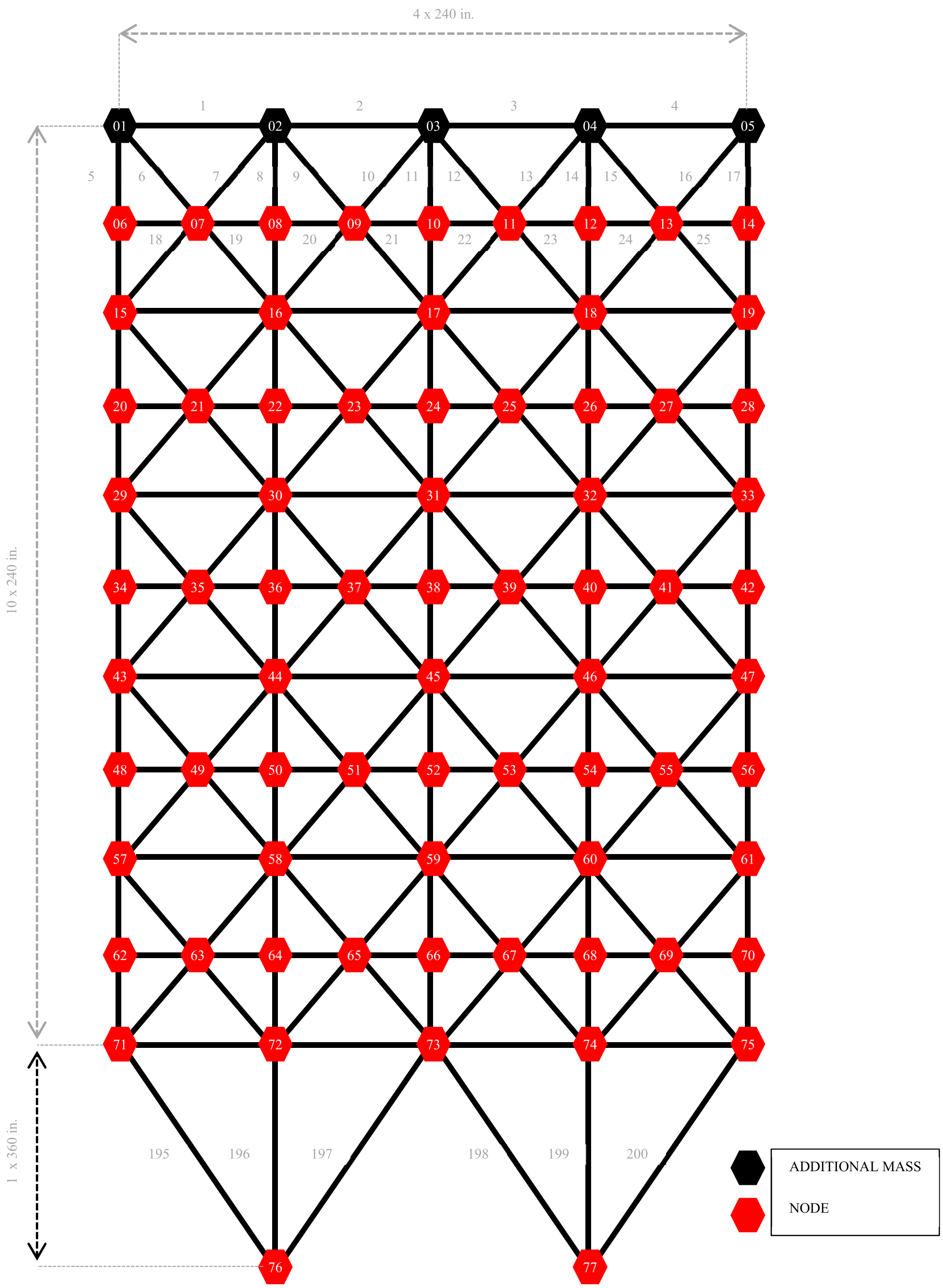

FIGURE 16. **The 200-bar planar truss structure.**

trap. Moreover, after 2400 analyses, DAOA has reached satisfactory solutions. The best and average convergence curves of best runs for AOA and DAOA are depicted in Fig 14.

The DAOA has the best weight of 8890.044 *Kg*, demonstrating that the new approach is more effective than the standard version of AOA. This is an optimal design improvement using the current algorithm. As regards Table 12, this approach still satisfies frequency constraints. Fig 15. demonstrates 20 individual runs of the final weights for AOA and DAOA.

4) 200-BAR PLANAR TRUSS

This study solved the fourth test problem concerning reducing weight of a planar structure of 200 bar shown in Fig 16. The design considerations for this problem are shown in Table 6. This example comprises 29 size variables for the cross-sectional areas of the element groups listed in Table 13.

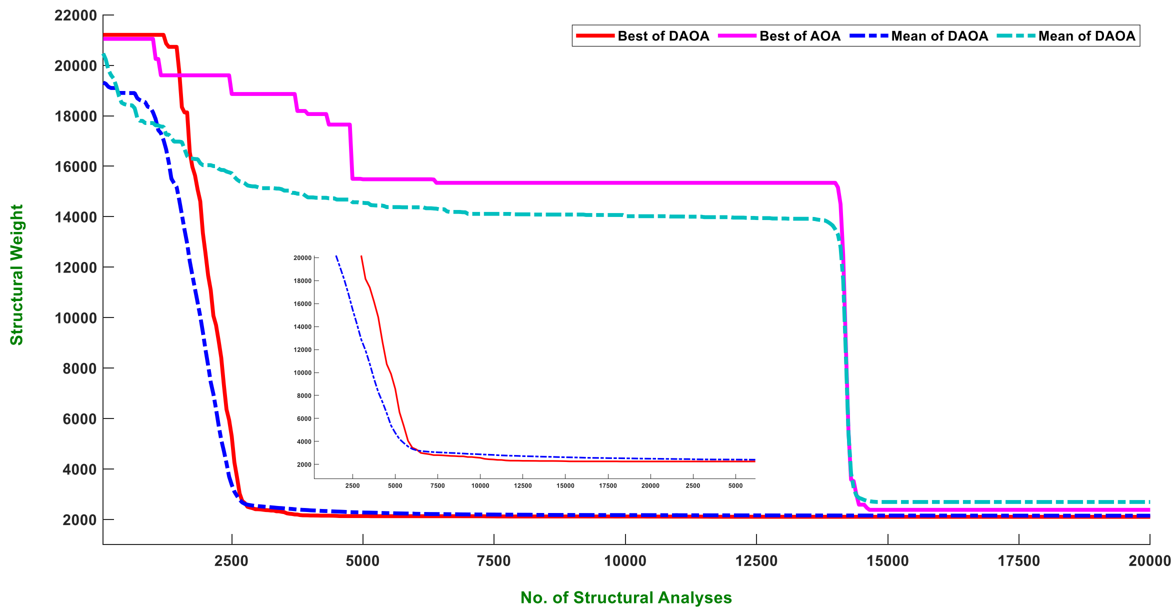

FIGURE 17. Best and average convergence curve obtained by AOA and DAOA for the 200-bar planar truss structure.

TABLE 13. Element grouping for 200- planar bar truss.

Group	Member Number	Group	Member Number
1	1,2,3,4	16	82,83,85,88,89,91,92,103,104,106,107,109,110,112,113
2	5,8,11,14,17	17	115,116,117,118
3	19,20,21,22,23,24	18	119,122,125,128,131
4	18,25,56,63,94,101,132,139,170,177	19	133,134,135,136,137,138
5	26,29,32,35,38	20	140,143,146,149,152
6	6,7,9,10,12,13,15,16,27,28,30,31,33,34,36,37	21	120,121,123,124,126,127,129,130,141,142,144,145,147,148,150,151
7	39,40,41,42	22	153,154,155,156
8	43,46,49,52,55	23	157,160,163,166,169
9	57,58,59,60,61,62	24	171,172,173,174,175,176
10	64,67,70,73,76	25	178,181,184,187,190
11	44,45,47,48,50,51,53,54,65,66,68,69,71,72,74,75	26	158,159,161,162,164,165,167,168,179,180,182,183,185,186,188,189
12	77,78,79,80	27	191,192,193,194
13	81,84,87,90,93	28	195,197,198,200
14	95,96,97,98,99,100	29	196,199
15	102,105,108,111,114		

The frequency restrictions are taken as follows: $\omega_1 \geq 5\ Hz$, $\omega_2 \geq 10\ Hz$, $\omega_3 \geq 15\ Hz$. The upper nodes (1 to 5) of the truss are supplemented with 100 Kg non-structural masses.

Table 16 demonstrates the lightest weight of structure obtained by DAOA is better than those other algorithms by considering population size 50 and function number evaluations as 20000. The DAOA has the best weight of 2102.458 Kg, demonstrating that the new approach is more effective than the other algorithms. This best of DAOA is 47.27%, 6.96%, 2.5%, 2.5%, 3.57%, 2.71% and 11.86% lighter than those of PSO [36], CSS [35], SBO [63], TLBO [39], SOS [28],CBO [65] and AOA. Fig 17. shows the best and mean convergence curves for the standard and dynamic version of AOA.

Table 14 shows that the DAOA algorithm's average is lower than that of other algorithms, demonstrating the DAOA algorithm's superior performance. Compared with some other researchers, minimum weight and associated cross-sections of AOA and DAOA are acquired, and the findings are shown in Table 14. The natural frequencies of the best design obtained by other algorithms structures are shown in Table 15, which are satisfied by AOA and DAOA. In this study, the final weight of the 20 independent runs for AOA and DAOA is seen in Fig 18. This example's outcomes reveal DAOA surpasses the compared algorithms in regards to performance and accuracy.

The robustness of DAOA compared with AOA and other metaheuristic algorithms is proved by statistical results

TABLE 14. Comparison of optimized the 200-bar planar truss obtained through AOA and DAOA with other algorithms.

Member group	PSO [36]	CSS [35]	SBO [63]	TLBO [39]	SOS [28]	CBO [65]	AOA	DAOA
1	2.4662	1.2439	0.3040	0.3030	0.4781	0.3059	0.7883	0.4954
2	0.1000	1.1438	0.4478	0.4479	0.4481	0.4476	0.9203	0.4681
3	0.1000	0.3769	0.1000	0.1001	0.1049	0.1000	0.6556	0.1000
4	0.1000	0.1494	0.1000	0.1000	0.1045	0.1001	0.1000	0.1000
5	0.1000	0.4835	0.5075	0.5124	0.4875	0.4944	0.5741	0.4284
6	2.8260	0.8103	0.8219	0.8205	0.9353	0.8369	0.7967	0.8675
7	0.1000	0.4364	0.1003	0.1000	0.1200	0.1001	0.2237	0.1000
8	4.6937	1.4554	1.4240	1.4499	1.3236	1.5514	1.2699	1.4766
9	0.1000	1.0103	0.1001	0.1001	0.1015	0.1000	1.4582	0.1000
10	1.7291	2.1382	1.5929	1.5955	1.4827	1.5286	1.3703	1.5250
11	1.8842	0.8583	1.1597	1.1556	1.1384	1.1547	1.0161	1.1323
12	0.1000	1.2718	0.1275	0.1242	0.1020	0.1000	0.1000	0.1336
13	3.7185	3.0807	2.9765	2.9753	2.9943	2.9980	3.8052	2.8694
14	0.1000	0.2677	0.1001	0.1000	0.1562	0.1017	0.2392	0.1000
15	2.3450	4.2403	3.2456	3.2553	3.4330	3.2475	4.1158	3.2891
16	0.9164	2.0098	1.5818	1.5762	1.6816	1.5213	1.6529	1.5511
17	0.1000	1.5956	0.2566	0.2680	0.1026	0.3996	1.4986	0.2786
18	7.1603	6.2338	5.1118	5.0692	5.0739	4.7557	5.3584	4.4097
19	30.000	2.5793	0.1001	0.1000	0.1068	0.1002	1.8317	0.1000
20	6.1670	3.0520	5.4337	5.4281	6.0176	5.1359	4.7853	5.5276
21	3.1906	1.8121	2.1016	2.0942	2.0340	2.1181	2.1296	2.0481
22	0.2150	1.2986	0.6794	0.6985	0.6595	0.9200	5.1310	0.9720
23	18.1871	5.8810	7.6581	7.6663	6.9003	7.3084	5.9364	6.5951
24	0.1000	0.2324	0.1006	0.1008	0.2020	0.1185	0.1000	0.1605
25	30.0000	7.7536	7.9468	7.9899	6.8356	7.6901	7.0717	7.0515
26	2.02330	2.6871	2.7835	2.8084	2.6644	3.0895	3.2941	2.7489
27	16.0615	12.5094	10.5277	10.4661	12.1430	10.6462	11.0283	10.0690
28	30.0000	29.5704	21.3027	21.2466	22.2484	20.7190	23.8101	21.3774
29	30.0000	8.2910	10.6207	10.7340	8.9378	11.7463	6.5236	9.5784
Best weight	3987.61	2259.86	2156.51	2156.54	2180.32	2161.15	2380.115	2102.458
Average weight	5027.78	N/A	2156.79	2157.54	2303.30	2447.52	2691.489	2148.591
Standard deviation	708.95	N/A	0.21	1.54	83.58	301.29	148.88	42.480
No. analyses	20000	10000	23000	23000	10000	20000	20000	6900

TABLE 15. Comparison of natural frequencies (Hz) for the best design of a 200-bar planar truss.

No. Frequency	*PSO*	CSS	SBO	TLBO	SOS	CBO	AOA	DAOA
f_1	5.0650	5.0000	5.0000	5.0000	5.0001	5.0000	5.0034	5.0000
f_2	13.1800	15.9610	12.2141	12.2171	13.4306	12.221	12.6790	13.6291
f_3	16.0970	16.4070	15.0192	15.0380	15.2645	15.088	15.1075	15.3609
f_4	17.6810	20.7480	16.6870	16.7047	17.0225	16.7590	16.0997	17.2544
f_5	18.1050	21.9030	21.4109	21.4016	21.8468	21.4190	21.9830	21.7242
f_6	18.5580	26.9950	21.4570	21.4534	N/A	21.5010	27.4196	22.3558

obtained from 60 independent runs. Due to the introduction of two novel functions, the algorithm is able to break out of local optima and achieve great performance. The most remarkable attribute of DAOA is that there is no need for tuning parameters. The performance of DAOA is tested for four different truss structures. Performance and accuracy of

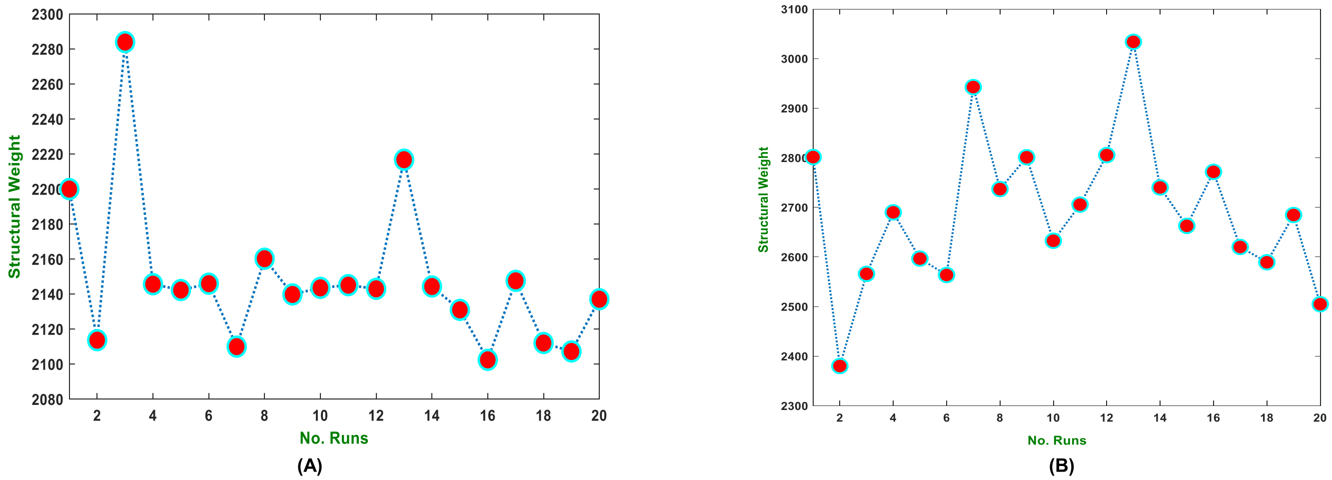

FIGURE 18. Twenty independent runs were obtained by (a) DAOA and (b) AOA for the 200-bar planar truss structure.

the dynamic version of AOA surpass the standard version of AOA and compared algorithms.

VI. CONCLUSION

In this paper, the Dynamic Arithmetic Optimization Algorithm (DAOA) approach was proposed and tested for optimum weight design of four benchmark truss structures under frequency constraints. The DAOA benefits from two dynamic mechanism to alleviate the drawbacks of AOA. Truss optimization with natural frequency bound is a complicated problem in optimization, which has extraordinarily nonlinear and non-convex search areas with varying local optima. These examples are used to evaluate the proposed method's Efficiency (DAOA) against the standard version of AOA and some well-established metaheuristic algorithms. Four classical truss weight minimization problems (i.e., planar 37-bar, spatial 72-bar truss, 120-bar dome truss, 200-bar trusses), including up to 29 optimization variables, were used to prove the efficiency of the proposed algorithm. This new algorithm provides a proper balance between exploration and exploitation strategies that produce excellent accuracy and rapid convergence. The structural results of the design examples examined point to the algorithm's benefits in optimizing final solutions. The statistical results obtained by is considered as a competent rival for new metaheuristics. Also, the efficiency, accuracy, and performance of DAOA are much better than its standard version and other latest algorithm. The comparisons of convergence speeds also reveal that the algorithm provided is rapidly convergent. Results show that DAOA is an excellent approach for the sizing optimization of planar and spatial trusses and dome structures in the face of natural frequency design constraints. Another area of research that should be pursued in the future is the combination and tuning of DAOA with other algorithms.

REFERENCES

[1] S. Mirjalili, H. Faris, and I. Aljarah, *Evolutionary Machine Learning Techniques*. Springer, 2019.

[2] A. Kaveh, N. Khodadadi, B. F. Azar, and S. Talatahari, "Optimal design of large-scale frames with an advanced charged system search algorithm using box-shaped sections," *Eng. Comput.*, vol. 37, pp. 1–21, Oct. 2020.

[3] D. Whitley, "A genetic algorithm tutorial," *Statist. Comput.*, vol. 4, no. 2, pp. 65–85, Jun. 1994, doi: 10.1007/BF00175354.

[4] K.-L. Du and M. N. S. Swamy, "Particle swarm optimization," in *Search and Optimization by Metaheuristics*. Springer, 2016, pp. 153–173.

[5] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," *Theor. Comput. Sci.*, vol. 344, nos. 2–3, pp. 243–278, Nov. 2005.

[6] E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition," in *Proc. IEEE Congr. Evol. Comput.*, Sep. 2007, pp. 4661–4667.

[7] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014.

[8] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, Feb. 2016.

[9] A. H. Gandomi and A. H. Alavi, "Krill herd: A new bio-inspired optimization algorithm," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 17, pp. 4831–4845, May 2012.

[10] X.-S. Yang, "A new metaheuristic bat-inspired algorithm," in *Nature Inspired Cooperative Strategies for Optimization*. Springer, 2010, pp. 65–74.

[11] S. J. Mousavirad and H. Ebrahimpour-Komleh, "Human mental search: A new population-based metaheuristic optimization algorithm," *Appl. Intell.*, vol. 47, no. 3, pp. 850–887, 2017.

[12] R. V. Rao, V. J. Savsani, and D. P. Vakharia, "Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems," *Comput.-Aided Des.*, vol. 43, no. 3, pp. 303–315, Mar. 2011.

[13] F. Valdez and C. Peraza, "Dynamic parameter adaptation in the harmony search algorithm for the optimization of interval type-2 fuzzy logic controllers," *Soft Comput.*, vol. 24, no. 1, pp. 179–192, Jan. 2020.

[14] O. Castillo, D. Hidalgo, L. Cervantes, P. Melin, and R. M. Soto, "Fuzzy parameter adaptation in genetic algorithms for the optimization of fuzzy integrators in modular neural networks for multimodal biometry," *Computación Sistemas*, vol. 24, no. 3, pp. 1093–1105, Sep. 2020.

[15] A. Kaveh, S. Talatahari, and N. Khodadadi, "The hybrid invasive weed optimization-shuffled frog-leaping algorithm applied to optimal design of frame structures," *Periodica Polytechnica Civil Eng.*, vol. 63, no. 3, pp. 882–897, Aug. 2019.

[16] L. Abualigah and A. J. Dulaimi, "A novel feature selection method for data mining tasks using hybrid sine cosine algorithm and genetic algorithm," *Cluster Comput.*, vol. 24, pp. 1–16, Feb. 2021.

[17] N. Khodadadi, M. Azizi, S. Talatahari, and P. Sareh, "Multi-objective crystal structure algorithm (MOCryStAl): Introduction and performance evaluation," *IEEE Access*, vol. 9, pp. 117795–117812, 2021.

[18] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, "GSA: A gravitational search algorithm," *J. Inf. Sci.*, vol. 179, no. 13, pp. 2232–2248, 2009.

[19] A. Kaveh and S. Talatahari, "A novel heuristic optimization method: Charged system search," *Acta Mech.*, vol. 213, nos. 3–4, pp. 267–289, Jan. 2010.

[20] O. K. Erol and I. Eksin, "A new optimization method: Big bang-big crunch," *Adv. Eng. Softw.*, vol. 37, no. 2, pp. 106–111, 2006.

[21] A. Kaveh, S. Talatahari, and N. Khodadadi, "Stochastic paint optimizer: Theory and application in civil engineering," *Eng. with Comput.*, vol. 8, pp. 1–32, Oct. 2020.

[22] P. J. M. Van Laarhoven and E. H. L. Aarts, "Simulated annealing," in *Simulated Annealing: Theory and Applications*. Springer, 1987, pp. 7–15.

[23] Z. W. Geem, J. H. Kim, and G. V. Loganathan, "A new heuristic optimization algorithm: Harmony search," *J. Simul.*, vol. 76, no. 2, pp. 60–68, Feb. 2001.

[24] A. Kaveh and V. R. Mahdavi, "Colliding bodies optimization: A novel meta-heuristic method," *Comput. Struct.*, vol. 139, pp. 18–27, Jan. 2014.

[25] S. D. Rajan, "Sizing, shape, and topology design optimization of trusses using genetic algorithm," *J. Struct. Eng.*, vol. 121, no. 10, pp. 1480–1487, 1995.

[26] G.-C. Luh and C.-Y. Lin, "Optimal design of truss-structures using particle swarm optimization," *Comput. Struct.*, vol. 89, nos. 23–24, pp. 2221–2232, Dec. 2011.

[27] S. O. Degertekin, H. Tutar, and L. Lamberti, "School-based optimization for performance-based optimum seismic design of steel frames," *Eng. Comput.*, vol. 37, no. 4, pp. 1–15, 2020.

[28] G. G. Tejani, V. J. Savsani, V. K. Patel, and S. Mirjalili, "Truss optimization with natural frequency bounds using improved symbiotic organisms search," *Knowl.-Based Syst.*, vol. 143, pp. 162–178, Mar. 2018.

[29] A. Kaveh, A. Dadras Eslamlou, and N. Khodadadi, "Dynamic water strider algorithm for optimal design of skeletal structures," *Periodica Polytechnica Civil Eng.*, vol. 64, pp. 904–916, Jun. 2020.

[30] A. Kaveh, S. Talatahari, and N. Khodadadi, "Hybrid invasive weed optimization-shuffled frog-leaping algorithm for optimal design of truss structures," *Iranian J. Sci. Technol., Trans. Civil Eng.*, vol. 44, no. 2, pp. 405–420, Jun. 2020.

[31] A. H. Gandomi, S. Talatahari, X.-S. Yang, and S. Deb, "Design optimization of truss structures using cuckoo search algorithm," *Structural Design Tall Special Buildings*, vol. 22, no. 17, pp. 1330–1349, Dec. 2013.

[32] L. Bellagamba and T. Y. Yang, "Minimum-mass truss structures with constraints on fundamental natural frequency," *AIAA J.*, vol. 19, no. 11, pp. 1452–1458, Nov. 1981.

[33] J. H. Lin, W. Y. Che, and Y. S. Yu, "Structural optimization on geometrical configuration and element sizing with statical and dynamical constraints," *Comput. Struct.*, vol. 15, no. 5, pp. 507–515, Jan. 1982.

[34] L. Wei, T. Tang, X. Xie, and W. Shen, "Truss optimization on shape and sizing with frequency constraints based on parallel genetic algorithm," *Struct. Multidisciplinary Optim.*, vol. 43, no. 5, pp. 665–682, May 2011.

[35] A. Mortazavi, "Size and layout optimization of truss structures with dynamic constraints using the interactive fuzzy search algorithm," *Eng. Optim.*, vol. 53, no. 3, pp. 369–391, Mar. 2021.

[36] A. Kaveh and A. Zolghadr, "Democratic PSO for truss layout and size optimization with frequency constraints," *Comput. Struct.*, vol. 130, pp. 10–21, Jan. 2014.

[37] L. F. F. Miguel and L. F. F. Miguel, "Shape and size optimization of truss structures considering dynamic constraints through modern Metaheuristic algorithms," *Expert Syst. Appl.*, vol. 39, no. 10, pp. 9458–9467, Aug. 2012.

[38] N. Pholdee and S. Bureerat, "Comparative performance of meta-heuristic algorithms for mass minimisation of trusses with dynamic constraints," *Adv. Eng. Softw.*, vol. 75, pp. 1–13, Sep. 2014.

[39] M. Farshchin, C. V. Camp, and M. Maniat, "Multi-class teaching–learning-based optimization for truss design with frequency constraints," *Eng. Struct.*, vol. 106, pp. 355–369, Jan. 2016.

[40] D. H. Wolper and W. G. Macready, "No free lunch theorems for optimization," *IEEE Trans. Evol. Comput.*, vol. 1, no. 1, pp. 67–82, Apr. 1997.

[41] L. Abualigah, A. Diabat, S. Mirjalili, M. A. Elaziz, and A. H. Gandomi, "The arithmetic optimization algorithm," *Comput. Methods Appl. Mech. Eng.*, vol. 376, Apr. 2021, Art. no. 113609.

[42] A. Kaveh, N. Khodadadi, and S. Talatahari, "A comparative study for the optimal design of steel structures using CSS and ACSS algorithms," *Iran Univ. Sci. Technol.*, vol. 11, no. 1, pp. 31–54, 2021.

[43] A. D. Belegundu and J. S. Arora, "A study of mathematical programming methods for structural optimization. Part I: Theory," *Int. J. Numer. Methods Eng.*, vol. 21, no. 9, pp. 1583–1599, 1985.

[44] J. S. Arora, *Introduction to Optimum Design*. Amsterdam, The Netherlands: Elsevier, 2004.

[45] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, "Water cycle algorithm—A novel metaheuristic optimization method for solving constrained engineering optimization problems," *Comput. Struct.*, vols. 110–111, pp. 151–166, Nov. 2012.

[46] A. H. Gandomi, X.-S. Yang, A. H. Alavi, and S. Talatahari, "Bat algorithm for constrained optimization tasks," *Neural Comput Appl.*, vol. 22, no. 6, pp. 1239–1255, 2013.

[47] L. Wang and L.-P. Li, "An effective differential evolution with level comparison for constrained engineering design," *Struct. Multidisciplinary Optim.*, vol. 41, no. 6, pp. 947–963, Jun. 2010.

[48] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems," *Appl. Math. Comput.*, vol. 188, no. 2, pp. 1567–1579, May 2007.

[49] F.-Z. Huang, L. Wang, and Q. He, "An effective co-evolutionary differential evolution for constrained optimization," *Appl. Math. Comput.*, vol. 186, no. 1, pp. 340–356, Jun. 2007.

[50] C. A. C. Coello, "Use of a self-adaptive penalty approach for engineering optimization problems," *Comput. Ind.*, vol. 41, no. 2, pp. 113–127, Mar. 2000.

[51] K. M. Ragsdell and D. T. Phillips, "Optimal design of a class of welded structures using geometric programming," *J. Eng. Ind.*, vol. 98, no. 3, pp. 1021–1025, Aug. 1976.

[52] A. Kaveh and A. Dadras Eslamlou, "Water strider algorithm: A new Metaheuristic and applications," *Structures*, vol. 25, pp. 520–541, Jun. 2020.

[53] S. Mirjalili, "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm," *Knowl.-Based Syst.*, vol. 89, pp. 228–249, Nov. 2015.

[54] A. H. Gandomi, X.-S. Yang, and A. H. Alavi, "Cuckoo search algorithm: A metaheuristic approach to solve structural optimization problems," *Eng. Comput.*, vol. 29, no. 1, pp. 17–35, 2011.

[55] A. Sadollah, A. Bahreininejad, H. Eskandar, and M. Hamdi, "Mine blast algorithm: A new population based algorithm for solving constrained engineering optimization problems," *Appl. Soft Comput.*, vol. 13, no. 5, pp. 2592–2612, May 2013.

[56] S. Mirjalili, "The ant lion optimizer," *Adv. Eng. Softw.*, vol. 83, pp. 80–98, May 2015.

[57] S. Mirjalili, "SCA: A sine cosine algorithm for solving optimization problems," *Knowl.-Based Syst.*, vol. 96, pp. 120–133, Mar. 2016.

[58] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp swarm algorithm: A bio-inspired optimizer for engineering design problems," *Adv. Eng. Softw.*, vol. 114, pp. 163–191, Dec. 2017.

[59] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, "Multi-verse optimizer: A nature-inspired algorithm for global optimization," *Neural Comput. Appl.*, vol. 27, no. 2, pp. 495–513, 2015.

[60] T. Ray and P. Saini, "Engineering design optimization using a swarm with an intelligent information sharing among individuals," *Eng. Optim.*, vol. 33, no. 6, pp. 735–748, Aug. 2001.

[61] J. F. Tsai, "Global optimization of nonlinear fractional programming problems in engineering design," *Eng. Optim.*, vol. 37, no. 4, pp. 399–409, Jan. 2005.

[62] H. Chickermane and H. C. Gea, "Structural optimization using a new local approximation method," *Int. J. Numer. Methods Eng.*, vol. 39, no. 5, pp. 829–846, 1996.

[63] M. Farshchin, C. V. Camp, and M. Maniat, "Optimal design of truss structures for size and shape with frequency constraints using a collaborative optimization strategy," *Expert Syst. Appl.*, vol. 66, pp. 203–218, Dec. 2016.

[64] A. Kaveh and M. I. Ghazaan, "Vibrating particles system algorithm for truss optimization with multiple natural frequency constraints," *Acta Mechanica*, vol. 228, no. 1, pp. 307–322, 2017.

[65] A. Kaveh and V. R. Mahdavi, "Colliding-bodies optimization for truss optimization with multiple frequency constraints," *J. Comput. Civ. Eng.*, vol. 29, no. 5, Sep. 2015, Art. no. 4014078.

[66] M.-Y. Cheng and D. Prayogo, "Symbiotic organisms search: A new metaheuristic optimization algorithm," *Comput. Struct.*, vol. 139, pp. 98–112, Jul. 2014.

[67] A. Kaveh and A. Zolghadr, ''Truss shape and size optimization with frequency constraints using tug of war optimization,'' *Asian J Civ. Eng*, vol. 7, no. 2, pp. 311–333, 2017.
[68] A. Kaveh and A. Zolghadr, ''Truss optimization with natural frequency constraints using a hybridized CSS-BBBC algorithm with trap recognition capability,'' *Comput. Struct.*, vols. 102–103, pp. 14–27, Jul. 2012.

NIMA KHODADADI (Member, IEEE) received the bachelor's degree in civil engineering and the master's degree in structural engineering from the University of Tabriz (one of the ten top universities in Iran). He is currently working as a Researcher with the Iran University of Science and Technology (IUST). His main research interests include the field of steel structures, particularly in the experimental and numerical investigation of steel braced frames. In addition, he has been actively involved in the area of engineering optimization, especially in evolutionary algorithms. Using comprehensive finite element analyses, he has also investigated the use of different shaped sections in real steel frames. Recently, he has been engaged in research in the area of engineering optimization, especially in solving large-scale and practical structural design problems.

VACLAV SNASEL (Senior Member, IEEE) is currently a Professor with the Department of Computer Science, VSB—Technical University of Ostrava, Czech Republic. He works as a Researcher and a University Teacher. He is also the Dean of the Faculty of Electrical Engineering and the Computer Science Department. He is also the Head of the Research Program IT4 Knowledge Management, European Center of Excellence IT4 Innovations. His research and development experience includes over 30 years in the industry and academia. He works in a multi-disciplinary environment involving artificial intelligence, social networks, conceptual lattice, information retrieval, semantic web, knowledge management, data compression, machine intelligence, neural networks, web intelligence, nature and bio-inspired computing, data mining, and applied to various real-world problems.

SEYEDALI MIRJALILI (Senior Member, IEEE) is currently a Professor and the Founding Director of the Centre for Artificial Intelligence Research and Optimization, Torrens University Australia. He is internationally recognized for his advances in optimization and swarm intelligence, including the first set of algorithms from a synthetic intelligence standpoint-a radical departure from how natural systems are typically understood-and a systematic design framework to reliably benchmark, evaluate, and propose computationally cheap robust optimization algorithms. He has published over 300 publications with over 40,000 citations and an H-index of 70. As the most cited researcher in robust optimization, he has been on the list of 1% highly-cited researchers and named as one of the most influential researchers in the world by Web of Science for three consecutive years, since 2019. In 2020, he was ranked 21st across all disciplines and 4th in artificial intelligence and image processing in the Stanford University's list of World's Top Scientists. In 2021, The Australian newspaper named him as the top researcher in Australia in three fields of artificial intelligence, evolutionary computation, and fuzzy systems. His research interests include optimization, swarm intelligence, evolutionary algorithms, and machine learning. He is an Associate Editor of several AI journals including *Neurocomputing*, *Applied Soft Computing*, *Advances in Engineering Software*, *Computers in Biology and Medicine*, *Healthcare Analytics*, *Applied Intelligence*, and IEEE ACCESS.