Enhanced artificial ecosystem-based optimization for global optimization and constrained engineering problems

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Enhanced artificial ecosystem-based optimization for global optimization and constrained engineering problems

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Abstract

Artificial ecosystem-based optimization (AEO) is a nature-inspired intelligent optimization algorithm that has been widely applied to various real-world optimization problems. However, AEO has several limitations, including slow convergence and difficulty in escaping from local optima. To address these drawbacks, this study proposes an enhanced variant of AEO called enhanced artificial ecosystem-based optimization (EAEO). First, Latin hypercube sampling is introduced to achieve uniform population initialization. Then, a quadratic interpolation mechanism is embedded to accelerate convergence and improve accuracy. Finally, an adaptive neighborhood search inspired by animal migration behavior is designed to help to jump out of local optima. The performance of EAEO is evaluated using twenty-three benchmark functions and the CEC2017 test suite. Experimental results indicate that EAEO outperforms the original AEO and other comparison algorithms in terms of accuracy and stability. The proposed EAEO is applied to solve four engineering optimization problems. The results demonstrate the superiority of EAEO in addressing practical problems.

Keywords: Artificial ecosystem-based optimization, Latin hypercube sampling, Quadratic interpolation, Adaptive neighborhood search, Global optimization, Constrained engineering problems

1 Introduction

Optimization problems are prevalent across diverse domains, such as machine learning [1], scheduling and planning [2], economic optimization [3], and image processing [4]. Challenges often arise due to the multi-peak nature, high dimensionality, and nonlinearity inherent in these problems. Conventional optimization approaches often face challenges in efficiently discovering optimal solutions for intricate problems within a feasible time. Moreover, traditional methods often yield imprecise solutions. Consequently, the development of effective and efficient optimization algorithms remains a significant challenge, especially in addressing the growing diversity and complexity of problems.

1.1 Brief literature review

In recent years, metaheuristic algorithms (MAs) that emulate natural phenomena, physical laws, and animal social and life behaviors have received widespread attention [5]. The widespread acceptance of MAs can be attributed to their flexibility, simplicity, derivation-free mechanism, and ability to circumvent local optima [6]. While these algorithms cannot guarantee optimal solutions, their stochastic and indeterminate nature allows them to provide approximate answers to complex problems within a reasonable time. It has been proven that MAs are effective in addressing diverse optimization problems involving continuous or discrete variables, multidimensional spaces, and nonlinearities [7–9]. Different MAs have been developed inspired by biological and natural processes. For instance, particle swarm optimization (PSO) algorithm [10] draws inspiration from the regular flocking activities observed in birds. Similarly, cuckoo search (CS) [11] algorithm mimics the parasitic brooding behavior of cuckoo birds, which search for optimal nests to hatch eggs through random wandering. Grey wolf optimizer (GWO) [12] is motivated by the social dominance hierarchy and hunting behavior of grey wolves. Whale optimization algorithm (WOA) [13] simulates the hunting behaviors of humpback whales. Recently, novel algorithms, including harris hawks optimization (HHO) [14], sparrow search algorithm (SSA) [15], spider wasp optimization (SWO) [16], and nutcracker optimization algorithm (NOA) [17], have been introduced.

Inspired by energy flow mechanism observed in natural ecosystems, Zhao et al. [18] propose a novel swarm intelligence algorithm called artificial ecosystem-based optimization (AEO). This approach has garnered significant focus from both academia and industry due to its efficacy in attaining highly accurate solutions through a simple architecture. Consequently, AEO finds widespread applications in various fields. The No Free Lunch (NFL) theorem, as introduced by Wolpert D H et al. [19], emphasizes that there is no universal metaheuristic optimization algorithm that can excel across all types of optimization problems. When AEO gets stuck in a local optimum, the random wandering of the consumption factor with Levy flight characteristics alone is insufficient to facilitate a better detachment. Furthermore, the reliance of AEO on randomness results in a slow convergence speed. Hence, scholars have made significant efforts to develop improved or enhanced AEO algorithms customized for various optimization problems. The typical applications of AEO and its variants are presented in Table 1.

In swarm intelligence algorithms, the quality of population initialization directly influences the accuracy and convergence speed of the algorithm. Latin hypercube sampling (LHS) is a statistical technique designed to ensure a more uniform and efficient sampling of the multidimensional parameter space. It achieves this by dividing the cumulative distribution of each variable into intervals and randomly selecting values from these intervals. Rosli S J et al. [31] improve the identification capability of a random population using LHS. Mousavirad S J et al. [32] integrate a modified LHS and opposition-based learning with differential evolution to address the challenges posed by deceptiveness in the landscape. Quadratic interpolation (QI) is a mathematical technique that uses information from specific points in the objective function to construct a parabolic approximation. This enables the identification of near-optimal solutions and enhances convergence speed and accuracy in optimization algorithms. Sun Y et al. [33] introduce a modified whale optimization algorithm (WOA) incorporating QI, resulting in a faster convergence rate and higher solution accuracy compared to both the standard WOA and other population-based algorithms. Zhao W et al. [34] propose quadratic interpolation optimization (QIO) algorithm, inspired by mathematical principles, as a promising alternative for addressing numerical optimization and engineering challenges. Adaptive neighborhood search is a local search strategy that dynamically adjusts the exploration radius to facilitate escaping from local optima in optimization algorithms. Zeng N et al. [35] introduce a dynamic-neighborhood-based switching PSO algorithm. This approach incorporates a novel velocity updating mechanism that adjusts the individual best location and the global best location by a distance-based dynamic neighborhood. Zhou X et al. [36] devise a novel neighborhood-based variant of the artificial bee colony algorithm, employing adaptive neighborhood topologies, resulting in highly competitive performance.

1.2 Our contributions

Following the preceding analysis, this study proposes an enhanced artificial ecosystem-based optimization (EAEO) algorithm for global optimization and constrained engineering problems. The graphical abstract, elucidating the key components of this study is presented in Fig. 1. The main contributions are summarized as follows:

1. Latin hypercube sampling is employed for population initialization to enhance the quality of initial individuals and augment population diversity.
2. A quadratic interpolation strategy is implemented after updating the decomposition position, which aids in swiftly discovering optimal solutions and accelerates convergence.

Table 1: Applications of AEO and its variants

Author	Algorithm	Field	Year	Database
Elkholy M M et al. [20]	AEO	Photovoltaic cell	2020	Wiley
Eid A et al. [21]	Enhanced AEO	Distributed generator	2020	IEEE
Ewees A A et al. [22]	Modified AEO	Image segmentation	2021	MDPI
Nguyen T T [23]	AEO	Network reconfiguration	2021	Springer
Shaheen A et al. [24]	AEO	Power distribution system	2021	Elsevier
Nguyen T T et al. [25]	AEO	Photovoltaic cell	2022	Springer
Mostafa Reham R et al. [26]	AEO	Feature selection	2022	Elsevier
Bhattacharjee K et al. [27]	AEO	Economic load dispatch	2022	Taylor & Francis
Thanh N T et al. [28]	AEO	Energy storage system	2022	Elsevier
Wilberforce T et al. [29]	AEO	Fuel cell	2023	Elsevier
Van Thieu N et al. [30]	Augmented AEO	Groundwater level modeling	2023	Elsevier

3. An adaptive neighborhood search strategy combats stagnation by expanding the exploration scope based on population fitness standard deviation, determined by the standard deviation of population fitness. This enables the algorithm to escape from local optima and explore new regions within the search space.
4. The effectiveness of EAEO has been validated on twenty-three benchmark functions and the CEC2017 test suite.
5. The capability of EAEO in solving real-world problems is evaluated by applying it to four classical engineering problems.

The rest of this study is structured as follows: Section 2 introduces the main principles of the AEO algorithm. while Section 3 presents the proposed EAEO algorithm and analyzes its time complexity. Section 4 assesses the performance of EAEO on benchmark functions, demonstrating its superiority over other swarm intelligence algorithms. Section 5 demonstrates the applicability of EAEO on four engineering problems. Finally, the main findings of this study are summarized, and potential directions for future work are provided in Section 6.

2 Artificial ecosystem-based optimization

This section briefly reviews AEO [18], which simulates the energy flow derived from inter-species feeding relationships within an ecosystem. The ecosystem consists of three types of organisms: producers, consumers, and decomposers. Consequently, AEO employs three primary operators: production, consumption, and decomposition. The production operator enhances the balance between exploration and exploitation, the consumption operator improves the exploration capability, and the decomposition operator is utilized to promote exploitation performance.

2.1 Population initialization

The initialization process of AEO is randomly generates individuals in the search space, following a Gaussian distribution, as shown in below:

$$x_{rand} = \mathbf{r} \cdot (U - L) + L \tag{1}$$

where $\mathbf{r}$ is a random vector within the range of $[0, 1]$, L and U are the lower and upper limits for a D-dimensional problem, respectively.

The position matrix of the initial population is expressed as:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ \vdots & \vdots & \vdots & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,D} \end{bmatrix} \tag{2}$$

where N is the population size.

2.2 Production

The production operator allows AEO to generate a new individual randomly, replacing the previous one within the search space, positioned between the best individual and another randomly generated individual. The mathematical model of the production operator is described as:

$$x_1^{t+1} = (1 - a) \cdot x_{best}^t + a \cdot x_{rand}^t \tag{3}$$

$$a = (1 - t/T) \cdot r_1 \tag{4}$$

where x_{best} is the position of the best individual, a is a weight coefficient that increases linearly with the number of iterations, t is the current iterations, T is the maximal number of iterations, r_1 is a random number within the range of [0, 1], and x_{rand} is the position of the individual randomly generated population mentioned in Eq. (1).

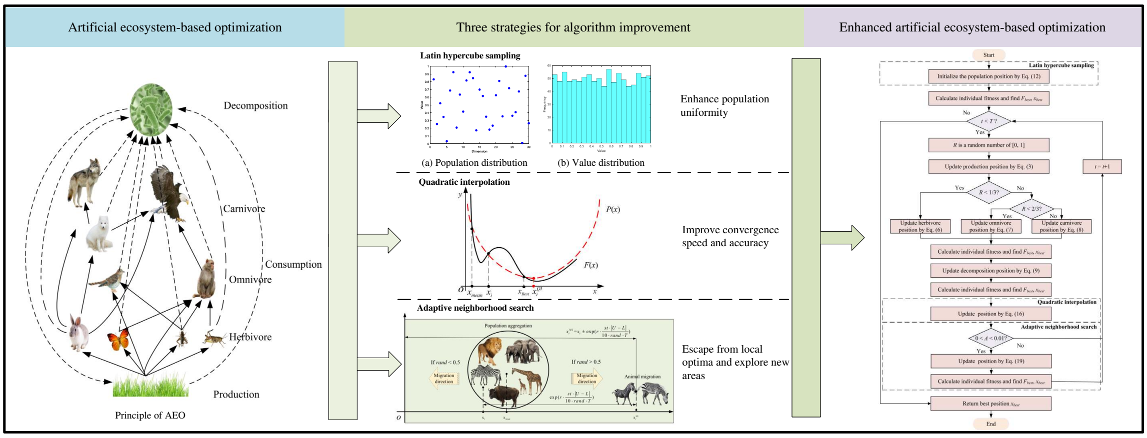


Fig. 1: Graphical abstract of this study

2.3 Consumption

The consumers are classified into herbivores, omnivores, and carnivores. To acquire food energy, each consumer has the option to consume either a randomly selected consumer with a lower energy level or a producer, or both. After the execution of the production operator, all consumers may undergo the consumption operator.

Levy flight is a type of random walk that efficiently explores the search space, with some steps covering significantly longer distances over time. This trait makes it promising for discovering global optima. A simple and parameter-free random walk, incorporating the Levy flight feature, known as the consumption factor, is defined as:

$$C = \frac{1}{2} \cdot \frac{V_1}{|V_2|}\ , V_1 \sim N(0,1)\ , V_2 \sim N(0,1) \quad (5)$$

where $N(0,\,1)$ is a normal distribution with the mean of 0 and the standard deviation of 1.

The consumption operator aids each consumer in the quest for food, with different consumer types adopting diverse consumption strategies. The process of updating the position of all consumers is as follows:

Herbivore: The consumer, when randomly selected as an herbivore, relies solely on the producer for its nutritional needs. The consumption behavior of herbivores can be mathematically represented by:

$$x_i^{t+1} = x_i^t + C \cdot (x_i^t - x_1^t), i \in \{2, \ldots, N\} \quad (6)$$

Omnivore: The consumer, when randomly designated as an omnivore, it can randomly prey on consumers with higher energy levels or edible producers. The equation describing the consumption behavior of omnivores is as follows:

$$\begin{aligned} x_i^{t+1} &= x_i^t + C \cdot (r_2 \cdot x_i^t - x_1^t) + (1 - r_2) \\ &\quad \cdot (x_i^t - x_1^t), \quad i \in \{3, \ldots, N\}. \end{aligned} \quad (7)$$

where r_2 is a random number within the interval of $[0, 1]$.

Carnivore: The consumer, when randomly choosen as a carnivore, its sole feeding option is to randomly prey upon a consumer with a high energy level. The equation representing the consumption behavior of a carnivore is given by:

$$x_i^{t+1} = x_i^t + C \cdot (x_i^t - x_j^t), i \in \{3, \ldots, N\} \quad (8)$$

where j is a random integer in the range $[2, i-1]$.

2.4 Decomposition

After the consumption phase completes, the decomposition phase starts. Here, the organism x_i within the ecosystem dies and is subsequently decomposed by the decomposer x_{best}. This process utilizes the optima solution to find superior solutions near the solution space, thereby enhancing the algorithm's local search capability. The mathematical model corresponding to the decomposition behavior is given as follows:

$$x_{best}^{t+1} = x_{best}^t + D \cdot (e \cdot x_{best}^t - h \cdot x_1^t) \quad (9)$$

$$e = r_3 \cdot \text{randi}([1\ 2]) - 1 \quad (10)$$

$$h = 2 \cdot r_3 - 1 \quad (11)$$

Here, $D = 3u$ ($u \sim N(0, 1)$) is the decomposition factor, r_3 is a random number in the interval $(0, 1)$, e and h are the weight coefficients. The function randi($[a\ b]$) returns a random integer 1 or 2.

3 The proposed EAEO

This section proposes an enhanced artificial ecosystem optimization (EAEO) algorithm incorporating Latin Hypercube Sampling, quadratic interpolation strategy, and adaptive neighborhood search. The algorithmic flowchart of EAEO is depicted in Fig.2, and the pseudocode is provided in Algorithm1.

3.1 Initialization based on Latin hypercube sampling

Metaheuristic algorithms lies in iteratively generating candidate solutions. Consequently, the initial values significantly influence the precision and convergence speed of the algorithm. However, the population initialization process in the original AEO relies on Gaussian distribution, posing a challenge to ensure ergodicity and diversity of the population. To address this issue, Latin hypercube sampling (LHS) [37] is introduced to facilitate a more diverse set of initial solutions, thereby enhancing the effectiveness of the algorithm in discovering the optimal solution.

As a statistical technique, LHS generates random samples from a multivariate distribution. It ensures a more uniform sample distribution by allowing only one sample per row and column, similar to a Latin square. LHS achieves this by partitioning the cumulative distribution of each variable into n small intervals and randomly selecting a value from each interval. These values are then combined with those from other variables. This approach is particularly suitable for scenarios with a limited sample size.

The essential steps of LHS are outlined as follows:

1. Divide the range $[0, 1]$ into n equal segments and generate random numbers within each interval $\left[\frac{i}{n}, \frac{i+1}{n}\right]$ obeying the uniform distribution.
2. Randomize the sequence of the n generated numbers.
3. These n numbers represent the probabilities associated with each random sample, and the random distribution values are generated employing the inverse function of the probability distribution function.

The comprehensive coverage and equal-probability sampling features of LHS contribute to a more uniformly distributed set of samples compared to random sampling. Therefore, employing LHS for population initialization enhances the distribution of the initial population, improving both global optimization and convergence speed. The population initialization based on LHS is described as:

$$x_{rand} = (U - L) \cdot \text{lhs}(1, D) + L \tag{12}$$

Here, lhs is the LHS function.

In Fig. 3, population initialization using LHS has a more uniform distribution compared to random initialization. Additionally, the effectiveness of LHS becomes more apparent with a population size set to 1000, as indicated by histograms in Fig. 4.

3.2 Quadratic interpolation strategy

Quadratic interpolation (QI) utilizes information from specific points of the objective function (function values or derivative values) to construct an interpolating polynomial $P(x)$ in proximity to the objective function $F(x)$ [38]. By identifying the minimizer of the polynomial $P(x)$, QI approximates the minimum point of the function $F(x)$, as illustrated in Fig. 5.

In optimization, the QI strategy is commonly incorporated into various optimization techniques to improve their search performance [39–41]. In EAEO, the QI strategy is incorporated into the algorithm after the position of decomposer updates, with the intention of enhancing the convergence speed and accuracy of the solution. The interpolating polynomial $P(x)$ is construct by three known points: the current population position x_i, the average position of the population x_{mean}, and the optimal position of the population x_{best}. By determining minima through this mathematical approach, the algorithm swiftly enhances convergence and accuracy without requiring gradient information, using only the positional information of three points to find the optimal value. The QI method is implemented as follows. First, the QI function is defined as:

$$P(x) = a_0x^2 + a_1x + a_2, \; a_0, a_1, a_2 \in R \tag{13}$$

where a_0 , a_1, and a_2 are coefficients to be determined. In accordance with the interpolation conditions, the function value $F(x)$ is equivalent to $P(x)$ at the interpolation points x_i, x_{best}, and x_{mean}, as delineated below:

$$P(x) = a_0x^2 + a_1x + a_2 = F(x) \tag{14}$$

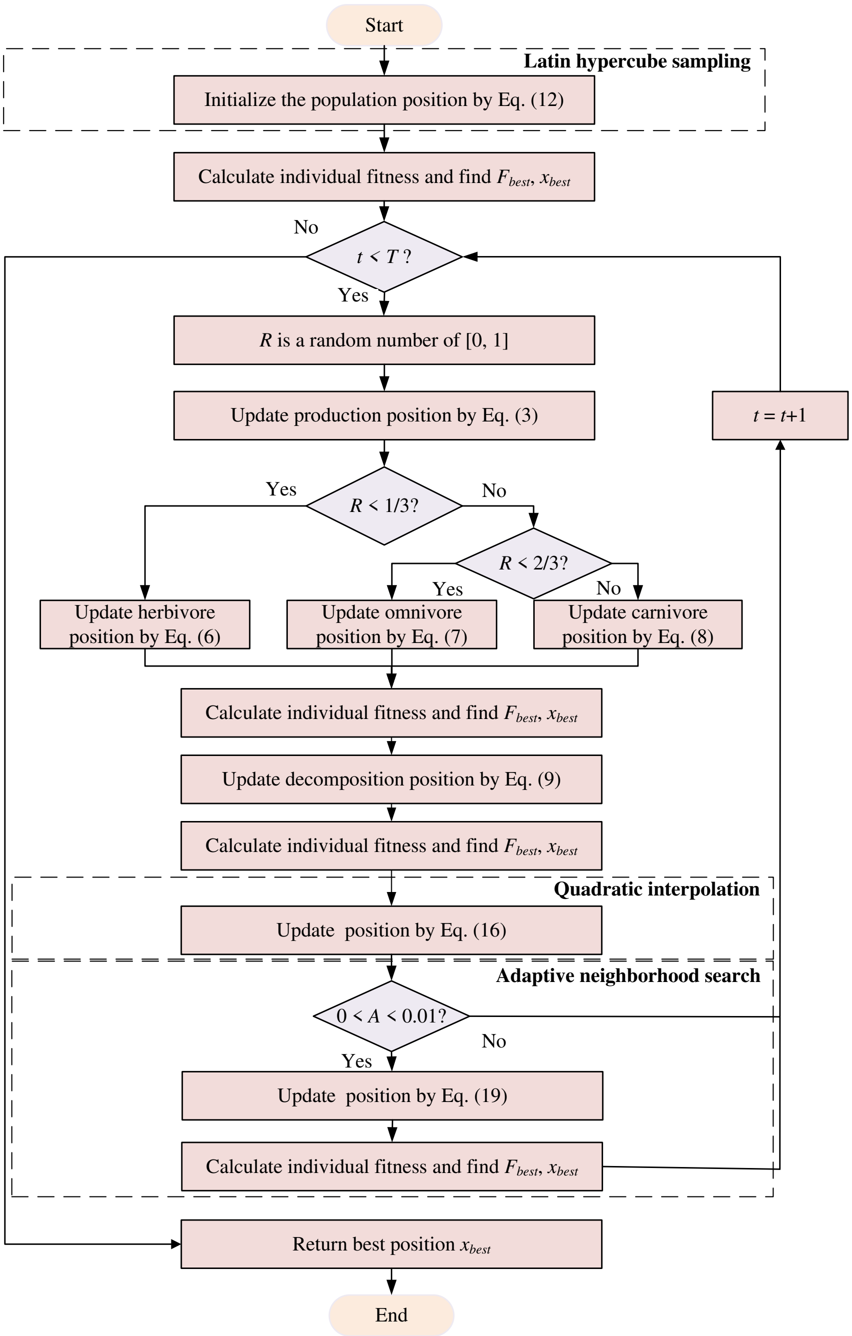


Fig. 2: Flowchart of EAEO

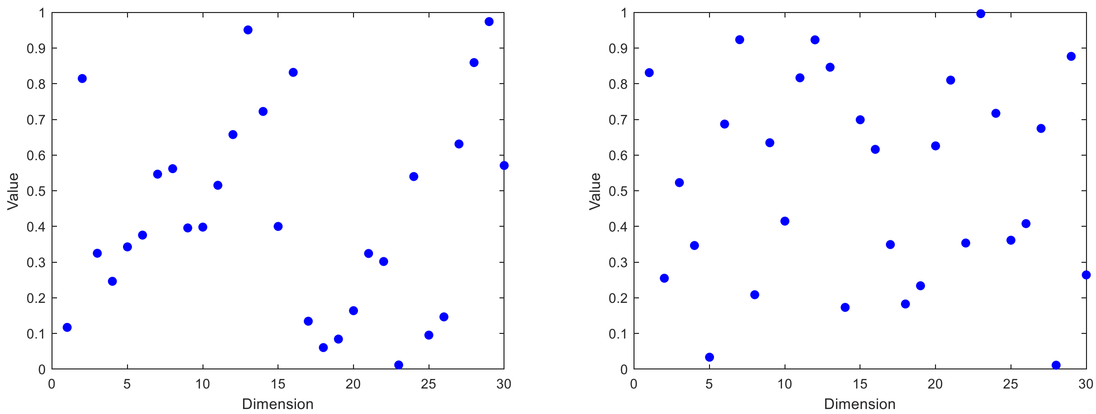
The values of a_0, a_1, and a_2 can be calculated from the above equation. The minimum value point of $P(x)$, denoted as $x_{\min} = -a_1/2a_0$, determines the expression for the minimum value of the curve fitted by the QI function, as shown in Eq. (15).

$$x_i^{QI} = \frac{((x_i)^2 - (x_{mean})^2) \cdot F(x_{best}) + ((x_{mean})^2 - (x_{best})^2) \cdot F(x_i) + ((x_{best})^2 - (x_i)^2) \cdot F(x_{mean})}{2(x_i - x_{mean}) \cdot F(x_{best}) + (x_{mean} - x_{best}) \cdot F(x_i) + (x_{best} - x_i) \cdot F(x_{mean})} \tag{15}$$

The QI strategy has the potential to identify an optimal individual with superior fitness compared to the original x_i. Ultimately, a greedy strategy is employed to choose the individual with superior fitness as new individual between x_i and x_i^{QI}, the equation of greedy strategy is

Algorithm 1 Pseudo-code of EAEO

Input: Population size (N), maximum number of iterations (T), and $t = 0$
Output: Best position (x_{best})
  Initialize the population position by Eq. (12) ▷ Latin hypercube sampling strategy
  Calculate fitness values and rank them from highest to lowest
  while $t < T$ **do**
    Renew the position by Eq. (3) ▷ Production
    for $i = 2 : N$ **do**
      $R = rand(0, 1)$
      if $R < \frac{1}{3}$ **then**
        Renew the position by Eq. (6) ▷ Herbivore
      else
        if $\frac{1}{3} < R < \frac{2}{3}$ **then**
          Renew the position by Eq. (7) ▷ Omnivore
        else
          Renew the position by Eq. (8) ▷ Carnivore
        end if
      end if
    end for
    Calculate fitness values and find F_{best} and x_{best}
    Renew the position by Eq. (9) ▷ Decomposition
    Calculate fitness values and find F_{best} and x_{best}
    Calculate the position x^* by Eq. (15) ▷ Quadratic interpolation strategy
    Calculate fitness values, update population position by Eq. (16), and find F_{best} and x_{best}
    Calculate A by Eq. (17) ▷ Adaptive neighborhood search strategy
    if $0 < A < 10^{-2}$ **then**
      Neighborhood search by Eq. (18)
      Calculate fitness values, update population position by Eq. (19), and find F_{best} and x_{best}
    end if
    $t = t + 1$
  end while
  Return x_{best}



(a) Random initialization (b) Initialization using LHS

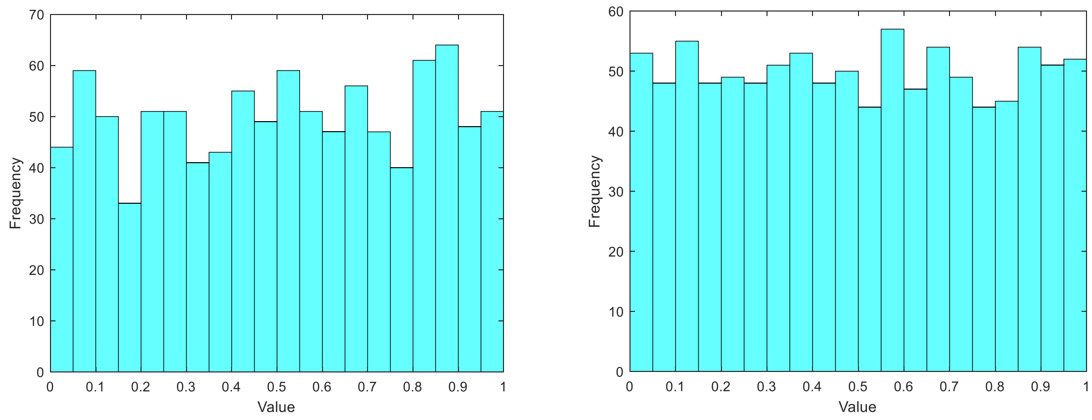
Fig. 3: Population distribution results of two initialization methods

shown as follows:

$$x_i^* = \begin{cases} x_i^{QI}, & \text{if } F(x_i) > F(x_i^{QI}) \\ x_i, & \text{otherwise} \end{cases} \tag{16}$$

3.3 Adaptive neighborhood search

During the optimization process of AEO, the population has a tendency to converge towards the optimal solution x_{best}. Although



(a) Random initialization

(b) Initialization using LHS

Fig. 4: Value distribution results of two initialization methods

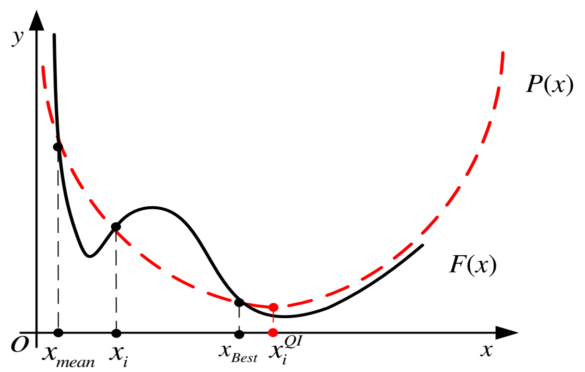


Fig. 5: Principle of quadratic interpolation

this enhances algorithmic accuracy by extensively exploring the current optima, it restricts population diversity, potentially resulting in entrapment in local optima. To address this issue, EAEO draws inspiration from natural animal migration behavior, aiming to improveits capacity to escape local optima. The principle of adaptive neighborhood search is illustrated in Fig. 6.

After applying the QI strategy, the individuals in the population undergo fitness evaluation and are then ranked in descending order. The bottom column of the population matrix is then selected for additional analysis. Define the degree of population aggregation as:

$$A = \sqrt{\frac{\sum_{i=1}^{D} \left(F(x_i) - F(x_{mean})\right)^2}{D}} \tag{17}$$

When the algorithm is trapped in local optima, individuals within the population cluster together, and the fitness of the population remains unchanged. If $0 < A < 0.01$, it signals that the algorithm's progress has stalled, triggering the initiation of adaptive neighborhood search. The formula for adaptive neighborhood search is provided below:

$$x_i^{NS} = \begin{cases} x_i + \exp\left(\mathbf{r} \cdot \frac{st \cdot |U\text{-}L|}{10 \cdot rand \cdot T}\right), & \text{if } rand < 0.5 \\ x_i - \exp\left(\mathbf{r} \cdot \frac{st \cdot |U\text{-}L|}{10 \cdot rand \cdot T}\right), & \text{otherwise} \end{cases} \tag{18}$$

where $\mathbf{r}$ is a random vector within [0, 1], and $rand$ is a uniformly distributed random number within the interval $(0, 1)$, and st is the stagnation factor.

If the algorithm is considered to be at a local optima, st is incremented by 1. If $rand < 0.5$, the population migrates in the decreasing direction; otherwise, it migrates in the increasing direction. The migration distance exponentially increases with st and is influenced by the search space's size and the iterations' maximum number. If st surpasses 20, it is reset to 0. This corresponds to the phenomenon of animal populations facing mortality after prolonged migrations when they fail to find sufficient food. Furthermore, restarting the neighborhood search from the origin prevents the algorithm from neglecting optimal values in the vicinity. This facilitates a comprehensive exploration of the search space, thereby mitigating issues related to premature convergence [42]. Fig. 7 illustrates the adaptive neighborhood search by an example. Similarly, utilize a greedy strategy to preserve the individual with superior fitness as the new individual.

$$x_i^* = \begin{cases} x_i^{NS}, & \text{if } F(x_i) > F(x_i^{NS}) \\ x_i, & \text{otherwise} \end{cases} \tag{19}$$

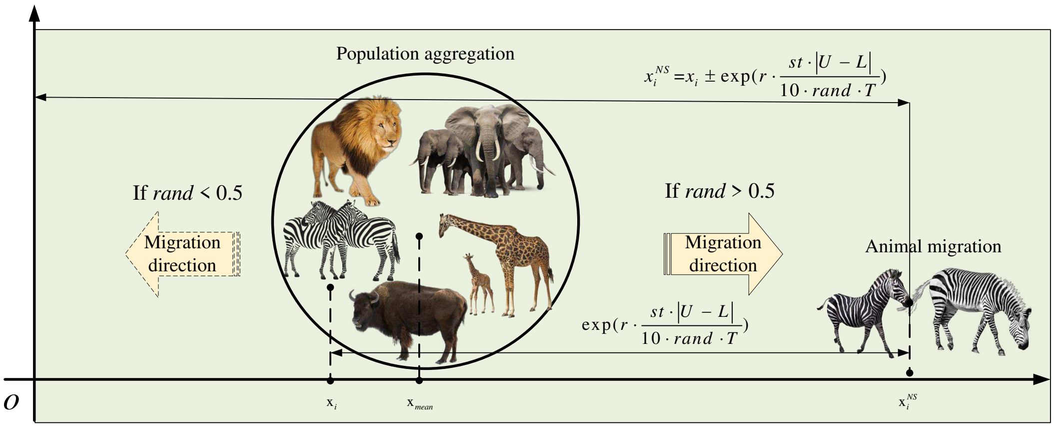


Fig. 6: Principle of adaptive neighbourhood search

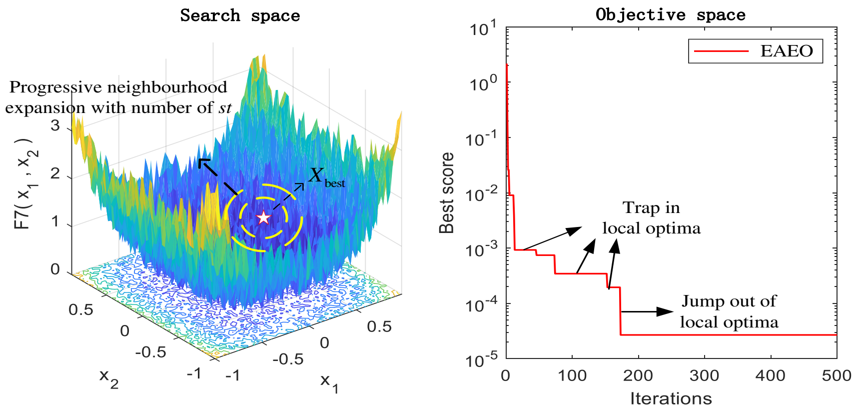


Fig. 7: Illustration of adaptive neighbourhood search

3.4 Time complexity analysis

The time complexity of an algorithm is a critical criterion for performance evaluation, determining operational efficiency and reflecting the ability to handle complex optimization problems. The time complexity analysis of AEO and EAEO is presented below.

In AEO, with population size N, problem dimension D, and maximum number of iterations T, the time complexity for population initialization is $O(N \times D)$, individual fitness calculation is $O(N \times D)$, production position update is $O(D)$, consumption position update is $O((N-1) \times D)$, and decomposition position update is $O(T \times N \times D)$. The overall time complexity of AEO is $O(D+3N\times D+T\times N\times D)$.

In EAEO, sharing the similar settings as AEO, the time complexity for population initialization using LHS is $O(N \times D)$, quadratic interpolation method is $O(T \times N \times D)$. Furthermore, the best-case time complexity of adaptive neighborhood search is 0, while the worst-case is $O(T \times N \times D)$. The overall time complexity of EAEO is $O(D + 3N \times D + 3T \times N \times D)$.

Despite having a slightly higher time complexity, EAEO operates within the same order of magnitude as AEO. The increased computational complexity is often acceptable due to the superior performance it offers.

4 Experimental results and analysis

In this section, diverse experiments are conducted to evaluate the performance and robustness of EAEO. First, an ablation study of EAEO is performed to verify the validity of the used three strategies and assess whether different enhancement strategies can produce synergistic effects. Second, the algorithm is evaluated using twenty-three benchmark functions, comparing it with classical swarm intelligence algorithms. Subsequently, a Wilcoxon rank test is conducted at a 5% significance level to assess whether EAEO outperforms other competitive algorithms. Finally, for a overall evaluation, the latest algorithms proposed within the last five years are selected for comparison with EAEO using the CEC2017 test suite. Specific descriptions of the twenty-three benchmark functions and the CEC2017 test suite are provided in Tables 2 and 3.

4.1 Experimental design and evaluation criteria

Experimental simulations are carried out using MATLAB R2022a on a Windows 10 64-bit laptop with an Intel(R) Core(TM) i5-9300H CPU running at 2.4 GHz and 24.00 GB RAM. To ensure the fairness of the experiments, we standardized the iterations' maximum number (T=500) and population's size (N=30) for all algorithms, with thirty independent experiments conducted for each algorithm. The evaluation criteria for the minimization problem are defined below:

(1) Best and worst values:

$$\begin{cases} \text{Best} = \min(\text{Best}F_1, \text{Best}F_2, \ldots, \text{Best}F_K) \\ \text{Worst} = \max(\text{Best}F_1, \text{Best}F_2, \ldots, \text{Best}F_K) \end{cases} \tag{20}$$

where BestF_i denotes the optimal fitness value at the i-th run, and $K = 30$ indicates 30 runs. These index measures reflects the algorithm's solution precision.

(2) Average value:

$$\text{Mean} = \frac{1}{K}\sum_{i=1}^{K} \text{Best}F_i \tag{21}$$

The average value serves as a fair measure to represent the algorithm's performance, mitigating the impact of other factors during the optimization problem-solving process.

(3) Standard deviation:

$$\text{Std} = \sqrt{\frac{1}{K-1}\sum_{i=1}^{K}(\text{Best}F_i - \text{Mean})^2} \tag{22}$$

The standard deviation serves as an indicator of the divergence among the solutions.

(4) Rank:

This criterion ranks different algorithms based on their mean performance. If two algorithms exhibit the same mean, the standard deviation is employed for sorting.

(5) Wilcoxon rank test

The Wilcoxon rank test is a non-parametric test employed in the scenario of hypothesis testing for two independent groups. Its purpose is to identify a significant difference in the behaviors of two algorithms [43].

4.2 Comparison algorithms and parameter settings

To evaluate the effectiveness of the proposed approach, we compare it against several classical algorithms, including PSO [10], CS [11], GWO [12], WOA [13], HHO [14], SSA [15], and AEO [18]. The parameter settings for each algorithm, as detailed in Table 4, are adopted from the original papers. These algorithms have demonstrated success in real engineering optimization problems. Additionally, to facilitate a comprehensive comparison with emerging algorithms, we select recent algorithms from the last five years, including HHO [14], SSA [15], AEO [18], GJO [44], RSO [45], BOA [46], and BWO [47]. These algorithms represent recent advancements in metaheuristics and exhibit commendable performance. The parameter configurations for each algorithm, as listed in Table 5, are extracted from the original papers. The results, encompassing the best, worst, mean, and standard deviation (Std), are documented for all algorithms, with the best outcomes emphasized in bold.

4.3 Ablation study of EAEO

In this section, we perform an ablation study to systematically analyze the effect of incorporating each strategy on the optimization capability of EAEO. This analysis aims to demonstrate the synergistic effects achieved by combining multiple strategies. The three strategies mentioned in Section 3, including Latin hypercube sampling, quadratic interpolation, and adaptive neighborhood search, are individually integrated into the original AEO algorithm. The resulting modified algorithms, denoted as LAEO, QAEO, and AAEO, are then compared with both AEO and EAEO. We select representative functions, namely F1, F5, F7, F12, F13, F15, F20, and F23, from the twenty-three benchmark functions. The experimental parameters align with those outlined in Section 4.2, and the corresponding test results are presented in Table 6.

Generally, EAEO demonstrates superior performance compared to AEO and a single improvement strategy for the majority of the benchmark functions. Notably, both EAEO and QAEO exhibit enhanced performance in function F1, attributed to their utilization of quadratic interpolation, enabling accurate identification of the optimal value for this simple

Table 2: Description of the twenty-three benchmark functions.

Function Type	No.	Name	Dim	Range	f_{min}
Unimodal	$F1$	Sphere	30	[-100,100]	0
	$F2$	Schwefel 2.22	30	[-10,10]	0
	$F3$	Schwefel 1.2	30	[-100,100]	0
	$F4$	Schwefel 2.21	30	[-100,100]	0
	$F5$	Rosenbrock	30	[-30,30]	0
	$F6$	Cigar	30	[-100,100]	0
	$F7$	Quartic	30	[-1.28,1.28]	0
Multimodal	$F8$	Schwefel 2.26	30	[-500,500]	-418.9829×Dim
	$F9$	Rastrigin	30	[-32,32]	0
	$F10$	Ackley	30	[-600,600]	0
	$F11$	Griewank	30	[-50,50]	0
	$F12$	Penalized 1	30	[-50,50]	0
	$F13$	Penalized 2	30	[-50,50]	0
Fixed-dimension multimodal	$F14$	Shekel's Foxholes	2	[-65,65]	1
	$F15$	Kowalik	4	[-5,5]	0.0003075
	$F16$	Six-hump camel back	2	[-5,5]	-1.0316285
	$F17$	Branin	2	[-5,5]	0.398
	$F18$	Goldstein-Price	2	[-2,2]	3
	$F19$	Hartman 3	3	[0,1]	-3.86
	$F20$	Hartman 6	6	[0,1]	-3.32
	$F21$	Shekel 5	4	[0,10]	-10
	$F22$	Shekel 7	4	[0,10]	-10
	$F23$	Shekel 10	4	[0,10]	-10

function. Although a single strategy contributes to improvement in functions F5 and F7 when applied to AEO, EAEO surpasses the performance of the LAEO, QAEO, and AAEO algorithms, highlighting the superior impact of multi-strategy fusion on benchmark functions compared to individual strategies. The algorithm's search capability sees substantial enhancement, particularly owing to the influence of the QI strategy in functions F12 and F13. In function F20, the performance improvement of the algorithm is primarily attributed to the LHS initialization. The adaptive neighborhood search strategy plays a crucial role in significantly improving the algorithm's capability to navigate away from local optima, leading to enhanced overall results. Although LAEO, QAEO, and EAEO produce identical optimization results in function F23, EAEO exhibits a smaller standard deviation, indicating better stability. This implies that multi-strategy fusion contributes to improved stability of EAEO.

4.4 Performance comparison on twenty-three benchmark functions

In this section, EAEO is pitted against PSO, CS, GWO, WOA, HHO, SSA, and AEO. The experimental design is outlined in Section 4.1, and the parameter configurations for each algorithm are specified in Table 4. The comparative outcomes of the proposed EAEO alongside other algorithms on twenty-three benchmark functions are presented in Table 7.

The results in Table 7 demonstrate that EAEO significantly outperforms AEO and the six popular swarm intelligence algorithms on twenty-three benchmark functions for finding optimal results. EAEO excels in all benchmark functions except function F8. For the seven unimodal test functions (F1–F7), EAEO achieves the theoretical optimum value on functions F1–F6. Even on function F7, where the theoretical optima is not reached, EAEO's performance surpasses that of the other seven algorithms by a significant margin. The multimodal benchmark functions (F8–F13) assess the algorithm's global exploration ability and its capability to escape from local optima. EAEO achieves the best results in multimodal benchmark functions, excluding function F8. Notably, for functions F12 and F13, the enhanced algorithm is otens of orders of magnitude more effective than AEO in finding optimal results. These outcomes highlight EAEO's robust global detection ability and the capability to escape from local optima.

Table 3: Description of the CEC2017 test suite

Function type	No.	Name	f_{min}
Unimodal functions	F1	Shifted and Rotated Bent Cigar Function	100
	F3	Shifted and Rotated Zakharov Function	300
Multimodal functions	F4	Shifted and Rotated Rosenbrock's Function	400
	F5	Shifted and Rotated Rastrigin's Function	500
	F6	Shifted and Rotated Expanded Scaffer's F6 Function	600
	F7	Shifted and Rotated Lunacek Bi_Rastrigin Function	700
	F8	Shifted and Rotated Non-Continuous Rastrigins Function	800
	F9	Shifted and Rotated Levy Function	900
	F10	Shifted and Rotated Schwefel's Function	1000
Hybrid functions	F11	Hybrid Function 1 (N = 3)	1100
	F12	Hybrid Function 2 (N = 3)	1200
	F13	Hybrid Function 3 (N = 3)	1300
	F14	Hybrid Function 4 (N = 4)	1400
	F15	Hybrid Function 5 (N = 4)	1500
	F16	Hybrid Function 6 (N = 4)	1600
	F17	Hybrid Function 6 (N = 5)	1700
	F18	Hybrid Function 6 (N = 5)	1800
	F19	Hybrid Function 6 (N = 5)	1900
	F20	Hybrid Function 6 (N = 6)	2000
Composition functions	F21	Composition Function 1 (N = 3)	2100
	F22	Composition Function 2 (N = 3)	2200
	F23	Composition Function 3 (N = 3)	2300
	F24	Composition Function 4 (N = 3)	2400
	F25	Composition Function 5 (N = 3)	2500
	F26	Composition Function 6 (N = 3)	2600
	F27	Composition Function 7 (N = 3)	2700
	F28	Composition Function 8 (N = 3)	2800
	F29	Composition Function 9 (N = 3)	2900
	F30	Composition Function 10 (N = 3)	3000

Table 4: Parameter settings of eight classical algorithms

Algorithm	Parameter
EAEO	$r_1, r_2, r_3 \in [0, 1]$
AEO	$r_1, r_2, r_3 \in [0, 1]$
WOA	a decreases linearly from 2 to 0
GWO	a decreases linearly from 2 to 0, $r_1, r_2 \in [0, 1]$
HHO	$r_1, r_2, r_3, r_4, q \in [0, 1]$; $E_0 \in (-1, 1)$; J
PSO	$c_1 = 1.5$; $c_2 = 1.5$; $w = 0.7$; $V_{\max} = 0.5$; $V_{\min} = -0.5$
CS	$p_a = 0.25$; $\beta = 1.5$
SSA	$P_{\text{percent}} = 0.2$

Fixed-dimension multimodal benchmark functions represent a category of standard benchmark functions with constant dimensionality. Similarly, the examination of Table 7 suggests that EAEO exhibits optimal performance on fixed-dimension multimodal functions in comparison to the other seven algorithms. Although the Best term results are comparable across most algorithms, distinctions become evident in the Mean term. Notably, EAEO consistently approaches the optimal value in the Mean, highlighting the algorithm's stability. The Std metric provides additional support for this conclusion. The results demonstrate that EAEO can effectively handle optimization problems in different dimensions. In summary, EAEO significantly outperforms AEO and other six algorithms in obtaining optimal results on twenty-three

Table 5: Parameter settings of eight state-of-the-art algorithms

Algorithm	Parameter
EAEO	$r_1, r_2, r_3 \in [0, 1]$
AEO	$r_1, r_2, r_3 \in [0, 1]$
RSO	$R \in [1, 5]$, $C \in [0, 2]$
GJO	$E_1 \in [0, 1.5]$
HHO	$r_1, r_2, r_3, r_4, q \in [0, 1]$, $E_0 \in (-1, 1)$
BOA	$a = 0.1$, $p = 0.6$, $c_0 = 0.01$
SSA	$P_{\text{percent}} = 0.2$
BWO	$W_f \in [0.01, 0.5]$

Table 6: Comparisons results of AEO algorithm with different strategies on twenty-three benchmark functions

	Item	AEO	LAEO	QAEO	AAEO	EAEO
F1	Best	9.25E-185	4.15E-185	**0.00E+00**	1.53E-180	**0.00E+00**
	Worst	8.28E-158	5.64E-159	**0.00E+00**	2.35E-159	**0.00E+00**
	Mean	2.76E-159	1.89E-160	**0.00E+00**	8.88E-161	**0.00E+00**
	Std	1.51E-158	1.03E-159	**0.00E+00**	4.31E-160	**0.00E+00**
F5	Best	2.27E+01	2.19E+01	**0.00E+00**	2.06E-05	**0.00E+00**
	Worst	2.75E+01	2.53E+01	2.45E+01	2.43E+01	**0.00E+00**
	Mean	2.44E+01	2.41E+01	7.94E+00	3.97E+00	**0.00E+00**
	Std	9.31E-01	6.82E-01	1.14E+01	9.03E+00	**0.00E+00**
F7	Best	1.07E-04	2.62E-05	1.60E-06	2.24E-05	**1.83E-07**
	Worst	1.30E-03	2.97E-03	6.10E-04	2.66E-03	**4.53E-04**
	Mean	5.36E-04	5.52E-04	1.02E-04	5.68E-04	**5.67E-05**
	Std	3.23E-04	6.20E-04	1.15E-04	5.44E-04	**6.22E-05**
F12	Best	3.41E-07	3.16E-08	**1.57E-32**	6.55E-09	**1.57E-32**
	Worst	1.04E-01	6.59E-06	**1.57E-32**	2.92E-06	**1.57E-32**
	Mean	3.50E-03	1.09E-06	**1.57E-32**	3.92E-07	**1.57E-32**
	Std	1.89E-02	1.46E-06	**5.57E-48**	5.91E-07	**5.57E-48**
F13	Best	7.81E-05	1.01E-06	**1.35E-32**	1.38E-09	**1.35E-32**
	Worst	2.96E+00	5.48E-02	**1.35E-32**	1.11E-02	**1.35E-32**
	Mean	8.99E-01	6.39E-03	**1.35E-32**	5.24E-04	**1.35E-32**
	Std	1.01E+00	1.48E-02	**5.57E-48**	2.17E-03	**5.57E-48**
F15	Best	**3.07E-04**	**3.07E-04**	**3.07E-04**	**3.07E-04**	**3.07E-04**
	Worst	1.20E-03	3.07E-04	4.24E-04	1.22E-03	**3.07E-04**
	Mean	3.69E-04	3.07E-04	3.15E-04	3.42E-04	**3.07E-04**
	Std	2.32E-04	1.41E-18	2.96E-05	1.68E-04	**4.69E-19**
F20	Best	**-3.32E+00**	**-3.32E+00**	**-3.32E+00**	**-3.32E+00**	**-3.32E+00**
	Worst	**-3.20E+00**	**-3.20E+00**	**-3.20E+00**	**-3.20E+00**	**-3.20E+00**
	Mean	-3.27E+00	-3.28E+00	-3.27E+00	-3.28E+00	**-3.29E+00**
	Std	6.03E-02	5.83E-02	5.92E-02	5.70E-02	**5.35E-02**
F23	Best	**-1.05E+01**	**-1.05E+01**	**-1.05E+01**	**-1.05E+01**	**-1.05E+01**
	Worst	-2.81E+00	**-1.05E+01**	**-1.05E+01**	-3.84E+00	**-1.05E+01**
	Mean	-1.01E+01	**-1.05E+01**	**-1.05E+01**	-1.03E+01	**-1.05E+01**
	Std	1.84E+00	1.44E-15	1.36E-15	1.22E+00	**1.04E-15**
Total	Rank	5	3	2	4	1

benchmark functions. The mean result ranking outlines the order of algorithm superiority on these functions as follows: EAEO > SSA > HHO > AEO > GWO > WOA > PSO > CS.

4.5 Wilcoxon rank test

To further assess the efficiency of EAEO, Wilcoxon rank test is conducted. Thirty additional independent runs are performed at the $a = 5\%$ significance level, and the results of

Table 7: Comparisons results of different algorithms on twenty-three benchmark functions

	Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
F1	Best	**0.0000E+00**	9.2456E-185	9.3191E-88	3.3985E-29	5.7114E-116	1.6160E-01	3.4483E+00	**0.0000E+00**
	Worst	**0.0000E+00**	8.2791E-158	4.0587E-73	6.7451E-27	6.6358E-94	6.7100E-01	1.7411E+01	2.6264E-57
	Mean	**0.0000E+00**	2.7598E-159	2.2666E-74	1.7471E-27	2.2121E-95	3.6010E-01	8.7219E+00	8.7591E-59
	Std	**0.0000E+00**	1.5116E-158	8.2575E-74	1.8836E-27	1.2115E-94	1.3840E-01	3.9849E+00	4.7950E-58
F2	Best	**0.0000E+00**	1.4393E-94	5.7556E-58	2.0272E-17	4.6343E-63	2.6041E+00	5.4131E+00	1.4364E-263
	Worst	**0.0000E+00**	1.6468E-78	7.0089E-50	2.5247E-16	9.6958E-48	8.6588E+00	1.9989E+01	2.8213E-25
	Mean	**0.0000E+00**	1.0428E-79	3.4673E-51	8.6267E-17	3.2517E-49	5.0852E+00	1.0686E+01	9.4050E-27
	Std	**0.0000E+00**	3.9706E-79	1.3203E-50	6.2635E-17	1.7699E-48	1.6580E+00	3.9777E+00	5.1509E-26
F3	Best	**0.0000E+00**	7.5822E-174	1.3700E+04	3.0389E-09	2.5180E-97	6.2410E-01	1.1816E+03	**0.0000E+00**
	Worst	**0.0000E+00**	2.5442E-143	8.1638E+04	5.4662E-04	2.9226E-71	6.5581E+00	2.5440E+03	3.6033E-19
	Mean	**0.0000E+00**	8.4826E-145	4.4775E+04	4.8455E-05	9.7909E-73	3.0190E+00	1.9534E+03	1.2012E-20
	Std	**0.0000E+00**	4.6450E-144	1.7216E+04	1.2775E-04	5.3351E-72	1.2762E+00	4.0070E+02	6.5787E-20
F4	Best	**0.0000E+00**	6.8323E-90	1.1052E+00	1.5507E-07	7.6918E-59	5.6450E-01	6.2424E+00	2.7425E-157
	Worst	**0.0000E+00**	2.9439E-78	8.3553E+01	3.0647E-06	3.6123E-46	1.4051E+00	1.8318E+01	2.6655E-26
	Mean	**0.0000E+00**	1.0643E-79	5.1523E+01	7.8158E-07	1.3240E-47	8.9530E-01	9.8915E+00	9.4976E-28
	Std	**0.0000E+00**	5.3730E-79	2.7730E+01	6.6859E-07	6.5993E-47	1.9810E-01	2.8938E+00	4.8664E-27
F5	Best	**0.0000E+00**	2.2695E+01	2.6952E+01	2.5741E+01	4.9568E-09	4.8250E+01	2.2750E+02	2.5536E-09
	Worst	**0.0000E+00**	2.7526E+01	2.8741E+01	2.8759E+01	1.4000E-03	4.0920E+02	1.2553E+03	2.8070E-04
	Mean	**0.0000E+00**	2.4360E+01	2.7881E+01	2.7186E+01	1.2526E-04	1.2538E+02	5.1979E+02	2.0342E-05
	Std	**0.0000E+00**	9.3130E-01	4.5210E-01	9.3490E-01	2.6319E-04	7.4279E+01	2.6151E+02	5.2179E-05
F6	Best	**0.0000E+00**	2.8170E-06	9.2900E-02	5.8461E-05	1.0809E-07	1.5740E-01	2.5355E+00	1.3022E-14
	Worst	**0.0000E+00**	2.2780E-04	6.7260E-01	2.0068E+00	6.0246E-04	5.7950E-01	1.9694E+01	3.0511E-10
	Mean	**0.0000E+00**	5.8775E-05	3.5660E-01	7.8140E-01	8.2482E-05	2.9750E-01	7.7564E+00	1.9933E-11
	Std	**0.0000E+00**	5.6215E-05	1.5170E-01	4.3820E-01	1.4130E-04	9.0100E-02	3.4846E+00	5.7998E-11
F7	Best	**1.8348E-07**	1.0739E-04	1.8630E-04	4.3863E-04	8.6746E-06	2.4730E-01	4.2500E-02	1.3128E-05
	Worst	**4.5262E-04**	1.3000E-03	1.6900E-02	4.6000E-03	8.9919E-04	5.3981E+01	1.2770E-01	4.9884E-03
	Mean	**5.6720E-05**	5.3612E-04	5.3000E-03	2.2000E-03	1.8100E-04	6.6818E+00	7.7200E-02	1.5886E-03
	Std	**6.2207E-05**	3.2251E-04	4.7000E-03	8.9923E-04	1.9165E-04	1.4559E+01	2.1600E-02	1.2791E-03
F8	Best	-1.0871E+04	-1.0712E+04	-1.2568E+04	-6.8601E+03	**-1.2569E+04**	-2.1895E+02	-8.6431E+03	-1.0173E+04
	Worst	-9.3223E+03	-9.0924E+03	-7.6598E+03	-3.7089E+03	**-1.1909E+04**	-1.1824E+02	-7.6639E+03	-7.4521E+03
	Mean	-1.0027E+04	-9.8232E+03	-1.0715E+04	-5.9418E+03	**-1.2547E+04**	-1.4380E+02	-8.0555E+03	-8.4726E+03
	Std	4.2664E+02	3.7324E+02	1.7357E+03	6.6812E+02	1.2051E+02	**2.5319E+01**	2.4635E+02	5.1759E+02
F9	Best	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	5.1080E+01	7.7770E+01	**0.0000E+00**
	Worst	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	1.8714E+01	**0.0000E+00**	1.0476E+02	1.3698E+02	**0.0000E+00**
	Mean	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	3.0134E+00	**0.0000E+00**	6.7105E+01	1.0248E+02	**0.0000E+00**
	Std	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	4.6759E+00	**0.0000E+00**	1.3481E+01	1.4836E+01	**0.0000E+00**
F10	Best	**8.8818E-16**	**8.8818E-16**	**8.8818E-16**	6.8390E-14	**8.8818E-16**	1.6050E+00	3.6079E+00	**8.8818E-16**
	Worst	**8.8818E-16**	**8.8818E-16**	7.9936E-15	1.4655E-13	**8.8818E-16**	3.6450E+00	1.4132E+01	**8.8818E-16**
	Mean	**8.8818E-16**	**8.8818E-16**	4.7962E-15	9.8351E-14	**8.8818E-16**	2.6298E+00	7.6466E+00	**8.8818E-16**
	Std	**0.0000E+00**	**0.0000E+00**	2.1580E-15	1.8488E-14	**0.0000E+00**	5.6290E-01	2.9186E+00	**0.0000E+00**
F11	Best	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	8.7000E-03	1.0330E+00	**0.0000E+00**
	Worst	**0.0000E+00**	**0.0000E+00**	2.1440E-01	2.5800E-02	**0.0000E+00**	3.9300E-02	1.1492E+00	**0.0000E+00**
	Mean	**0.0000E+00**	**0.0000E+00**	7.1000E-03	2.7000E-03	**0.0000E+00**	2.3000E-02	1.0736E+00	**0.0000E+00**
	Std	**0.0000E+00**	**0.0000E+00**	3.9100E-02	6.9000E-03	**0.0000E+00**	9.8000E-03	2.3700E-02	**0.0000E+00**
F12	Best	**1.5705E-32**	3.4064E-07	2.6000E-03	6.8000E-03	9.2873E-09	1.6000E-03	1.6119E+00	1.9493E-15
	Worst	**1.5705E-32**	1.0370E-01	1.0310E-01	1.8480E-01	3.6741E-05	1.8260E-01	5.0778E+00	3.5055E-11
	Mean	**1.5705E-32**	3.5000E-03	2.6500E-02	4.6200E-02	1.0558E-05	3.6400E-02	3.2505E+00	1.7279E-12
	Std	**5.5674E-48**	1.8900E-02	2.1700E-02	3.1000E-02	1.2501E-05	5.2600E-02	7.8510E-01	6.4008E-12
F13	Best	**1.3498E-32**	7.8114E-05	5.9800E-02	1.1180E-01	2.7532E-07	1.7290E-01	2.2982E+00	1.0598E-15
	Worst	**1.3498E-32**	2.9583E+00	8.7450E-01	1.1986E+00	6.9801E-04	3.9429E+00	2.5709E+01	9.0671E-11
	Mean	**1.3498E-32**	8.9900E-01	4.6750E-01	6.5310E-01	1.5751E-04	9.0290E-01	1.0309E+01	1.0634E-11
	Std	**5.5674E-48**	1.0129E+00	2.2620E-01	2.6910E-01	2.0385E-04	7.0670E-01	5.3812E+00	2.1241E-11
F14	Best	**9.9800E-01**	**9.9800E-01**	**9.9800E-01**	**9.9800E-01**	**9.9800E-01**	1.2671E+01	**9.9800E-01**	**9.9800E-01**
	Worst	**9.9800E-01**	**9.9800E-01**	1.0763E+01	1.2671E+01	1.9920E+00	1.2671E+01	**9.9800E-01**	1.2671E+01
	Mean	**9.9800E-01**	**9.9800E-01**	2.8293E+00	5.4333E+00	1.0643E+00	1.2671E+01	**9.9800E-01**	4.7642E+00
	Std	**0.0000E+00**	4.1233E-17	3.2714E+00	4.4801E+00	2.5220E-01	1.5115E-13	5.8892E-16	5.3117E+00
F15	Best	**3.0749E-04**	**3.0749E-04**	3.1242E-04	**3.0749E-04**	3.0916E-04	**3.0749E-04**	3.7094E-04	**3.0749E-04**
	Worst	**3.0749E-04**	1.2000E-03	2.0000E-03	2.0400E-02	4.2498E-04	1.6000E-03	6.2810E-04	3.4644E-04
	Mean	**3.0749E-04**	3.6853E-04	7.6968E-04	3.7000E-03	3.4354E-04	5.1344E-04	4.1405E-04	3.0878E-04
	Std	**4.6850E-19**	2.3232E-04	5.4006E-04	7.6000E-03	3.0753E-05	4.6240E-04	9.5323E-05	7.1122E-06
F16	Best	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**
	Worst	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**
	Mean	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**	**-1.0316E+00**
	Std	**6.7122E-16**	6.6486E-16	9.8808E-10	2.4690E-08	4.0395E-10	6.3208E-16	5.2964E-16	5.6835E-16
F17	Best	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**
	Worst	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9800E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**
	Mean	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**	**3.9790E-01**
	Std	**0.0000E+00**	**0.0000E+00**	1.2663E-05	3.1962E-06	2.4221E-05	1.2310E-06	1.1030E-13	**0.0000E+00**
F18	Best	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**
	Worst	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	8.4000E+01	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**
	Mean	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	5.7000E+00	**3.0000E+00**	**3.0000E+00**	**3.0000E+00**	3.9000E+00
	Std	**1.3323E-15**	1.9074E-15	7.6728E-05	1.4789E+01	9.1581E-07	1.6118E-15	1.4590E-15	4.9295E+00
F19	Best	**-3.8628E+00**	**-3.8628E+00**	**-3.8628E+00**	**-3.8628E+00**	**-3.8628E+00**	**-3.8628E+00**	**-3.8628E+00**	**-3.8628E+00**
	Worst	**-3.8628E+00**	**-3.8628E+00**	-3.6961E+00	-3.8555E+00	-3.8391E+00	-2.4915E+00	**-3.8628E+00**	-3.0898E+00
	Mean	**-3.8628E+00**	**-3.8628E+00**	-3.8509E+00	-3.8615E+00	-3.8602E+00	-3.7794E+00	**-3.8628E+00**	-3.8370E+00
	Std	**2.7101E-15**	2.6402E-15	3.0300E-02	2.3000E-03	4.6000E-03	2.6500E-01	2.5094E-15	1.4113E-01

Table 7: (continued)

	Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
F20	Best	**-3.3220E+00**	**-3.3220E+00**	-3.3219E+00	**-3.3220E+00**	-3.3054E+00	**-3.3220E+00**	**-3.3220E+00**	**-3.3220E+00**
	Worst	**-3.2031E+00**	**-3.2031E+00**	-2.8385E+00	-3.0903E+00	-2.6737E+00	-7.6070E-01	-3.3220E+00	**-3.2031E+00**
	Mean	**-3.2903E+00**	-3.2665E+00	-3.2178E+00	-3.2445E+00	-3.0840E+00	-2.3365E+00	-3.3220E+00	-3.2665E+00
	Std	5.3500E-02	6.0300E-02	1.1720E-01	7.8900E-02	1.3690E-01	8.6110E-01	**2.5923E-07**	6.0300E-02
F21	Best	**-1.0153E+01**	**-1.0153E+01**	**-1.0152E+01**	-1.0153E+01	-9.7947E+00	-5.0552E+00	**-1.0153E+01**	**-1.0153E+01**
	Worst	**-1.0153E+01**	-2.6305E+00	-2.6256E+00	-2.2801E+00	-5.0201E+00	-5.0552E+00	-1.0153E+01	-5.0552E+00
	Mean	**-1.0153E+01**	-9.4009E+00	-8.0191E+00	-9.7203E+00	-5.2076E+00	-5.0552E+00	-1.0153E+01	-9.1335E+00
	Std	6.7360E-15	2.2954E+00	2.6651E+00	1.6806E+00	8.6640E-01	**9.8958E-16**	4.9373E-06	2.0740E+00
F22	Best	**-1.0403E+01**	**-1.0403E+01**	-1.0400E+01	-1.0403E+01	-1.0371E+01	-5.0877E+00	**-1.0403E+01**	**-1.0403E+01**
	Worst	**-1.0403E+01**	-2.7659E+00	-5.0866E+00	-1.0400E+01	-5.0684E+00	-5.0877E+00	**-1.0403E+01**	-5.0877E+00
	Mean	**-1.0403E+01**	-9.7031E+00	-7.9054E+00	-1.0401E+01	-5.2600E+00	-5.0877E+00	**-1.0403E+01**	-8.9855E+00
	Std	**1.0431E-15**	2.1403E+00	2.6815E+00	7.0025E-04	9.6530E-01	3.4870E-15	1.5943E-06	2.3907E+00
F23	Best	**-1.0536E+01**	**-1.0536E+01**	-1.0535E+01	-1.0536E+01	-1.0505E+01	-5.1285E+00	-1.0536E+01	**-1.0536E+01**
	Worst	**-1.0536E+01**	-2.8066E+00	-2.4211E+00	-2.4217E+00	-5.1110E+00	-5.1285E+00	-1.0536E+01	-5.1285E+00
	Mean	**-1.0536E+01**	-1.0055E+01	-7.5665E+00	-1.0264E+01	-5.6488E+00	-5.1285E+00	-1.0536E+01	-8.7338E+00
	Std	**1.0431E-15**	1.8356E+00	3.1935E+00	1.4812E+00	1.6034E+00	4.2659E-15	8.0891E-05	4.1330E-01
Total	Rank	1	4	6	5	3	7	8	2

EAEO, compared with the other seven algorithms, are subjected to the Wilcoxon rank test. Typically, when $P < 0.05$, it indicates a significant difference between two algorithms. The R column in the Wilcoxon rank test table displays the test results, and N/A indicates that the results are close. The symbols +, −, and = denote that EAEO outperforms, underperforms, and equals the comparison algorithm, respectively.

The outcomes of the Wilcoxon rank test unmistakably demonstrate that EAEO exhibits significantly higher effectiveness than the comparison algorithms, except for functions F9, F10, F11, and F12. Furthermore, as shown in Table 8, EAEO demonstrates superiority on 22 of these functions, accounting for 95.7%. The experimental findings consistently highlight that EAEO outperforms the comparison algorithms on twenty-three benchmark functions.

4.6 Boxplot behavior analysis

In this section, boxplot analysis is conducted to visually represent the distribution of data, aiding in understanding the distribution of results and demonstrating the stability of algorithms. Fig. 9 presents boxplots depicting the performance of each algorithm on benchmark functions. The compact boxplots indicate strong data consistency.

According to the results in Fig. 9, EAEO displays a thinner boxplot compared to other algorithms, signifying improved performance due to the incorporation of the enhanced strategies. Additionally, it is evident that EAEO has relatively narrow boxplots, indicating lower values for most functions except function F16. The boxplot for function F20 highlights that the obtained solution is prone to abrupt changes and deviations from the value. Nevertheless, it is crucial to note that EAEO still outperforms other algorithms. This conclusion implies EAEO's potential as a reliable choice for addressing complex optimization problems.

4.7 Performance comparison on the CEC2017 test suite

Experiments on twenty-three benchmark functions demonstrate the competitiveness of EAEO in solving traditional problems. However, with the emergence of new metaheuristic algorithms, new test suites like the CEC2017 test suite are widely utilized, as outlined in Table 3. The solutions for these functions fall within the constraint range $[-100, 100]^d$. For a more comprehensive performance analysis of EAEO, it is pitted against some recently proposed algorithms on the CEC2017 test suite. The selected algorithms, including HHO, SSA, AEO, GJO, RSO, BOA, and BWO, are metaheuristic algorithms that proposed in the last five years that have demonstrated good performance. The population size and iterations' number remain consistent with those outlined in Section 4.1. The parameter settings for the compared algorithms are detailed in Table 5, extracted directly from the original literature.

Fig. 10 presents the convergence curves of EAEO and other seven algorithms on the CEC2017 test suite. The curves clearly demonstrate that EAEO excels over the other seven algorithms in both convergence speed and accuracy. Notably, EAEO rapidly converges to the proximity of the optimal solution for 93.1% of the functions, outpacing all comparison algorithms in terms of speed and accuracy. For function F1, EAEO is second only to SSA and significantly outperforms the other algorithms. Additionally, EAEO and SSA exhibit comparable convergence speeds in functions F4, F25, and F28, all approaching the optimal solution closely. It is noteworthy that EAEO surpasses all comparison algorithms in functions other than

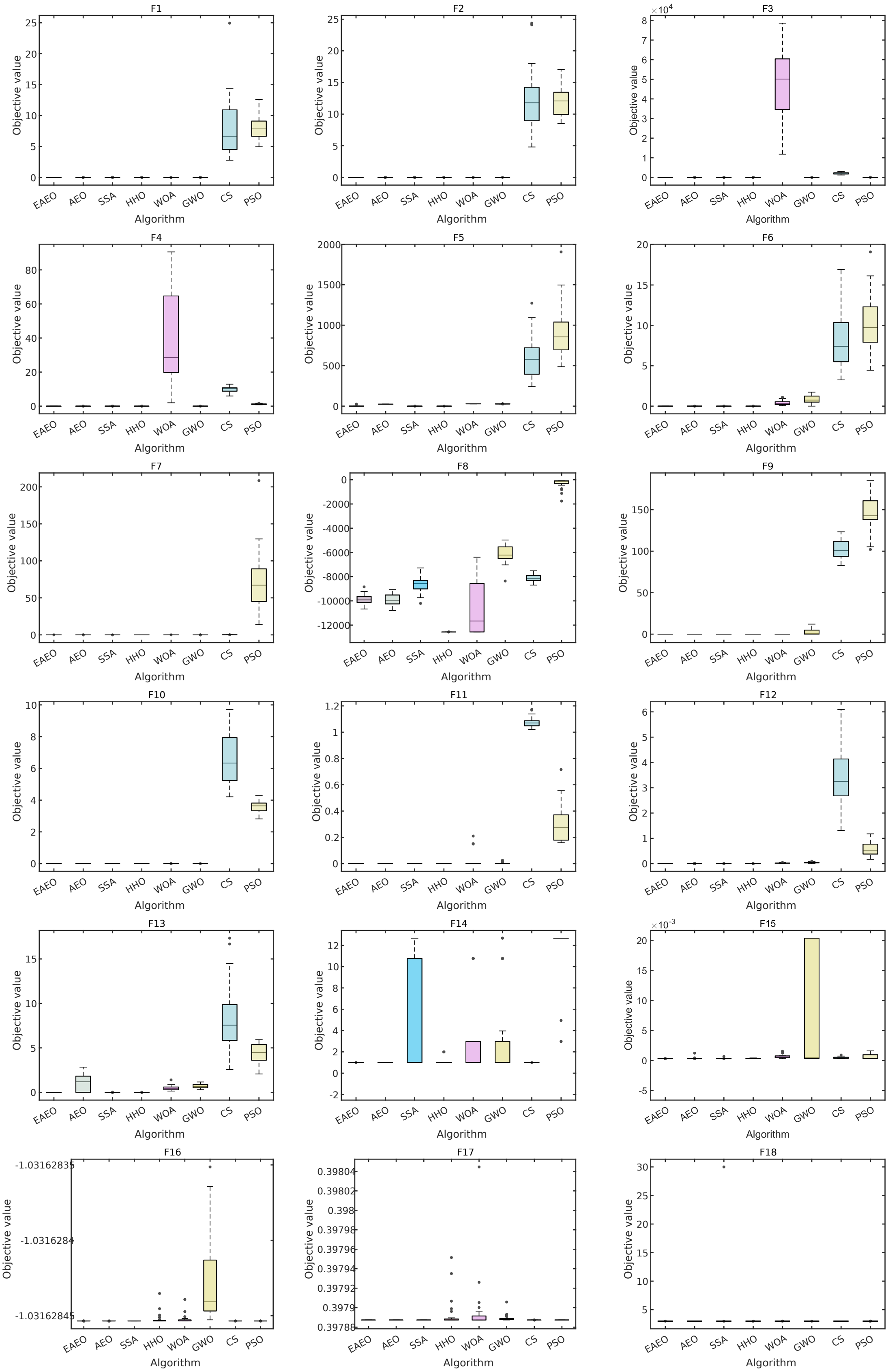


Fig. 8: Boxplots of eight algorithms on twenty-three benchmark functions

Table 8: Wilcoxon rank test results on twenty-three benchmark functions

	EAEO vs AEO		EAEO vs SSA		EAEO vs HHO		EAEO vs WOA		EAEO vs GWO		EAEO vs CS		EAEO vs PSO	
	P value	R	P value	R	P value	R	P value	R	P value	R	P value	R	P value	R
F1	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+
F2	1.21E-12	+	4.57E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+
F3	1.21E-12	+	4.57E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+
F4	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+
F5	3.21E-11	+	1.24E-09	+	2.48E-08	+	3.16E-12	+	1.72E-12	+	1.72E-12	+	2.37E-12	+
F6	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+
F7	3.18E-04	+	4.62E-10	+	7.28E-01	+	1.43E-08	+	3.02E-11	+	3.02E-11	+	3.02E-11	+
F8	6.31E-01	+	2.23E-09	+	3.02E-11	-	1.27E-02	-	3.02E-11	+	4.08E-11	+	3.02E-11	+
F9	NaN	=	NaN	=	NaN	=	1.61E-01	+	1.64E-11	+	1.21E-12	+	1.21E-12	+
F10	NaN	=	NaN	=	NaN	=	9.83E-08	+	1.10E-12	+	1.21E-12	+	1.21E-12	+
F11	NaN	=	NaN	=	NaN	=	4.19E-02	+	1.37E-03	+	1.21E-12	+	1.21E-12	+
F12	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+
F13	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.21E-12	+
F14	3.34E-01	+	1.85E-05	+	2.36E-12	+	1.21E-12	+	1.72E-12	+	1.08E-10	+	1.10E-12	+
F15	5.94E-01	+	5.49E-10	+	7.71E-09	+	2.97E-11	+	2.89E-09	+	8.43E-09	+	6.51E-05	+
F16	7.29E-01	+	1.77E-03	+	6.19E-12	+	4.08E-12	+	1.72E-12	+	3.46E-06	+	6.54E-01	+
F17	NaN	=	NaN	=	1.21E-12	+	1.21E-12	+	1.21E-12	+	1.82E-10	+	NaN	=
F18	3.96E-01	+	1.26E-02	+	2.85E-11	+	2.34E-11	+	2.91E-11	+	9.03E-01	+	1.37E-02	+
F19	3.13E-01	+	1.52E-09	+	1.72E-12	+	1.21E-12	+	2.36E-12	+	3.91E-03	+	2.46E-02	+
F20	2.55E-01	+	8.22E-01	+	1.21E-10	+	3.01E-03	+	4.71E-07	+	2.40E-02	+	1.79E-04	+
F21	5.20E-01	+	1.17E-04	+	1.46E-11	+	1.41E-11	+	1.46E-11	+	1.34E-11	+	1.20E-11	+
F22	6.77E-01	+	8.70E-06	+	4.08E-12	+	5.14E-12	+	6.32E-12	+	5.14E-12	+	5.86E-13	+
F23	7.14E-01	+	6.80E-06	+	1.46E-11	+	1.14E-11	+	1.46E-11	+	1.25E-11	+	9.88E-10	+

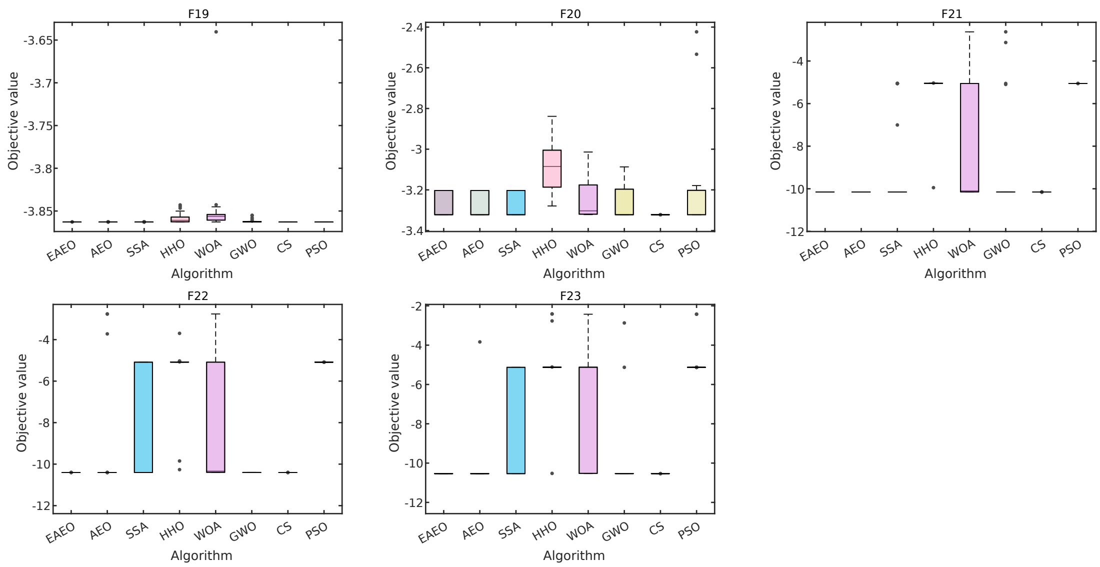


Fig. 8: (continued)

those mentioned above. These findings indicate that EAEO excels in convergence accuracy and speed, surpassing the comparison algorithms in overall performance.

The results obtained by various algorithms across 30 runs are displayed in Table 9. Experiments are evaluated using four metrics (best, worst, mean, and Std), with best results highlighted in bold. Table 9 illustrates EAEO achieving superior results in functions F3, F4, F8–F26, F29, and F30. In the CEC2017 test suite, EAEO claims the top rank in 79.3% of functions. In unimodal functions, EAEO's average performance on function F1 is second to the SSA algorithm. Notably, EAEO outperforms other algorithms on function F3. In simple multimodal functions, EAEO excels, ranking first in 4 of 7 functions and securing the second position in function F5, F6, and F7. EAEO demonstrates a significant advantage in combinatorial functions, claiming the top position in 7 of 9 functions. Notably, in functions F27 and F28, although the best and mean values of EAEO are second to SSA, the difference is not significant; however, the Std value of EAEO significantly outperforms that of SSA. The mean result ranking outlines the algorithm superiority order on these functions as

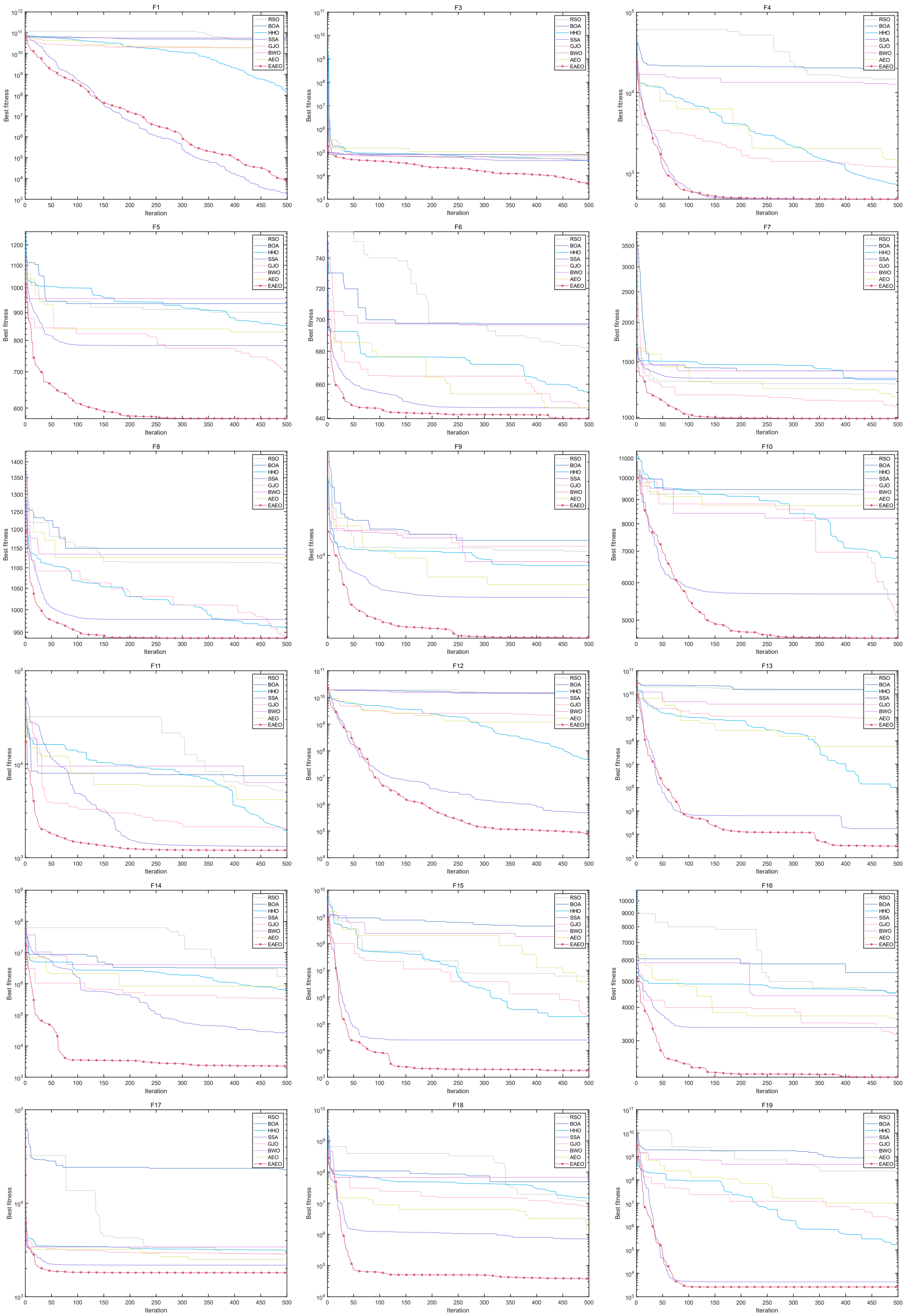


Fig. 9: Convergence curves of EAEO and other algorithms on the CEC2017 test suite

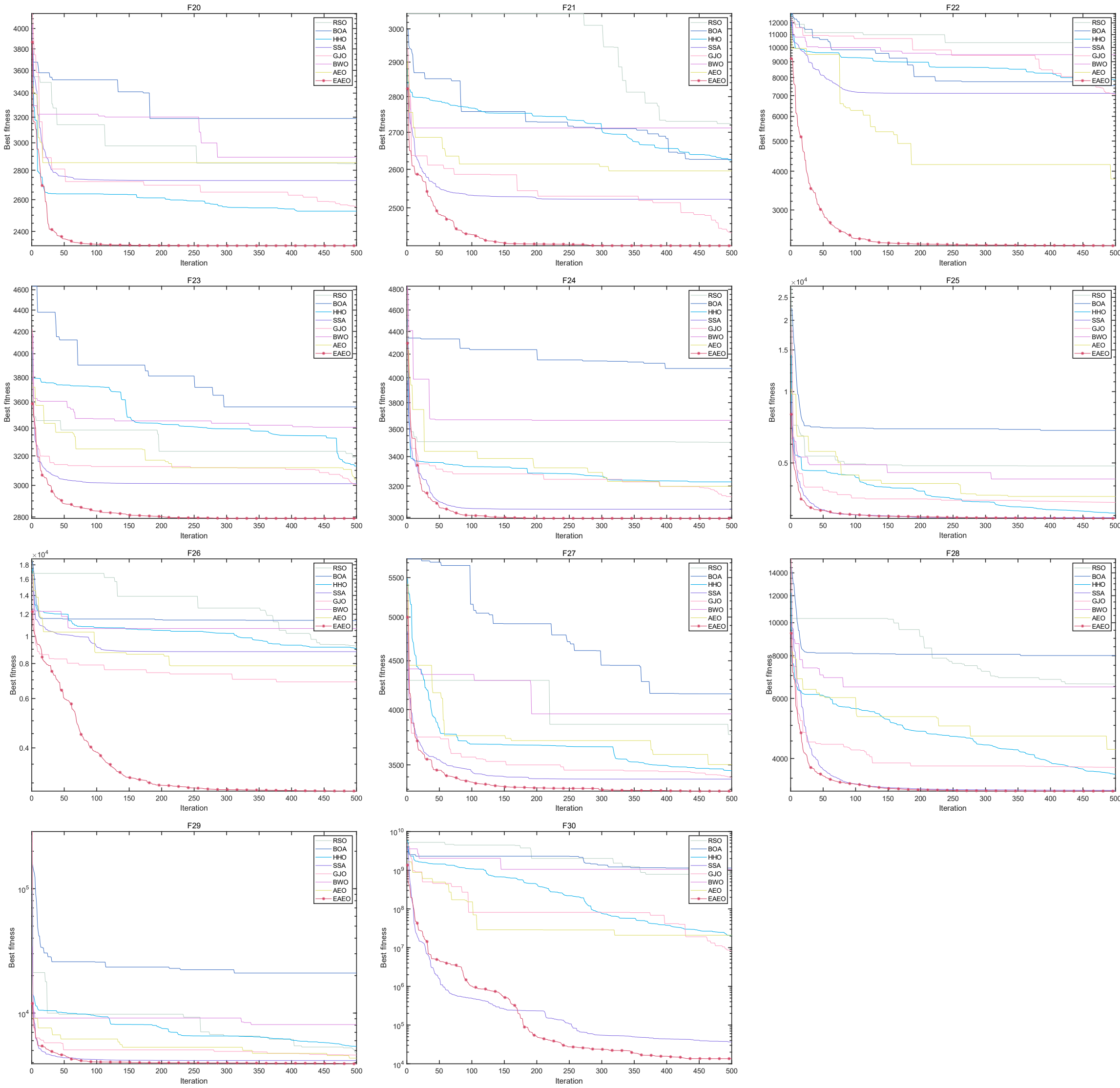


Fig. 9: (continued)

follows: EAEO > SSA > HHO > AEO > GJO > RSO > BWO > BOA.

In the average ranking of results, AEO holds the fourth position among the eight algorithms. The noticeable performance gap between EAEO and AEO implies that incorporating Latin hypercube sampling initialization, quadratic interpolation, and adaptive neighborhood search strategies significantly improves the accuracy and stability of AEO. The experimental results on the CEC2017 test suite highlight EAEO's reliable performance and its proficiency in solving complex problems. Particularly noteworthy is EAEO's superior optimization performance in multimodal benchmark and mixed functions. Combining results from twenty-three benchmark functions and the CEC2017 test suite, we conclude that EAEO exhibits robust optimization ability. This is mainly attributed to the algorithm's exceptional convergence accuracy and its capacity to evade local optima. The enhanced algorithm consistently achieves solutions with the highest accuracy and maintains stability, emphasizing its significant relevance for addressing practical optimization problems.

5 Engineering applications

This section explores the promising applications of EAEO in engineering, demonstrating its effectiveness in practical scenarios. Eight algorithms, including CS, PSO, GWO, WOA, HHO, SSA, AEO, and EAEO, are employed to address four well-known engineering optimization problems. For each algorithm, the size of population is set to $N = 30$, and the iterations' maximum number is fixed at $T = 500$.

Table 9: Comparisons results of different algorithms on the CEC2017 test suite

	Item	EAEO	AEO	HHO	SSA	GJO	RSO	BOA	BWO
F1	Best	4.03E+03	6.09E+09	1.15E+08	**2.58E+02**	5.33E+09	2.98E+10	2.88E+10	4.67E+10
	Worst	5.63E+04	2.10E+10	1.09E+09	**2.11E+04**	2.12E+10	4.65E+10	7.12E+10	5.99E+10
	Mean	2.74E+04	1.17E+10	4.19E+08	**6.61E+03**	1.20E+10	3.79E+10	5.28E+10	5.41E+10
	Std	1.40E+04	3.65E+09	2.30E+08	**7.35E+03**	4.57E+09	4.10E+09	9.64E+09	3.43E+09
F3	Best	**2.12E+03**	7.33E+04	4.05E+04	3.74E+04	4.41E+04	4.69E+04	6.36E+04	6.02E+04
	Worst	**1.23E+04**	1.17E+05	6.83E+04	6.57E+04	8.03E+04	9.08E+04	9.46E+04	9.14E+04
	Mean	**5.81E+03**	8.90E+04	5.74E+04	5.06E+04	6.13E+04	7.44E+04	8.45E+04	7.89E+04
	Std	**2.10E+03**	1.16E+04	5.71E+03	6.77E+03	1.08E+04	8.94E+03	6.55E+03	7.34E+03
F4	Best	**4.63E+02**	1.32E+03	5.55E+02	4.68E+02	5.98E+02	8.17E+03	9.65E+03	7.58E+03
	Worst	**5.74E+02**	4.26E+03	1.02E+03	5.91E+02	2.00E+03	2.20E+04	2.86E+04	1.55E+04
	Mean	**5.11E+02**	2.23E+03	7.46E+02	5.14E+02	1.23E+03	1.49E+04	2.17E+04	1.26E+04
	Std	**2.60E+01**	7.45E+02	1.20E+02	2.60E+01	4.07E+02	3.48E+03	4.63E+03	1.59E+03
F5	Best	6.22E+02	7.50E+02	7.08E+02	6.33E+02	**6.10E+02**	8.55E+02	8.63E+02	8.70E+02
	Worst	**7.29E+02**	8.63E+02	8.22E+02	8.23E+02	8.30E+02	9.44E+02	9.52E+02	9.65E+02
	Mean	**6.69E+02**	7.98E+02	7.73E+02	7.42E+02	7.27E+02	8.92E+02	9.20E+02	9.29E+02
	Std	2.95E+01	2.29E+01	2.83E+01	6.02E+01	5.51E+01	2.26E+01	2.44E+01	**2.23E+01**
F6	Best	6.24E+02	6.33E+02	6.59E+02	**6.23E+02**	6.23E+02	6.74E+02	6.75E+02	6.79E+02
	Worst	**6.55E+02**	6.72E+02	6.80E+02	6.67E+02	6.72E+02	7.01E+02	7.02E+02	7.01E+02
	Mean	**6.40E+02**	6.49E+02	6.68E+02	6.46E+02	6.41E+02	6.88E+02	6.90E+02	6.92E+02
	Std	7.55E+00	1.07E+01	5.76E+00	1.11E+01	1.00E+01	5.97E+00	5.87E+00	**5.36E+00**
F7	Best	**9.39E+02**	1.08E+03	1.20E+03	9.78E+02	9.47E+02	1.21E+03	1.33E+03	1.28E+03
	Worst	**1.16E+03**	1.40E+03	1.42E+03	1.35E+03	1.25E+03	1.50E+03	1.48E+03	1.49E+03
	Mean	1.09E+03	1.22E+03	1.30E+03	1.22E+03	**1.06E+03**	1.34E+03	1.41E+03	1.40E+03
	Std	5.83E+01	8.01E+01	6.35E+01	1.19E+02	6.09E+01	6.77E+01	**3.91E+01**	5.09E+01
F8	Best	**8.86E+02**	9.95E+02	9.43E+02	8.96E+02	9.09E+02	1.04E+03	1.10E+03	1.12E+03
	Worst	**9.74E+02**	1.13E+03	1.04E+03	1.07E+03	1.08E+03	1.12E+03	1.18E+03	1.17E+03
	Mean	**9.42E+02**	1.07E+03	9.89E+02	9.77E+02	9.84E+02	1.09E+03	1.14E+03	1.15E+03
	Std	2.31E+01	3.18E+01	2.50E+01	3.98E+01	3.68E+01	2.13E+01	1.88E+01	**1.16E+01**
F9	Best	**2.85E+03**	3.43E+03	5.70E+03	3.25E+03	3.55E+03	7.70E+03	9.01E+03	7.53E+03
	Worst	**5.26E+03**	9.52E+03	1.07E+04	5.66E+03	7.46E+03	1.26E+04	1.40E+04	1.31E+04
	Mean	**4.25E+03**	6.01E+03	8.63E+03	5.20E+03	5.37E+03	9.73E+03	1.15E+04	1.15E+04
	Std	6.38E+02	1.56E+03	1.00E+03	**5.46E+02**	1.25E+03	1.49E+03	1.26E+03	1.13E+03
F10	Best	**3.85E+03**	7.24E+03	4.53E+03	4.13E+03	4.19E+03	6.63E+03	8.43E+03	7.79E+03
	Worst	**5.66E+03**	9.23E+03	7.81E+03	6.95E+03	9.36E+03	9.27E+03	9.75E+03	9.31E+03
	Mean	**4.89E+03**	8.19E+03	6.22E+03	5.54E+03	6.66E+03	8.41E+03	9.08E+03	8.69E+03
	Std	4.48E+02	4.74E+02	8.04E+02	7.07E+02	1.55E+03	7.05E+02	**2.98E+02**	3.70E+02
F11	Best	**1.15E+03**	2.32E+03	1.26E+03	1.18E+03	1.53E+03	4.31E+03	4.37E+03	4.92E+03
	Worst	**1.29E+03**	5.14E+03	2.09E+03	1.55E+03	6.29E+03	9.42E+03	1.10E+04	1.03E+04
	Mean	**1.22E+03**	3.77E+03	1.56E+03	1.31E+03	3.47E+03	6.28E+03	8.03E+03	8.28E+03
	Std	**4.16E+01**	7.84E+02	1.77E+02	8.73E+01	1.32E+03	1.41E+03	1.88E+03	1.38E+03
F12	Best	**1.05E+05**	1.09E+08	2.06E+07	1.09E+05	2.46E+08	6.63E+09	6.10E+09	8.32E+09
	Worst	**2.53E+06**	3.26E+09	4.90E+08	3.67E+06	2.62E+09	1.65E+10	2.26E+10	1.47E+10
	Mean	**9.76E+05**	8.79E+08	9.12E+07	1.19E+06	8.45E+08	1.29E+10	1.38E+10	1.14E+10
	Std	**7.47E+05**	6.55E+08	1.16E+08	9.71E+05	6.09E+08	1.99E+09	4.66E+09	1.67E+09
F13	Best	**2.42E+03**	7.53E+06	5.75E+05	2.59E+03	3.59E+05	4.27E+09	3.08E+09	2.20E+09
	Worst	**4.40E+04**	6.55E+08	8.31E+07	4.44E+06	2.57E+09	2.42E+10	2.26E+10	1.24E+10
	Mean	**1.32E+04**	1.46E+08	4.50E+06	1.79E+05	3.56E+08	1.17E+10	1.17E+10	7.46E+09
	Std	**1.08E+04**	1.46E+08	1.50E+07	8.06E+05	5.58E+08	4.15E+09	5.59E+09	2.01E+09
F14	Best	**1.57E+03**	1.75E+04	5.14E+04	1.05E+04	3.97E+04	3.03E+05	7.53E+05	1.01E+06
	Worst	**1.26E+04**	1.20E+06	4.98E+06	1.79E+05	2.70E+06	1.11E+07	4.75E+07	1.41E+07
	Mean	**4.96E+03**	3.20E+05	1.25E+06	7.47E+04	8.96E+05	4.25E+06	7.37E+06	5.12E+06
	Std	**2.80E+03**	2.99E+05	9.77E+05	4.75E+04	8.25E+05	2.51E+06	1.06E+07	3.24E+06
F15	Best	**1.69E+03**	7.59E+05	4.16E+04	1.90E+03	8.73E+04	8.06E+06	2.92E+07	9.97E+07
	Worst	**1.11E+04**	7.80E+07	1.93E+05	6.25E+04	2.57E+08	1.19E+09	1.51E+09	8.00E+08
	Mean	**4.00E+03**	9.78E+06	1.06E+05	1.50E+04	1.90E+07	1.75E+08	6.79E+08	2.82E+08
	Std	**2.38E+03**	1.61E+07	4.44E+04	1.37E+04	5.19E+07	3.11E+08	4.60E+08	1.30E+08
F16	Best	2.22E+03	2.62E+03	2.65E+03	**2.02E+03**	2.42E+03	3.95E+03	5.22E+03	4.27E+03
	Worst	**3.14E+03**	4.26E+03	4.50E+03	3.51E+03	4.01E+03	5.13E+03	1.41E+04	6.72E+03
	Mean	**2.75E+03**	3.64E+03	3.62E+03	2.79E+03	3.11E+03	4.49E+03	8.15E+03	5.65E+03
	Std	**2.49E+02**	3.72E+02	4.99E+02	3.38E+02	4.56E+02	3.18E+02	2.35E+03	6.01E+02
F17	Best	**1.79E+03**	2.08E+03	1.90E+03	1.91E+03	1.85E+03	2.67E+03	2.82E+03	3.45E+03
	Worst	**2.65E+03**	2.91E+03	3.35E+03	3.10E+03	3.00E+03	3.57E+03	3.99E+04	4.95E+03
	Mean	**2.23E+03**	2.52E+03	2.66E+03	2.46E+03	2.40E+03	3.17E+03	1.10E+04	4.14E+03
	Std	**1.93E+02**	2.23E+02	3.75E+02	3.12E+02	2.82E+02	2.32E+02	8.52E+03	4.08E+02

Table 9: (continued)

	Item	EAEO	AEO	HHO	SSA	GJO	RSO	BOA	BWO
F18	Best	**2.12E+04**	2.49E+05	2.32E+05	5.38E+04	1.11E+05	1.27E+06	1.64E+06	6.75E+06
	Worst	**2.94E+05**	1.38E+07	3.93E+07	4.37E+06	2.89E+07	3.93E+07	4.48E+08	8.81E+07
	Mean	**1.01E+05**	3.27E+06	4.07E+06	7.78E+05	3.90E+06	9.93E+06	6.17E+07	4.77E+07
	Std	**6.07E+04**	2.98E+06	7.20E+06	8.54E+05	6.89E+06	8.13E+06	9.16E+07	2.39E+07
F19	Best	**1.97E+03**	1.15E+06	7.20E+04	2.02E+03	1.27E+05	2.68E+08	2.04E+08	1.22E+08
	Worst	**1.27E+04**	7.14E+07	6.06E+06	5.65E+04	1.37E+08	1.45E+09	2.83E+09	8.32E+08
	Mean	**5.51E+03**	1.14E+07	2.23E+06	9.75E+03	1.75E+07	7.01E+08	9.29E+08	4.55E+08
	Std	**3.47E+03**	1.78E+07	1.75E+06	1.14E+04	3.92E+07	2.81E+08	6.27E+08	1.76E+08
F20	Best	**2.26E+03**	2.38E+03	2.46E+03	2.32E+03	2.30E+03	2.69E+03	2.73E+03	2.63E+03
	Worst	**2.77E+03**	3.03E+03	3.33E+03	3.30E+03	3.18E+03	3.31E+03	3.25E+03	3.24E+03
	Mean	**2.57E+03**	2.78E+03	2.85E+03	2.73E+03	2.67E+03	2.99E+03	3.11E+03	3.02E+03
	Std	1.45E+02	1.58E+02	2.10E+02	2.23E+02	2.66E+02	1.70E+02	**1.23E+02**	1.52E+02
F21	Best	**2.39E+03**	2.52E+03	2.50E+03	2.42E+03	2.41E+03	2.63E+03	2.48E+03	2.64E+03
	Worst	**2.52E+03**	2.62E+03	2.70E+03	2.62E+03	2.61E+03	2.79E+03	2.82E+03	2.80E+03
	Mean	**2.45E+03**	2.57E+03	2.59E+03	2.51E+03	2.50E+03	2.70E+03	2.73E+03	2.73E+03
	Std	2.94E+01	**2.37E+01**	4.79E+01	5.85E+01	4.79E+01	3.79E+01	6.43E+01	3.57E+01
F22	Best	2.30E+03	3.15E+03	2.95E+03	**2.30E+03**	3.09E+03	7.21E+03	5.85E+03	6.43E+03
	Worst	**2.31E+03**	5.40E+03	1.02E+04	8.83E+03	1.09E+04	1.07E+04	9.56E+03	9.53E+03
	Mean	**2.30E+03**	3.86E+03	7.48E+03	6.87E+03	5.32E+03	9.55E+03	7.42E+03	8.71E+03
	Std	**1.32E+00**	5.51E+02	1.08E+03	1.41E+03	2.07E+03	1.07E+03	1.10E+03	7.23E+02
F23	Best	2.80E+03	2.92E+03	3.05E+03	2.80E+03	**2.79E+03**	3.15E+03	3.00E+03	3.22E+03
	Worst	**3.00E+03**	3.14E+03	3.59E+03	3.11E+03	3.05E+03	3.43E+03	3.82E+03	3.45E+03
	Mean	**2.87E+03**	3.06E+03	3.30E+03	2.90E+03	2.92E+03	3.27E+03	3.53E+03	3.35E+03
	Std	**4.90E+01**	6.03E+01	1.63E+02	7.74E+01	6.90E+01	7.17E+01	1.71E+02	5.17E+01
F24	Best	2.98E+03	3.12E+03	3.28E+03	2.97E+03	**2.97E+03**	3.30E+03	3.63E+03	3.47E+03
	Worst	**3.18E+03**	3.32E+03	3.83E+03	3.34E+03	3.21E+03	3.69E+03	4.55E+03	3.74E+03
	Mean	**3.07E+03**	3.23E+03	3.52E+03	3.10E+03	3.10E+03	3.52E+03	4.11E+03	3.60E+03
	Std	**5.14E+01**	5.64E+01	1.50E+02	1.02E+02	6.87E+01	9.01E+01	2.70E+02	6.30E+01
F25	Best	2.89E+03	3.15E+03	2.93E+03	**2.88E+03**	3.02E+03	4.14E+03	4.71E+03	4.17E+03
	Worst	**2.93E+03**	4.37E+03	3.12E+03	2.94E+03	4.16E+03	5.89E+03	7.26E+03	4.86E+03
	Mean	**2.90E+03**	3.47E+03	3.01E+03	2.90E+03	3.26E+03	4.92E+03	5.81E+03	4.49E+03
	Std	**1.17E+01**	2.56E+02	4.08E+01	1.82E+01	2.36E+02	4.07E+02	6.84E+02	1.64E+02
F26	Best	**2.80E+03**	4.58E+03	6.60E+03	2.90E+03	4.74E+03	8.23E+03	9.75E+03	9.53E+03
	Worst	**7.48E+03**	8.99E+03	1.03E+04	9.53E+03	7.88E+03	1.05E+04	1.38E+04	1.17E+04
	Mean	**4.43E+03**	7.15E+03	8.27E+03	6.45E+03	6.12E+03	9.24E+03	1.17E+04	1.08E+04
	Std	1.62E+03	1.04E+03	9.35E+02	1.55E+03	6.64E+02	6.08E+02	8.38E+02	**5.34E+02**
F27	Best	3.26E+03	3.41E+03	3.31E+03	**3.22E+03**	3.27E+03	3.77E+03	3.83E+03	3.74E+03
	Worst	**3.42E+03**	3.82E+03	4.21E+03	3.47E+03	3.69E+03	5.03E+03	5.54E+03	4.44E+03
	Mean	3.30E+03	3.60E+03	3.62E+03	**3.28E+03**	3.41E+03	4.09E+03	4.44E+03	4.05E+03
	Std	**3.63E+01**	8.78E+01	2.40E+02	6.20E+01	9.56E+01	2.94E+02	3.74E+02	1.64E+02
F28	Best	3.21E+03	3.54E+03	3.34E+03	**3.20E+03**	3.51E+03	5.67E+03	6.75E+03	5.70E+03
	Worst	**3.29E+03**	5.08E+03	3.66E+03	3.31E+03	4.64E+03	8.09E+03	8.98E+03	6.99E+03
	Mean	3.26E+03	4.12E+03	3.50E+03	**3.23E+03**	3.96E+03	6.53E+03	8.05E+03	6.42E+03
	Std	**2.15E+01**	3.19E+02	8.44E+01	2.60E+01	3.37E+02	5.13E+02	6.16E+02	3.34E+02
F29	Best	**3.70E+03**	4.45E+03	4.11E+03	3.73E+03	3.73E+03	4.50E+03	6.98E+03	5.55E+03
	Worst	**4.32E+03**	5.41E+03	5.96E+03	4.88E+03	4.97E+03	6.53E+03	3.46E+04	8.85E+03
	Mean	**4.01E+03**	4.92E+03	5.01E+03	4.26E+03	4.34E+03	5.44E+03	1.17E+04	7.07E+03
	Std	**2.02E+02**	2.63E+02	4.77E+02	3.19E+02	3.29E+02	5.38E+02	5.96E+03	7.94E+02
F30	Best	**7.51E+03**	4.14E+06	8.54E+05	8.28E+03	3.49E+06	2.71E+08	2.54E+08	2.87E+08
	Worst	**9.47E+04**	4.89E+07	1.37E+08	1.53E+05	1.08E+08	2.39E+09	2.33E+09	1.65E+09
	Mean	2.70E+04	2.42E+07	1.44E+07	**2.21E+04**	4.36E+07	1.18E+09	1.22E+09	1.05E+09
	Std	**1.80E+04**	1.24E+07	2.46E+07	2.54E+04	2.98E+07	6.43E+08	6.65E+08	4.41E+08
	Rank	1	4	3	2	5	6	8	7

5.1 Welded beam design

Minimization of economic costs through optimization of parameters is the goal of the welded beam design problem. such as thickness (h), length (l), height (t), and thickness (b), along with the weld of the beam bars. The configuration of the welded beam design is illustrated in Fig. 10, and its associated mathematical model is provided below.

Consider:

$$\vec{x} = [x_1, x_2, x_3, x_4] = [h, l, t, b]$$

Minimize:

$$f(\vec{x}) = 1.10471x_1^2x_2 + 0.04811x_3x_4\,(14 + x_2)$$

Subject to:

$$\begin{cases} h_1 = \tau(x) - \tau_{\max} \le 0, h_2 = \sigma(x) - \sigma_{\max} \le 0, \\ h_3 = \delta(x) - \delta_{\max} \le 0, h_4 = x_1 - x_4 \le 0, \\ h_5 = P - P_C \le 0, h_6 = 0.12 - x_1 \le 0, \\ h_7 = 1.10471{x_1}^2 x_2 + 0.04811 x_3 x_4 (14 + x_2) \\ -5 \le 0 \end{cases}$$

Variable's range:

$$0.1 \le x_1 \le 2,\ 0.1 \le x_2 \le 10,\ 0.1 \le x_3 \le 10,\\ 0.1 \le x_4 \le 2$$

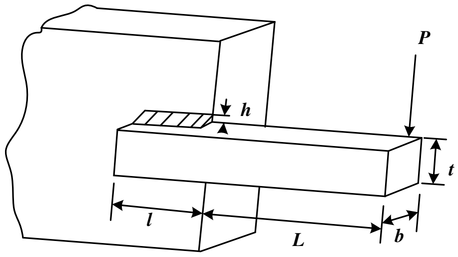


Fig. 10: Structure of welded beam design

The statistical results of the welded beam design problem after 30 runs are presented in Table 10. EAEO outperforms other algorithms in the three indicators of best value, worst value, and mean value, with the Std value ranking second only to GWO, indicating the excellent performance of EAEO. Despite obtaining the same best result as AEO, EAEO outperformed in terms of worst value, mean value, and Std value, implying that EAEO is more stable than AEO. Table 11 presents the variable values corresponding to the best results for all algorithms. Setting x_1, x_2, x_3, and x_4 to 0.2057, 3.4704, 9.0365, and 0.2057, respectively, results in the lowest design cost for the welded beam design problem while satisfying the constraints.

5.2 Pressure vessel design

The design of pressure vessels is a prevalent engineering challenge in practical applications. The goal of this problem is to minimize the manufacturing cost of pressure vessels while ensuring their functional integrity. The variables involved in this problem encompass the thickness of the shell (T_s), thickness of the head (T_h), inner radius (R), and length of the cylindrical section excluding the head (L). The schematic representation of the pressure vessel design is depicted in Fig. 11, and the corresponding mathematical model for this optimization problem is detailed below.
Consider:

$$\vec{x} = [x_1, x_2, x_3, x_4] = [T_s, T_h, R, L]$$

Minimize:

$$f(\vec{x}) = 0.6224 x_1 x_3 x_4 + 1.7781 x_2 x_3^2 + 3.1661 x_1^2 x_4 + 19.84 x_1^2 x_3$$

Subject to:

$$\begin{cases} g_1(\vec{x}) = -x_1 + 0.0193 x_3 \le 0 \\ g_2(\vec{x}) = -x_2 + 0.00954 x_3 \le 0 \\ g_3(\vec{x}) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1296000 \le 0 \\ g_4(\vec{x}) = x_4 - 240 \le 0 \end{cases}$$

Variables range:

$$0 \le x_1 \le 99,\ 0 \le x_2 \le 99,\ 10 \le x_3 \le 200,\\ 10 \le x_4 \le 200$$

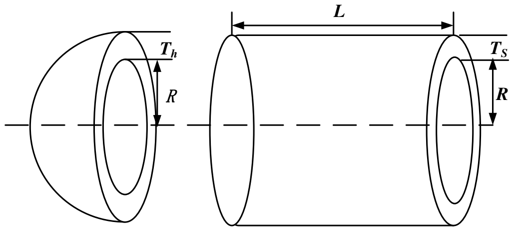


Fig. 11: Structure of pressure vessel design

Table 12 presents the statistical results of the pressure vessel design problem after 30 runs. EAEO secures the first position in best value, while holding the second position in worst value and the third position in both mean and Std values, surpassing the performance of AEO in all these aspects. Despite EAEO not having the best stability, it remains highly competitive due to its ability to find best value. Table 13 presents the variable values corresponding to the best results for all algorithms. Setting x_1, x_2, x_3, and x_4 to 0.7796, 0.3854, 40.3948, and 198.9556, respectively, results in the lowest manufacturing cost for the pressure vessel design problem while satisfying the constraints.

5.3 Speed reducer design

The speed reducer design problem is a constrained mixed-integer optimization problem characterized by seven design variables: tooth

Table 10: Statistical results of welded beam design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
Best	**1.7249**	**1.7249**	1.8154	1.7261	1.7821	2.0245	1.7281	1.7836
Worst	**1.7324**	2.0300	4.5693	1.7397	2.9633	9.23E+13	1.7752	5.3484
Mean	**1.7260**	1.7357	2.7905	1.7283	2.0405	5.07E+12	1.7502	2.9795
Std	0.0032	0.0556	0.8646	**0.0016**	0.2764	1.89E+13	0.0097	0.9748

Table 11: Best results for welded beam design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
$x_1(h)$	0.2057	0.2057	0.2065	0.2056	0.2049	0.1942	0.2044	0.2522
$x_2(l)$	3.4704	3.4704	4.0991	3.4761	3.4486	4.6834	3.5013	3.0002
$x_3(t)$	9.0365	9.0365	9.0175	9.0417	9.142	8.2549	9.0441	8.1642
$x_4(b)$	0.2057	0.2057	0.2066	0.2057	0.2114	0.2465	0.2057	0.2522
$f_{\min}$	**1.7249**	**1.7249**	1.8154	1.7261	1.7821	2.0245	1.7281	1.8950

surface width (B), tooth modulus (m), number of teeth in the pinion (z), length of the first shaft between bearings (l_1), length of the second shaft between bearings (l_2), diameter of the first shaft (d_1), and diameter of the second shaft (d_2). The primary objective is to minimize the weight of the reducer while adhering to constraints related to the bending stress of the gear teeth, surface stress, lateral deflection of the shaft, and stress within the shaft. The structure of the speed reducer design is illustrated in Fig. 12. The mathematical formulation of the problem is detailed below.
Consider:

$$\begin{aligned} \vec{x} &= [x_1, x_2, x_3, x_4, x_5, x_6, x_7] \\ &= [B, m, z, l_1, l_2, d_1, d_2] \end{aligned}$$

Minimize:

$$\begin{aligned} f(\vec{x}) =& 0.7854x_1x_2^2(3.3333x_3^2 + 14.9334x_3 \\ & - 43.0934) - 1.508x_1(x_6^2 + x_7^2) + 7.4777 \\ & (x_6^3 + x_7^3) + 0.7854(x_4x_6^2 + x_5x_7^2) \end{aligned}$$

Subject to:

$$\begin{cases} g_1(\vec{x}) = \frac{27}{x_1x_2^2x_3} - 1 \leq 0 \\ g_2(\vec{x}) = \frac{397.5}{x_1x_2^2x_3^2} - 1 \leq 0 \\ g_3(\vec{x}) = \frac{1.93x_4^2}{x_2x_6^4x_3} - 1 \leq 0 \\ g_4(\vec{x}) = \frac{1.93x_5^2}{x_2x_7^4x_3} - 1 \leq 0 \\ g_5(\vec{x}) = \frac{\left(\left(\frac{745x_4}{x_2x_3}\right)^2 + 16.9\times10^6\right)^{0.5}}{110x_6^3} - 1 \leq 0 \\ g_6(\vec{x}) = \frac{\left(\left(\frac{745x_5}{x_2x_3}\right)^2 + 157.5\times10^6\right)^{0.5}}{85x_7^3} - 1 \leq 0 \\ g_7(\vec{x}) = \frac{x_2x_3}{40} - 1 \leq 0 \\ g_8(\vec{x}) = \frac{5x_2}{x_1} - 1 \leq 0 \end{cases}$$

$$\begin{cases} g_9(\vec{x}) = \frac{x_1}{12x_2} - 1 \leq 0 \\ g_{10}(\vec{x}) = \frac{1.5x_6+1.9}{x_4} - 1 \leq 0 \\ g_{11}(\vec{x}) = \frac{1.1x_7+1.9}{x_5} - 1 \leq 0 \end{cases}$$

Variable's range:

$$2.6 \leq x_1 \leq 3.6,\ 0.7 \leq x_2 \leq 0.8,\ 17 \leq x_3 \leq 28,\ 7.3 \leq x_4 \leq 8.3,\ 7.3 \leq x_5 \leq 8.3,\ 2.9 \leq x_6 \leq 3.9,\ 5.0 \leq x_7 \leq 5.5.$$

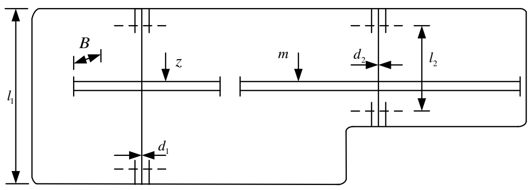


Fig. 12: Structure of speed reducer design

Table 14 presents the statistical results of the reducer design problem. As seen, EAEO offers the optimal solution, attaining an average minimum weight of the reducer at 2999.3, securing the first position among all algorithms. Furthermore, EAEO demonstrates the lowest Std value, highlighting its robustness. it can be concluded that EAEO is highly competitive for optimizing speed reducer design problems. Table 15 provides the variable values corresponding to the optimal solution for all algorithms. By setting $x1$, $x2$, $x3$, $x4$, $x5$, $x6$, and x_7 to 3.5000, 0.7000, 17.0000, 7.3000, 7.8000, 3.4583, and 5.2458, respectively, the lowest weight of the reducer is achieved while satisfying the constraints.

Table 12: Statistical results of pressure vessel design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
Best	**5.8878E+03**	5.8885E+03	6.6061E+03	5.8983E+03	6.3640E+03	1.6154E+05	5.8896E+03	6.1228E+03
Worst	6.6765E+03	6.8017E+03	1.8726E+04	6.9484E+03	7.8589E+03	2.7928E+06	**5.9513E+03**	1.6540E+05
Mean	6.1630E+03	6.2219E+03	8.1758E+03	6.0545E+03	7.0154E+03	7.9228E+05	**5.9131E+03**	3.3703E+04
Std	244.5186	252.4865	218.9445	326.0765	360.3355	6.4644E+05	**14.5523**	4.1926E+04

Table 13: Best results for pressure vessel design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
$x_1(T_s)$	0.7796	0.7785	0.8415	0.7794	0.9824	2.7077	0.7782	1.2054
$x_2(T_h)$	0.3854	0.3848	0.4861	0.3859	0.4918	11.8915	0.3861	0.7797
$x_3(R)$	40.3948	40.3294	40.5973	40.3725	50.8896	81.2359	40.3215	61.3406
$x_4(H)$	198.9556	199.9448	196.1697	199.6267	91.4402	63.6346	199.9761	28.5806
$f_{\min}$	**5.8878E+03**	5.8885E+03	6.6061E+03	5.8983E+03	6.3640E+03	1.6154E+05	5.8896E+03	6.1228E+03

5.4 Cantilever beam design

The cantilever beam design problem aims to minimize the weight of a cantilever beam using five hollow square blocks of constant thickness, as illustrated in Fig. 13. The beam must sustain a specified load at a fixed distance from the support, requiring the minimization of its weight while adhering only to the upper limit constraints. The mathematical model for the cantilever beam design problem is presented below.
Consider:

$$\vec{x} = [x_1, x_2, x_3, x_4, x_5]$$

Minimize:

$$f(\vec{x}) = 0.0624(x_1 + x_2 + x_3 + x_4 + x_5)$$

Subject to:

$$g_1(\vec{x}) = \frac{61}{x_1^3} + \frac{37}{x_2^3} + \frac{19}{x_3^3} + \frac{7}{x_4^3} + \frac{1}{x_5^3} - 1 \leq 0$$

Variable's range:

$$0.01 \leq x_i \leq 100, i \in [1, 5]$$

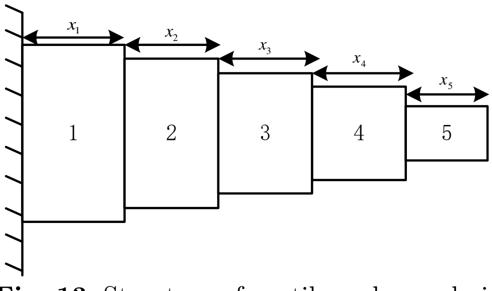


Fig. 13: Structure of cantilever beam design

The statistical results of the cantilever beam design problem are shown in Table 16, with EAEO providing the optimal solution. Notably, among the four algorithms simultaneously offering optimal solutions, EAEO demonstrates superior worst value, mean value, and Std value compared to the remaining seven algorithms, emphasizing its enhanced robustness. Table 17 lists the variable values corresponding to the best results for all algorithms. Setting x_1, x_2, x_3, x_4, and x_5 to 6.0290, 5.3044, 4.4886, 3.4968, and 2.1549, respectively, results in the lowest weight of the cantilever beam while satisfying the constraints.

6 Conclusion and future work

This study proposes an enhanced artificial ecosystem-based optimization (EAEO) for global optimization and constrained engineering problems. The enhancements stem from the utilization of Latin hypercube sampling for population initialization, quadratic interpolation for approximating the objective function, and an adaptive neighborhood search strategy to escape from local optima. Experimental evaluation on twenty-three benchmark functions and the CEC2017 test suite demonstrates the superior performance of EAEO over AEO and other conventional or emerging optimization algorithms. EAEO excels in solution accuracy, convergence speed, and robustness, achieving enhanced performance without an significant increase in computational complexity. Furthermore, EAEO is employed to tackle four real-world optimization challenges, demonstrating its practicality and efficiency in addressing complex engineering optimization challenges. Although EAEO has shown high effectiveness for single-objective continuous optimization problems, its potential

Table 14: Statistical results of speed reducer design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
Best	**2.9990E+03**	**2.9990E+03**	3.0167E+03	3.0042E+03	3.0157E+03	3.2396E+03	2.9992E+03	3.0070E+03
Worst	**3.0044E+03**	3.0061E+03	3.3001E+03	3.0185E+03	4.7556E+03	4.2621E+12	3.0035E+03	5.6161E+03
Mean	**2.9993E+03**	2.9996E+03	3.1014E+03	3.0102E+03	3.1503E+03	5.3156E+11	3.0004E+03	3.2223E+03
Std	**1.2841E+00**	1.4148E+00	6.1762E+01	4.1703E+00	3.1911E+02	9.5074E+11	1.0531E+00	5.1415E+02

Table 15: Best results for speed reducer design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
$x_1(B)$	3.5000	3.5000	3.5183	3.5010	3.5243	3.5776	3.5000	3.4990
$x_2(m)$	0.7000	0.7000	0.7000	0.7000	0.7000	0.7150	0.7000	0.7000
$x_3(z)$	17.0000	17.0000	17.0000	17.0000	17.0000	17.2459	17.0000	17.0000
$x_4(l_1)$	7.3000	7.3000	7.3000	7.4860	7.3000	7.9301	7.3000	7.4646
$x_5(l_2)$	7.8000	7.8000	7.8675	7.8203	8.0818	8.0118	7.8017	7.8000
$x_6(d_1)$	3.4583	3.4583	3.4912	3.4645	3.4584	3.4924	3.4585	3.4725
$x_7(d_2)$	5.2458	5.2458	5.2459	5.2473	5.2475	5.3619	5.2460	5.2075
$f_{\min}$	**2.9990E+03**	**2.9990E+03**	3.0167E+03	3.013E+03	3.0157E+03	3.2396E+03	2.9992E+03	3.0070E+03

for multi-objective optimization remains an area for future research. Moreover, exploring EAEO's hybridization with other meta-heuristic algorithms has the potential to enhance its overall performance. Future research will also explore the applicability of EAEO in variety of domains, such as parameter optimization, image processing, and path planning.

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Table 16: Statistical results of cantilever beam design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
Best	**1.3400**	**1.3400**	1.3797	**1.3400**	1.3412	3.4246	**1.3400**	1.3491
Worst	**1.3401**	1.3402	1.7196	1.3403	1.3472	12.8979	1.3402	2.5100
Mean	**1.3400**	**1.3400**	1.4804	1.3401	1.3432	7.9925	1.3401	1.9890
Std	**7.59E-05**	1.05E-04	0.1008	7.43E-05	0.0018	1.8828	5.96E-05	0.2626

Table 17: Best results for cantilever beam design problem

Item	EAEO	AEO	WOA	GWO	HHO	PSO	CS	SSA
x_1	6.0290	6.0229	7.3805	6.0177	5.9460	8.3873	6.0333	5.9980
x_2	5.3044	5.3144	4.7691	5.3316	5.2569	8.7397	5.3219	5.7819
x_3	4.4886	4.4751	4.4679	4.4792	4.6495	14.4726	4.4785	4.2070
x_4	3.4968	3.5067	3.5669	3.4988	3.4247	16.8933	3.5076	3.5677
x_5	2.1549	2.1548	1.9264	2.1474	2.2163	6.3889	2.1333	2.0653
f_{min}	**1.3400**	**1.3400**	1.3797	**1.3400**	1.3412	3.4246	**1.3400**	1.3491

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Statements and Declarations

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