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RESEARCH ARTICLE

Adaptive Chaotic Marine Predators Hill Climbing Algorithm for Large-Scale Design Optimizations

AMIN ABDOLLAHI DEHKORDI[1], BAHAREH ETAATI[2], MEHDI NESHAT[3,4], AND SEYEDALI MIRJALILI[3,5,6], (Senior Member, IEEE)
[1]Department of Computer Engineering, Islamic Azad University, Najafabad Branch, Najafabad 8514143131, Iran
[2]Josef Ressel Center for Symbolic Regression, University of Applied Sciences Upper Austria, 4232 Hagenberg, Austria
[3]Center for Artificial Intelligence Research and Optimization, Torrens University Australia, Brisbane, QLD 4006, Australia
[4]Faculty of Engineering and Information Technology, University of Technology Sydney, Ultimo, NSW 2007, Australia
[5]Yonsei Frontier Lab, Yonsei University, Seoul 03722, South Korea
[6]University Research and Innovation Center, Obuda University, 1034 Budapest, Hungary

Corresponding authors: Amin Abdollahi Dehkordi (amin.abdollahi.dehkordi@gmail.com) and Seyedali Mirjalili (ali.mirjalili@torrens.edu.au)

ABSTRACT Meta-heuristic algorithms have been effectively employed to tackle a wide range of optimisation issues, including structural engineering challenges. The optimisation of the shape and size of large-scale truss structures is complicated due to the nonlinear interplay between the cross-sectional and nodal coordinate pressures of structures. Recently, it was demonstrated that the newly proposed Marine Predator Algorithm (MPA) performs very well on mathematical challenges. The MPA is a meta-heuristic that simulates the essential hunting habits of natural marine predators. However, this algorithm has some disadvantages, such as becoming locked in locally optimal solutions and not exhibiting high exploratory behaviour. This paper proposes two hybrid marine predator algorithms, Nonlinear Marine Predator (HNMPA) and Nonlinear-Chaotic Marine Predator Algorithm (HNCMPA), as improved variations of the marine predator algorithm paired with a hill-climbing (HC) technique for truss optimisation on form and size. The major advantage of these techniques is that they seek to overcome the MPA's disadvantages by using nonlinear values and prolonging the exploration phase with chaotic values; also, the HC algorithm has been used to avoid locally optimum solutions. In terms of truss optimisation performance, the proposed algorithm is compared to fourteen well-known meta-heuristics, including the Dragonfly Algorithm (DA), Henry Gas Solubility optimisation (HGSO), Arithmetic optimisation Algorithm (AOA), Generalized Normal Distribution Optimisation (GNDO), Salp Swarm Algorithm (SSA), Marine Predators Algorithm (MPA), Neural Network Algorithm (NNA), Water Cycle Algorithm (WCA), Artificial Gorilla Troops Optimiser (GTO), Gray Wolf Optimiser (GWO), Moth Flame Optimiser (MFO), Multi-Verse Optimiser (MVO), Equilibrium Optimiser (EO), and Cheetah Optimiser (CO). Furthermore, seven algorithms were chosen to test HNCMPA performance on benchmark optimisation sets, including MPA, MVO, PSO, MFO, SSA, GWO, and WOA. The experiment results demonstrate that the optimisation techniques surpass previously established meta-heuristics in the field of optimisation, encompassing both traditional and CEC problems, by a margin of over 95% in terms of attaining a superior ultimate solution. Additionally, with regards to solving truss optimisation difficulties as a large-scale real-world engineering challenge, the outcomes indicate a performance boost of over 65% in obtaining significantly better solutions for problems involving 260-bar and 314-bar; conversely, in the case of 340-bar issues, the improvement rate is slightly lower at almost 25%.

INDEX TERMS Bio-inspired algorithms, hybrid algorithms, Marine predators algorithm, meta-heuristics, optimization method, truss optimization.

I. INTRODUCTION

The development of various meta-heuristic optimisation techniques over the last few decades has resulted in a significant

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increase in their application in a wide range of engineering problems. These techniques explore the search area in an optimisation problem without the need for a gradient, quasi-randomly, while keeping some fundamental principles for finding the optimal solution in mind. Their popularity in a variety of fields can be attributed to characteristics such as improved performance and efficiency, lower computing capacity, and easier implementation than fixed algorithms. These algorithms rely on simple principles to produce the best results, and the search is conducted to find the best results in a variety of fields. The use of random elements in the structure of meta-heuristic algorithms allows these algorithms to explore the entire search area to find the best solution and reduces the risk of these algorithms becoming trapped in local optimisation.

One of their notable shortcomings is the low convergence rate of meta-heuristic algorithms in the face of direct and straightforward problems. In other words, the use of gradient information in specific descending gradient algorithms is far more helpful in dealing with these issues than these algorithms [1].

Human, natural, physical, and artistic phenomena are the four categories of meta-heuristic algorithms used in optimisation problems. However, because many optimisation problems have an infinite and limitless solution space, using basic versions of meta-heuristic algorithms to explore the solution space of these problems may fail to find optimal solutions.

Some meta-heuristic optimisation algorithms inspired by animal social behaviour or human characteristics that have been used in various fields include Genetic Algorithm (GA) [2], Particle Swarm optimisation (PSO) [3], Ant Colony optimisation (ACO) [4], Imperialist Competitive Algorithm (ICA) [5], Gray Wolf Optimiser (GWO) [6], Whale optimisation Algorithm (WOA) [7], and Human Mental Search (HMS) [8].

The Gravitational Search Algorithm (GSA) [9], Charged System Search (CSS) [10], Stochastic Paint Optimiser (SPO) [11], Simulated Annealing (SA) [12], Harmony Search (HS) [13], and Colliding Bodies optimisation (CBO) [14] were all motivated by art, physical, and natural phenomena. When faced with optimisation problems, meta-heuristic algorithms approximate the optimal solution by either randomly identifying the expected optimal solution region or by creating better solutions to these problems with fewer constraints and fewer computational resources than descending gradient methods [15]. Due to its inherent and challenging difficulty, truss optimisation has become a difficult issue in structural engineering in recent decades. Many researchers have experimented with meta-heuristic techniques to optimise the size and arrangement of structures. Some of these techniques are: Genetic Algorithm (GA) [16], Particle Swarm optimisation (PSO) [17], School-Based optimisation (SBO) [18], Symbiotic Bodies optimisation (SBO) [19], Dynamic Water Strider Algorithm (DWSA) [20], Cuckoo Search Algorithm (CS) [21], and Dynamic Arithmetic optimisation Algorithm (DAOA) [22].

Natural frequency is a critical criterion in the issue of truss optimisation because it has a significant impact on the performance of a structure. This criterion is based on the understanding of structural dynamics, a field of study that provides critical information about the dynamic behaviour of structures. Over the last decade, researchers have paid close attention to the problem of truss optimisation based on frequency constraints. A significant practical challenge for the truss problem is to improve its dynamic behaviour by taking into account its natural frequencies. Better control of this criterion improves the structure's performance and prevents the phenomenon of resonance.

The design and construction of lightweight structures is a difficult and critical issue in engineering. The conflict between weight minimization and frequency constraints complicates the truss optimisation problem even more. As a result of the perceived need for effective optimisation techniques to design these structures and deal with their inherent limitations, an active research field has emerged in recent years. Researchers are expanding their knowledge and understanding of the subject as research expands. Some of these cases are discussed further below. Bellagamba and Yang [23] were pioneers in the field of truss optimisation with frequency constraints. Lin et al. [24] developed a bi-factor algorithm for these structures. Wei et al. [25] proposed a parallel genetic algorithm. Charged system search and enhanced CSS [26], democratic particle swarm optimisation (DPSO) [27], and tug of war optimisation (TWO) [28] were proposed by Kaveh and Zolghadr. Pholdee and Bureerat [29] experimented with various metaheuristic algorithms for this problem. Tejani et al. [19] proposed the search for symbiotic organisms (ISOS) in truss structures with a low frequency of occurrence. A learning algorithm based on multi-class training was used for truss structures with frequency constraints. In a recent study, the efficiency of the generalized normal distribution optimisation (GNDO) algorithm [30] was evaluated and compared with seven metaheuristic algorithms. The experimental results demonstrated that GNDO performed better than other latest algorithms regarding convergence speed and optimal solutions. However, the authors did not test the GNDO's performance for structures larger than 200 bar. In order to overcome the shortcomings of the original seagull optimisation algorithm (SOA), a strategy combined with mutualism and commensalism was proposed [31]. A wide range of numerical benchmarks and engineering problems were used to evaluate the improved SOA algorithm's performance, outperforming other methods.

Research in this field has confirmed the effectiveness of meta-heuristic optimisation algorithms in dealing with and managing many problems when solving a structural design problem. Given the No Free Launch (NFL) Theorem [32], no single optimisation technique can solve all optimisation problems. As a result, developing a new modified algorithm and improving its performance can improve the algorithm's ability to handle a set of problems compared to existing algorithms. Simultaneously, the method for dealing with optimisation problems in these methods will not change. This is the motivation for our efforts to improve the efficiency of the MPA optimisation algorithm, which has recently demonstrated excellent performance in optimisation problems, and to adapt it to structural design problems better.

Faramarzi et al. [33] recently proposed a marine predator optimisation algorithm based on the natural behaviour of marine predators for constrained and unconstrained optimisation problems. Despite the thriving performance of MPO, there are some technical areas for improvement in optimising real engineering problems. For example, the prey particles yield their route and converge on the predator particles in some multi-modal cases [34]. Shaheen et al. [34] proposed an improved MPO method to provide a better chance to prevent falling into local optimum by determining a random opportunity to combine three search stages. In another study [35], applying a differential operator is recommended to enhance the exploration phase of the standard MPA. To improve the performance of MPA in solving a nonlinear problem, the tracking the global MPP of shaded PV ystems [36], a combination of the Opposition Based Learning (OBL) method with Grey Wolf Optimiser (GWO) was proposed to control the searchability of MPA and acquire more rapid convergence rate.

Although multi-solution meta-heuristics have some intrinsic limitations, the literature suggests that these algorithms are now the primary method for solving optimisation issues. This research area is among the most popular in computational intelligence and has lately presented several methods. Having such a potential possibility to approach a solution indicated by a computationally effective optimisation algorithm capable of finding the best solution somewhat and efficiently has encouraged the development of an upgraded hybrid version of the MPA method.

It must be mentioned that related works in the meta-heuristics literature were thoroughly evaluated and described in the first part of this section. However, several research works, such as HHO, SSA, MVO, WOA, and other well-known meta-heuristics, are not natively developed and aim at large-scale and complex problems. For the first time in the literature, we customized and adjusted the MPA technique for large-scale challenges, particularly truss problems.

When the form and bar size parameters are combined, a multi-modal solution space with dynamic restrictions is created, resulting in a time-consuming optimisation process. As a result, the majority of actual truss problems are large and highly constrained, and scaling issues occur as the problem size increases. As a result, this paper employs the proposed optimisation methods (HNMPA, HNCMPA), an extended population-based meta-heuristic, to tackle structural design challenges. The aim of this research is to apply the proposed methods to build the optimal weight of truss structures described in the literature. To boost MPA's performance, two new features were successfully added to the basic version in the first phase (Nonlinear and chaotic parameters), and the hill-climbing method was integrated with the suggested algorithm in the second step to tackle truss optimisation problems more effectively. The optimisation of trusses considered a complex and practical engineering problem, presents a significant challenge for meta-heuristic algorithms due to extensive local optima caused by the problems' inherent complexity. As a result, merely having efficient exploration and exploitation approaches is inadequate to avoid getting trapped in these local optima. This study proposes hybrid methods that integrate hill-climbing, a renowned local search method, to address this issue and enable the algorithms to move beyond the local optima and approach the global optimum point. HNMPA and HNCMPA continue to apply to various groups of optimisation issues because no additional fine-tuning of MPA parameters is necessary to connect with these new versions.

To make a long story short, the primary contributions of this study are as follows:

- Proposing a new adaptive MPA algorithm employs an efficient nonlinear control parameter to achieve a good balance between exploration and exploitation strategies, as well as chaotic values to improve the exploration phase by providing the proposed algorithm's population with a sufficient degree of diversity, resulting in excellent accuracy and rapid convergence.
- Enhancing the performance of the proposed technique by employing a Hill Climbing (HC) local search algorithm to accelerate convergence and avoid trapping at local optimal points, hence resolving truss optimisation concerns.
- The optimisation results of several architectures with nonlinear and dynamic constraints are thoroughly analyzed and reviewed to assess the performance of the proposed approach. To address these issues, the weight of the structure with specific constraints on the problem is employed as a target function, together with distinct and continuous areas of design variables.

The paper's structure is as follows. Section II represents the formulation of two large-scale truss problems. Section IV explains the basic MPA initially, and then it describes the proposed IMPA in more detail. The experimental results are shown in Section V. Finally, Section VI draws a conclusion from the research findings and results.

II. FORMULATION OF TRUSS PROBLEMS

The goal of shape and sizing optimisation of truss structures is to find the minimal structural weight by simultaneously optimising nodal coordinates and cross-sectional areas. Additionally, the optimisation problem is supposed to satisfy natural frequencies, stress, and nodal displacement constraints while minimizing the structural weight. In this problem, the structural topology is assumed to be fixed and unalterable. Thus, the optimisation problem can be formulated as follows:

$$
\begin{aligned}
&\text{Find: } X = \{A_1, A_2, \ldots, A_m, C_1, C_2, \ldots, C_n\}\\
&\text{Min: } F(X) = \sum_{i=1}^{mn} A_i \rho_i L_i + \sum_{j=1}^{N} b_j\\
&\text{Where: } A_i^{min} \leq A_i \leq A_i^{max}\\
&\qquad C_i^{min} \leq C_i \leq C_i^{max}
\end{aligned}
\tag{1}
$$

where X is the structural design variable vector, including A_i and C_i as structural sizing and shape design variables, which are confined to the lower and upper bound $[A_i^{min}, A_i^{max}]$ and $[C_i^{min}, C_i^{max}]$, respectively. n and m represent the number of structural cross-sectional areas and nodal coordinates. Also, in the second formula, ρ_i, L_i, b_j, and $F(X)$ are the ith element's mass density, the ith element's length, the jth node's mass, and the objective function, respectively. Moreover, structural constraints can be formulated as follows;

$$
\begin{aligned}
|\sigma_i| - \sigma_i^{max} \leq 0\\
|\delta_j| - \delta_j^{max} \leq 0
\end{aligned}
\tag{2}
$$

where σ_i, σ_i^{max}, δ_j, and δ_i^{max} are the ith element's stress, ith element's maximal stress value, the jth nodal displacement value, and the $j$the maximal nodal displacement value, respectively.

Furthermore, in these problems, a penalty function is necessary to convert the constrained problem into an unconstrained problem. The penalty function we used in this paper is as follows:

$$
F_{Penalty}(X) = F(X) + \sum_{i=1}^{K} (\sigma_{Vio_i} + \delta_{Vio_i}) P_f \tag{3}
$$

where P_f and $F_{Penalty}(X)$ are the penalty factor and penalty function, respectively. Also, σ_{Vio_i} and δ_{Vio_i} are the stress and nodal displacement violation values for the design variable vector.

III. CASE STUDIES

In this section, we explain two case studies proposed by Bright Optimiser called ISCSO 2018 and ISCSO 2019 [37]. The optimisation problems include concurrent structural shape and sizing optimisation, while structural topology is immutable and predetermined. The goal is to minimize the structural weight while satisfying stress and nodal displacement constraints. In both case studies, for all truss elements, density, elastic modulus, and yield stress are equivalent to 7.85 ton/m^3, 200 GPa, and 248.2 MPa, respectively.

1) 314-BAR TRUSS

The first case study shown in Figure 1 (Part *a*) is a three-dimensional steel truss structure including 314 bars and 84 nodes. The structural design is subject to three independent load cases. The loads applied to all unsupported nodes include horizontal loads of 12 kN, horizontal loads of 6 kN, and vertical loads of 48 kN applied to positive x-direction, positive y-direction, and negative z-direction, respectively. Additionally, all nodes' displacements in the x, y, and z directions are confined to a maximum value of ± 50 mm. In this optimisation problem, cross-sectional areas and nodal coordinates variables can take only integer values within range [1, 37] and [9000, 20000], respectively.

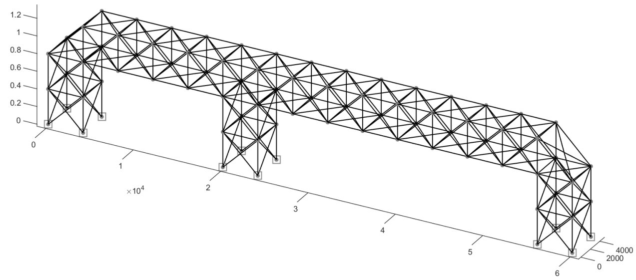


FIGURE 1. **314 bars and 84 nodes construct a steel truss structure. The optimisation variables incorporate elements of 14 shapes (*C*) and 314 sizings (*A*).**

2) 260-BAR TRUSS

The second case study shown in Figure 2 (Part *b*) is a three-dimensional steel truss structure including 260 bars and ten nodes. In the structural design, three independent load cases are considered to apply the loads to all unsupported nodes. They include horizontal loads of 5 kN, horizontal loads of 1 kN, and vertical loads of 5 kN applied to positive x-direction, positive y-direction, and negative z-direction, respectively. Additionally, all nodes' displacements in x, y, and z directions are confined to a maximum value of ± 25 mm. In this optimisation problem, cross-sectional areas and nodal coordinates variables can take only integer values within range [1, 37] and [-25000, 3500], respectively.

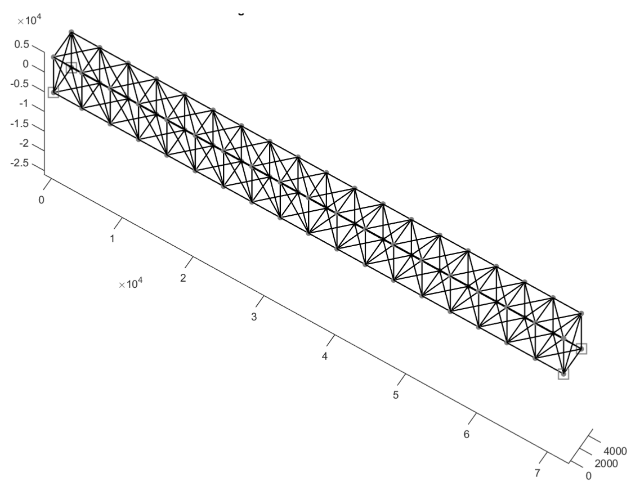


FIGURE 2. **260 bars and 76 nodes construct a steel truss structure. The optimisation variables incorporate elements of 10 shapes (*C*) and 260 sizings (*A*).**

3) 345-BAR TRUSS

The third case study is a 3D steel truss structure with 345 elements and 105 nodes with fixed topology, and just sizing optimisation is considered. The applied independent loads in this structure are i) in the positive X-coordination, a horizontal load is imposed at 20 kN. ii) the second load is similar to the first load size but in the positive Y-coordination. iii) 24 kN vertical load applied in the Z-coordination inversely. The total feasible displacements for all nodes are restricted to ± 5 mm. The yield stress of the truss material, elastic modulus, and material density are 248.2 MPa, 200 GPa, and 7.85 ton/m^3, respectively. Figure 3 shows a feasible design of a 345-bar truss structure with the same element size at 32.

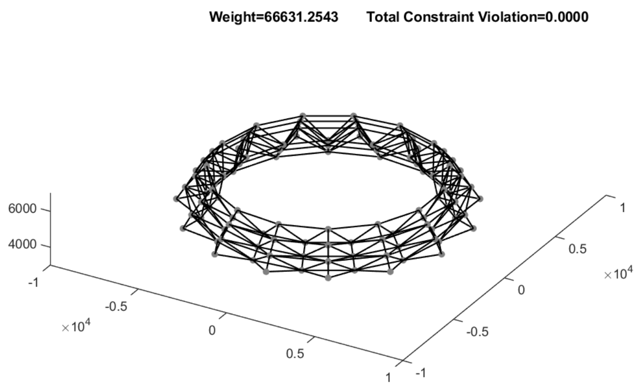


FIGURE 3. 345 bars and 105 nodes (including 15 supported nodes) construct a steel truss structure. The optimisation variables incorporate elements of 345 bars.

IV. METHODOLOGY

A. MARINE PREDATORS ALGORITHM (MPA)

Faramarzi et al. [38] developed a new algorithm inspired by the marine predator food search strategy to solve optimisation problems. This algorithm's structure is based on the predators' Lévy and Brownian movements and the optimal collision process in the biological interaction between predator and prey. This algorithm has the advantage of simulating the recall mechanism and memorising the successful hunting locations of marine predators. MPA, in other words, remembers the optimisation results as well as potential solution points. In MPA, finding the best solution requires fewer iterations. Therefore, using this algorithm to solve the truss optimisation problem is advantageous.

The two stages of marine predator search and the extent to which predators and prey interact in a marine ecosystem form the core structure of an MPA. Predators and prey are trying to hunt each other down and find natural food. They are pursuing a phenomenon known as the strongest survival, which increases hunters' chances of finding prey. MPA simulates its optimisation phase using Lévy and Brownian strategies. In this algorithm, these two strategies accurately depict the behaviour of marine predators.

Random walks in nature are an effective strategy in many animals' food search patterns. This optimal strategy allows hunters to improve their chances of survival by increasing the frequency of prey encounters in the wild. During predators' lives, this strategy evolved as an inherent process in these animals and nature, leading to the survival of the predator's generation. In MPA, the animal's next position is mathematically predicted based on its current position and the probability of moving to the next position.

The ratio of prey to predator speed is critical in MPA for simulating and transferring the optimisation process from one step to the next. The high speed of the prey in comparison to the predators is vital in the first phase of the algorithm, whereas in the later stages of the algorithm, the unit ratio and low speed are significant considerations in the optimisation process. The MPA has a low number of adjustable variables, a simple design, a low computational load, and no reliance on the gradient.

The following is a synopsis of the optimal search, food search, interaction, and memory processes used by wild marine predators to find prey:

- Marine predators employ the Levy strategy in areas with low hunting densities and the Brownian strategy in areas with multiple preys.
- Marine predators use the same percentage of levy and brownie movements when crossing different habitats.
- Marine predators remember food search locations as well as hunting areas.

1) MPA's OPTIMISATION PHASES

This process is divided into three significant stages in MPA, inspired by the natural life of predators and prey. These procedures are as follows:

Phase I: The prey is faster than the predator. When the prey is moving faster than the predator, the predator's best strategy is to remain still. The algorithm is currently in the exploration phase. In MPA, this step is represented as follows:

$$\begin{aligned} &\text{While: } Iter < \frac{1}{3} Max_{Iter} \\ &\overrightarrow{S}_l = \vec{R}_B \otimes \left(\overrightarrow{Elite_l} - \vec{R}_B \otimes \overrightarrow{Pray_l}\right) \\ &\overrightarrow{Pray_l} = \overrightarrow{Pray_l} + P.\vec{R} \otimes \overrightarrow{S}_l \end{aligned} \tag{4}$$

The R_B vector has random numbers and is based on the normal distribution of Brownian motion. This vector in Prey is multiplied to model prey movement. P is a constant equal to 0.5, and R is a vector of uniform random numbers in the range [0, 1]. This step occurs in $\frac{1}{3}$ of iterations when the movement speed is high to allow for high levels of exploration ($Iter$ mentions the current iteration, Max_{iter} is the maximum one).

Phase II: Both the prey and the predator move at the same rate. This MPA step occurs when the algorithm is moved from the exploration phase to the exploitation phase. Exploration and exploitation occur concurrently at this stage. Prey engages in exploitation, whereas predators explore.

$$\text{while } \frac{1}{3} Max_{Iter} < Iter < \frac{2}{3} Max_{Iter}. \tag{5}$$

$$\overrightarrow{S}_l = \vec{R}_L \otimes \left(\overrightarrow{Elite_l} - \vec{R}_L \otimes \overrightarrow{Pray_l}\right) \tag{6}$$

$$\overrightarrow{Pray_l} = \overrightarrow{Pray_l} + P.\vec{R} \otimes \overrightarrow{S}_l. \tag{7}$$

Prey motion is simulated for the first half of the population using the R_L random number vector based on the Levy distribution. The prey movement in nature is simulated by adding a step size to the prey position. The steps in the Levy distribution are typically small. The MPA defines the following for the second half of the population:

$$\vec{S}_l = \vec{R}_B \otimes \left(\vec{R}_B \otimes \overrightarrow{Elite_l} - \overrightarrow{Prey_l}\right) \tag{8}$$

$$\overrightarrow{Pray_l} = \overrightarrow{Elite_l} + P.CF \otimes \vec{S}_l \tag{9}$$

$$CF = \left(1 - \frac{Iter}{Max_{Iter}}\right)^{\left(2\frac{Iter}{Max_{Iter}}\right)} \tag{10}$$

The step size of the predators' movement is controlled by an adaptive parameter, CF, in MPA. The predator's movement is simulated using the Brownian method and multiplied by R_B. Elite simulates prey movement in MPA. Because the prey position is updated in relation to the predators' movement in Brownian motion.

Phase III: The predator is faster than the prey. This MPA step contributes to excessive exploitation.

At this step, the Predator's best strategy is to follow the Levy strategy. In the Levy strategy, predator motion is simulated by multiplying R_L. The position of the prey is updated in response to predator movement. In addition, the Elite position is simulated by increasing the step size. MPA defines this step as follows:

$$\text{while Iter} > \frac{2}{3}Max_{iter} \longrightarrow \tag{11}$$

$$\vec{S}_l = \vec{R}_L \otimes \left(\vec{R}_L \otimes \overrightarrow{Elite_l} - \overrightarrow{Pray_l}\right) \tag{12}$$

$$\overrightarrow{Pray_l} = \overrightarrow{Elite_l} + P.CF \otimes \vec{S}_l \tag{13}$$

MPA divides the process of finding an optimal solution into three steps and a limited number of iterations. These steps are inspired by natural predator behaviour and prey and simulate the predator's step size and movement during the hunting process to catch prey. A predator's percentage of Levy and Brownian motion is fixed in MPA. The predator is stationary and motionless in the early stages of the algorithm. The predator, however, uses Brownian motion to change its position in the second stage and Levy motion in the final stage. This scenario occurs due to the possibility of prey being predators in nature. The prey uses a Brownian movement in the first stage and a levy movement in the second stage to change its position.

The behaviour of marine predators may change throughout their lives as a result of environmental issues in their habitat. Fish Aggregating Devices (FADs), or eddy formation in nature, are one of the most well-known examples of these effects. Sharks, as one of the largest marine predators, spend more than 80% of their time near these FADs and the rest of their time searching in different directions and dimensions for environments with different prey. These FADs are considered local optima in MPA, and they prevent the algorithm from becoming trapped in the local optimal points during the optimisation process. In the algorithm, this model is represented as follows:

$$\overrightarrow{Pray_l} = \begin{cases} \text{if } r < FADs \\ \overrightarrow{Pray_l} + CF\left[\vec{Z}_{min} + R \otimes (\vec{Z}_{max} - \vec{Z}_{min}\right)] \otimes \vec{U} \\ \text{if } r > FADs \\ \overrightarrow{Pray_l} + [FADs\,(1-r) + r]\left(\overrightarrow{Pray_{r_1}} - \overrightarrow{Pray_{r_2}}\right) \end{cases} \tag{14}$$

r is a random number between 0 and 1. Whereas Z_{max} and Z_{min} are vectors representing the boundaries of the lower and upper dimensions. $FADs = 0.2$ to apply the effect of FADs on the optimisation process in MPA. A binary vector U is made up of two arrays, zero and one, which are defined by generating a vector of random values between [0, 1].

Although the performance of the standard MPA is considerable in solving most of the fundamental engineering problems, there are some reports of low performance of this meta-heuristic in some case studies. The first and foremost shortage of MPA is the low efficiency in local search [36]. As the step control parameter (CF) significantly impacts obtaining a proper balance of exploration and exploitation, some studies [39] proposed modified CF techniques to improve the general performance of MPA.

B. HYBRID NONLINEAR MARINE PREDATORS ALGORITHM (HNMPA)

The MPA has inspired predator and prey movement in accordance with the rules and points of multiple research and observable behaviours in nature. Despite having satisfactory exploration and exploitation rates, the MPA remains stuck in optimal local solutions rather than reaching the global optimum solution. The main goal of HNMPA is to improve MPA exploration and exploitation by trying to adjust the predator phase's size towards the prey and trying to balance the algorithm's exploration and exploitation phases using the presented control parameter. The MPA algorithm's second phase consists of two main stages: exploration and exploitation.

Modifications in this phase will improve the MPA's efficiency and effectiveness. This phase has been modified as follows: The nonlinear parameter is used as a control parameter by HNMPA to adjust the exploration and exploitation phases. This variable is as follows:

$$\omega = 2 \times exp\left(-0.99 \times \sqrt{\frac{Iter}{Max_{Iter}}}\right) \tag{15}$$

In the range [2, 0], ω decreases non-linearly. As a result, Eqs. 6 and 8 have been updated as follows:

$$\text{while } \frac{1}{3}Max_{Iter} < Iter < \frac{2}{3}Max_{Iter}. \tag{16}$$

$$\vec{S}_l = \vec{R}_L \otimes \left(\overrightarrow{Elite_l} - \vec{R}_L \otimes \overrightarrow{Pray_l}\right) \times (l = 1, \ldots, n/2) \tag{17}$$

$$\overrightarrow{Pray_l} = \omega \times \overrightarrow{Pray_l} + P.\vec{R} \otimes \vec{S}_l \tag{18}$$

Algorithm 1 B. Hybrid Nonlinear Marine Predators Algorithm

Initialise the control parameters $FADs$, P, N_{pop}, and ω
Initialise the first swarm ($Prey$), $Z_i \quad i \in \{1, 2, \ldots, N_{pop}\}$
Evaluate population $Prey$
while $iter \leq Max_{iter}$ **do**
  Compute $Elite$ matrix
  Calculate CF based on Eq.(10)
  for each $Prey \in Z_i$ **do**
    if $Iter < \frac{1}{3}Max_{Iter}$ **then**
      Update $Prey$ based on Eq.(4)
    else if $\frac{1}{3}Max\_Iter < Iter < \frac{2}{3}Max\_Iter$ **then**
      $\omega = 2 \times \exp(-0.99 \times \sqrt{Iter/Max_{Iter}})$
      if $i \leq n/2$ **then**
        Update $Prey$ based on Eq.(17)
      else
        Update $Prey$ based on Eq.(19)
      end if
    else
      Update $Prey$ based on Eq.(11)
    end if
  end for
  Evaluate population $Prey$
  Update $Prey$ using $FADs$ based on Eq.(14)
  Apply marine memory saving and update the best solution
  Compute improvement rate based on $Im_{Iter} = \frac{\sum_{i=1}^{10}(f_{Iter}-f_{Iter-i})}{10}$
  if $Im_{Iter} < \mu$ **then**
    Run Hill Climbing (HC) Algorithm 2
    if $HC_{Best_{sol}} < NCMPA_{Best_{sol}}$ **then**
      Update the population based on the best-found solution
    end if
  end if
end while

$$\overrightarrow{S}_l = \vec{R}_B \otimes \left(\vec{R}_B \otimes \overrightarrow{Elite}_l - \overrightarrow{Prey}_l\right) \times (l = n/2, \ldots n) \tag{19}$$

$$\overrightarrow{Pray}_l = \omega \times \overrightarrow{Elite}_l + P.CF \otimes \overrightarrow{S}_l \tag{20}$$

Algorithm 1 shows the technical details of the implementation of the proposed boosted MPA. The hill climb algorithm is used (Algorithm 2) in MPA's second change to prevent it from becoming trapped in local optimal points. If the proposed algorithm fails to improve the value of the cost function during the optimisation process and several consecutive iterations (for example, in a quarter of the algorithm's iterations), the HC algorithm is used, and it begins to try to improve the best answer and position obtained so far by the algorithm. It should be noted that this will continue until the cost function's value improves.

Algorithm 2 Hill Climbing Local Search

procedure Hill Climbing Local Search(HC)
Initialization
  $Initialize\ \sigma_i^{max}, \delta_j^{max}$ ▷ Initialize maximum allowable stress and nodal displacement in the ith element
  $Step_s = (Min_s + Max_s)/10$, $Step_c = (Max_c - Min_c)/10$ ▷ Compute the step size for GS
  $Truss_{iter}$={S, C} ▷ Read both sections (S) and coordinate (C) values
  $(Weight_b, \sigma_i, \delta_j)$=$Eval(Truss_{iter})$ ▷ Evaluate the design
  for $iter \leq Max_{iter}$ **do**
    while $t \leq N + M$ **do**
      $Temp = Truss_{iter}$
      if $t \leq N$ **then**
        $Temp_t = Temp_t \pm Step_s$ ▷ Neighborhood search
      else
        $Temp_t = Temp_t \pm Step_c$
      end if
      $(Weight_t, \sigma_i, \delta_j)$=$Eval(Temp_t)$
      if $\sum_{i=j=1}^{N,M}(\sigma_i + \delta_j) \neq 0$ **then** ▷ design is not feasible
        Apply the penalty function
      end if
      $t = t + 1$
    end while
    $Truss_{iter}$=Min($Weight_t$) ▷ Select the best feasible solution and update the truss
    $Step_s = Step_s - (\frac{iter}{Max_{iter}} Step_s) + 1$ ▷ $Step_c$ and $Step_s$ linearly decreased
  end for
  return $Truss_{iter}$
end procedure

C. HYBRID NONLINEAR-CHAOTIC MARINE PREDATORS ALGORITHM (HNCMPA)

1) CHAOTIC SEARCH BEHAVIORS

In optimisation algorithms, chaos theory is frequently used to improve the diversity of initialised solutions. Population diversity describes potential solutions, parts of solutions, or structures that can be effectively changed into solutions. According to the literature review, this optimisation algorithm is a population-based algorithm, which means it solves the problem by starting with a random solution and then evaluating it based on specified criteria. To solve the problems in the meta-heuristic, we need to use a search agent (in this work, the search agents are predator and prey). The original MPA's search agents start at a random point and generate random solutions, referred to as population distributions, contributing to a population diversity issue. In this paper, we use the Sine Chaotic Map function to set the position of these search agents and to improve the algorithm's exploration phase. As demonstrated by the definition of chaotic maps and their movement behaviour, there are more possible scenarios for the areas affected and the number of times they keep moving. Therefore, a specific map improves an optimisation technique's exploration of behaviour patterns. It is also worth noting that these maps were taken into account because they display a variety of behaviours when trying to generate chaotic values and have been shown to be efficient in experiments conducted [40], [41]. Using chaotic maps to enhance initialised solutions improves the efficiency of the algorithm. Furthermore, chaos theory can explore the solution space more extensively than random search [42]. However, it is critical to leverage solution space to try and make the initial population as efficient as possible. To help enhance diversity in the population, this work employs Chaos theory's Sine Map (SM) to initialise the HCCMPA. This is due to the fact that chaotic maps aid the optimisation technique's exploration of the search space. In other words, apart from a probability-based search, the exploration can be structured rather than random [41]. Furthermore, chaotic maps can help optimisation algorithms prevent optimal solutions while also boosting convergence [43], [44], [45]. The CM mathematical formulation is computed as in Eq 21.

$$ChaosSineMap = X_{n+1} = \frac{\alpha}{4} sin(\pi X_n), \alpha = 4 \tag{21}$$

2) HYBRIDISATION

The MPA has inspired predator and prey movement in accordance with the rules and points of considerable research and observable behaviours in nature. Despite having satisfactory exploration and exploitation rates, the MPA remains stuck in optimal local solutions rather than reaching the global optimum solution. The primary goal of HCCMPA is to improve MPA exploration and exploitation by attempting to balance the algorithm's exploration and exploitation phases using the presented control parameter and chaos values rather than random ones. Therefore, the first phase of the MPA is modified as follows.

$$\begin{aligned}
&\text{While: } Iter < \frac{1}{3} Max_{Iter} \\
&\vec{S}_l = \vec{R}_B \otimes \left(\overrightarrow{Elite_l} - \vec{R}_B \otimes \overrightarrow{Pray_l} \right) \\
&\overrightarrow{Pray_l} = \overrightarrow{Pray_l} + P.\vec{CM} \otimes \vec{S}_l
\end{aligned} \tag{22}$$

The MPA algorithm's second phase consists of two main stages: exploration and exploitation. Modifications in this phase will improve the MPA's efficiency and effectiveness. This phase has been modified as follows. The nonlinear parameter is used as a control parameter by HCCMPA to adjust the exploration and exploitation phases. This variable is as follows:

$$\omega = 2 \times exp\left(-(4 \times (\frac{Iter}{Max_{Iter}})^3) \right) \tag{23}$$

In the range [2, 0], w decreases non-linearly. As a result, Eqs. (12) and (13) have been updated as follows:

$$\text{while } \frac{1}{3} Max_{Iter} < Iter < \frac{2}{3} Max_{Iter}. \tag{24}$$

$$\vec{S}_l = \vec{R}_L \otimes \left(\overrightarrow{Elite_l} - \vec{R}_L \otimes \overrightarrow{Pray_l} \right) \times (l = 1, \ldots, n/2) \tag{25}$$

$$\overrightarrow{Pray_l} = \omega \times \overrightarrow{Pray_l} + P.\vec{CM} \otimes \vec{S}_l \tag{26}$$

$$\vec{S}_l = \vec{R}_B \otimes \left(\vec{R}_B \otimes \overrightarrow{Elite_l} - \overrightarrow{Prey_l} \right) \times (l = n/2, \ldots n) \tag{27}$$

$$\overrightarrow{Pray_l} = \omega \times \overrightarrow{Elite_l} + P.CF \otimes \vec{S}_l \tag{28}$$

The two proposed algorithms stated so far will eventually be combined by the Hill climb algorithm. Notably, the two proposed components can be utilized independently as distinct methodologies or in a combined approach that dynamically selects the algorithmic component most suited for resolving the challenges and alternating between them. Nonetheless, for the purposes of this investigation, they were applied as distinct modalities. Algorithm 2 shows the technical details of the implementation of the proposed HNCMPA. The hill climb algorithm is used (Algorithm 2) in MPA's second change to prevent it from becoming trapped in local optimal points. If the proposed algorithm fails to improve the value of the cost function during the optimisation process and several consecutive iterations (for example, in a quarter of the algorithm's iterations), the HC algorithm is used, and it begins to try to improve the best answer and position obtained so far by the algorithm. It should be noted that this will continue until the cost function's value improves.

The proposed hybrid method is able to keep a considerable balance between searchability and convergence rate in multimodal search space. Furthermore, integrating hill climbing as a robust local search improves the MPA and speeds up the convergence rate in the unimodal search space.

V. EXPERIMENTAL RESULTS

A. LANDSCAPE ANALYSIS

Recently, the applications of landscape analysis have been broadly expanded [46] for a better insight into complicated optimisation problems and clarifying behaviours of algorithms, predicting the performance of the optimisation methods, and automated configurations and selections. In this section, we performed some experiments for visualising a violation landscape as further insight into fitness landscapes for the truss optimisation problem with a constrained search space.

A violation landscape is restricted, utilising the identical features as a fitness landscape. Still, the fitness function is substituted using a violation function [47] that quantifies how a solution violates the constraints represented on the problem. Therefore, a violation landscape is characterised beyond the decision variable space and supplies a further landscape perspective to the fitness landscape. The features of violation landscapes can be studied concerning fitness landscapes to understand constrained optimisation benchmarks better.

In order to provide a technical landscape analysis, we used a grid search method. As the number of decision variables is enormous for both case studies, we assume the same value for all shape and sizing variables. Figure 4 demonstrates the fitness plus violation landscape analysis of the 260-bar truss problem. The whole decision variables include 10 shapes ($-25 \times 10^3 \leq C \leq 3500$) and 260 sizings ($1 \leq A \leq 37$) elements. The colour bar highlights the sum of the structure's weight and the penalty factor. It is noted that the landscape is multi-modal, and sizing variables less than 15 make a sharp violation consisting of stress and displacement. Moreover, we can see that the best range of shape variables is between 0 and -15000.

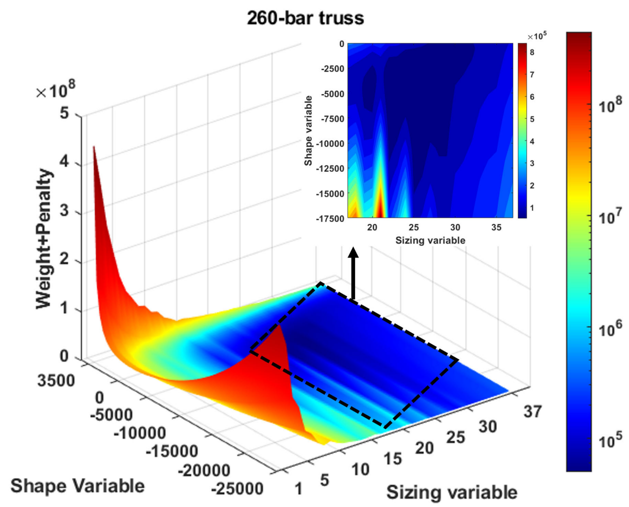


FIGURE 4. 3D landscape analysis of truss structure with 260 bars and 78 nodes. The whole decision variables include 10 shapes ($-25 \times 10^3 \leq C \leq 3500$) and 260 sizings ($1 \leq A \leq 37$) elements. The sum of the structure's weight and the penalty factor is highlighted by the colour bar. Dark blue shows the best-found designs based on the grid search analysis.

To have a more systematic insight into the violation landscape of the 260-bar truss, we re-performed the landscape analysis focused on the stress violation levels. Figure 5 shows the stress violations of different designs of 260-bar truss, and we can see the feasible areas highlighted by dark blue. Obviously, the fitness search space is multi-modal with non-linear constraints; however, the fitness landscape is simplified by the assumption of the same shape and sizing values. Furthermore, the impact of shape values on the stress violation is meaningful.

B. NUMERICAL BENCHMARKS

This study evaluated the proposed method's performance using various test functions. Two classes of well-known benchmarks are used for mathematical optimisation problems. The benchmark contains unimodal, multimodal, and composition functions to assess the HNCMPA and HNMPA's

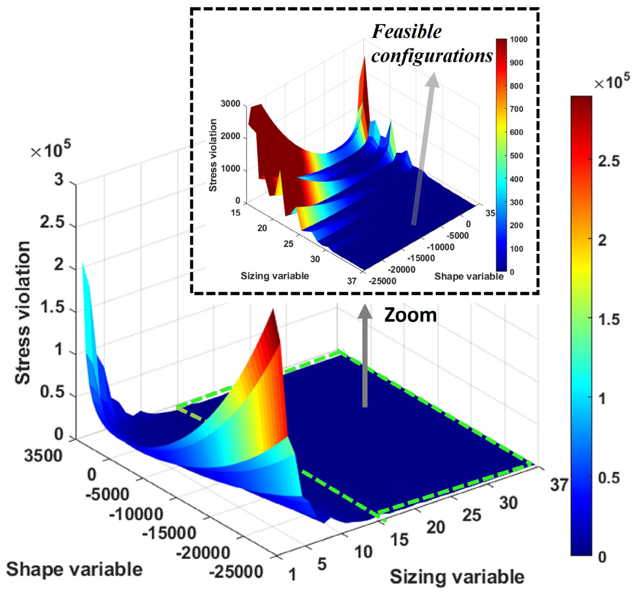


FIGURE 5. 3D stress violation landscape analysis of truss structure with 260 bars and 78 nodes. The stress violation of the structure is highlighted by the colour bar. Dark blue in the zoomed figure shows the best-found designs (feasible solution, $\sum |\delta_j| - \delta_i^{max} = 0$) based on the grid search analysis.

TABLE 1. The algorithm's parameter settings for numerical benchmarks.

Algorithm	Parameter	Value
MPA	FAD	0.2
	P	0.5
HNMPA,HNCMPA	FAD	0.2
	P	0.5
PSO	Topology fully connected Inertia factor	0.5
	C_1	2
	C_2	2
MVO	Maximum value of Wormhole Existence Probability	1
	Minimum value of Wormhole Existence Probability	0.2
MFO	Convergence constant a	[-1 -2]
SSA	C_1 (balancing parameter of exploration and exploitation)	[1 0]
GWO	Convergence constant a	[2 0]
WOA	Convergence constant a	[2 0]

capability to explore, exploit, and escape from local minima. Unimodal test functions (F1-F6) are intended to test an algorithm's exploitation ability, whereas multimodal test functions (F7-F13) are used to experiment with the algorithm's exploration phase effectiveness. These two classes of functions are examined in 300 dimensions. The composition functions (F14-F20) are intended to assess the general performance of the proposed algorithm. However, their complexity is similar to real and challenging optimisation problems because they have too many local minima. Wu et al. [48] contains more information on these test functions. Tables 1 and 2 outline the parameters for meta-heuristic algorithms

TABLE 2. The statistical performance criteria for the proposed hybrid methods and other eight optimisation algorithms for unimodal functions.

Func		MPA	HNMPA	HNCMPA	PSO	MFO	MVO	SSA	GWO	WOA
F1	Ave	1.02E-85	8.22E-103	**0.00E+00**	1.76E+02	2.88E+05	8.11E+02	1.33E+03	1.35E-37	6.71E-298
	Std	2.16E-85	1.43E-102	0.00E+00	3.66E+01	2.96E+04	8.41E+01	3.07E+02	1.34E-37	0.00E+00
F2	Ave	4.23E-50	3.05E-63	**0.00E+00**	2.84E+02	7.76E+02	3.82E+104	1.26E+02	1.09E-22	1.85E-203
	Std	9.07E-50	7.14E-63	0.00E+00	1.83E+02	5.49E+01	2.08E+105	1.24E+01	3.99E-23	0.00E+00
F3	Ave	7.42E+01	8.93E-14	**0.00E+00**	1.26E+05	1.11E+06	4.46E+05	2.74E+05	3.79E+03	1.00E+07
	Std	1.13E+02	1.68E-13	0.00E+00	2.39E+04	2.34E+05	2.69E+04	1.09E+05	3.56E+03	2.26E+06
F4	Ave	1.15E-29	1.53E-38	**0.00E+00**	1.98E+01	9.81E+01	8.32E+01	3.53E+01	2.10E+01	8.07E+01
	Std	1.22E-29	1.23E-38	0.00E+00	1.11E+00	5.53E-01	2.94E+00	2.86E+00	7.87E+00	2.28E+01
F5	Ave	**2.94E+02**	2.95E+02	2.96E+02	2.44E+05	9.78E+08	3.40E+04	1.50E+05	2.98E+02	2.96E+02
	Std	**1.31E+00**	1.07E+00	9.51E-01	5.96E+04	1.38E+08	8.92E+03	4.88E+04	3.99E-01	3.14E-01
F6	Ave	4.13E+00	1.37E+01	2.31E+01	1.72E+02	2.73E+05	8.15E+02	1.39E+03	4.87E+01	**4.99E+00**
	Std	8.53E-01	1.39E+00	1.97E+00	3.65E+01	2.40E+04	9.78E+01	3.16E+02	1.57E+00	**1.52E+00**
F7	Ave	5.20E-04	4.56E-04	**1.57E-05**	1.84E+04	4.25E+03	3.35E+00	9.31E+00	2.45E-03	1.44E-03
	Std	2.42E-04	1.98E-04	1.63E-05	1.48E+03	7.62E+02	3.46E-01	1.21E+00	8.78E-04	1.71E-03

TABLE 3. The statistical performance criteria for the proposed hybrid methods and eight other optimisation algorithms for multimodal functions.

Func		MPA	HNMPA	HNCMPA	PSO	MFO	MVO	SSA	GWO	WOA
F8	Ave	-7.51E+04	-7.19E+04	-7.40E+04	-6.17E+04	-5.78E+04	-6.67E+04	-6.50E+04	-4.10E+04	**-1.19E+05**
	Std	**1.88E+03**	2.29E+03	2.02E+03	1.12E+04	4.51E+03	2.94E+03	4.20E+03	6.22E+03	9.60E+03
F9	Ave	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.31E+03	2.99E+03	2.59E+03	5.85E+02	1.02E-12	3.03E-14
	Std	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.64E+02	1.17E+02	1.46E+02	7.10E+01	2.85E-13	1.66E-13
F10	Ave	4.44E-15	1.84E-15	**8.88E-16**	5.47E+00	2.00E+01	2.04E+01	1.22E+01	7.50E-14	4.32E-15
	Std	0.00E+00	1.60E-15	**0.00E+00**	3.11E-01	1.47E-02	9.89E-02	5.74E-01	6.03E-15	2.72E-15
F11	Ave	**0.00E+00**	**0.00E+00**	**0.00E+00**	7.04E-01	2.42E+03	8.41E+00	1.21E+01	3.32E-04	0.00E+00
	Std	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.23E-01	3.17E+02	7.70E-01	2.85E+00	1.82E-03	0.00E+00
F12	Ave	2.91E-02	6.53E-02	1.10E-01	1.54E+01	2.23E+09	4.68E+01	3.77E+01	5.89E-01	**1.13E-02**
	Std	4.29E-03	8.34E-03	1.63E-02	4.08E+00	4.73E+08	7.75E+00	5.27E+00	4.06E-02	**2.97E-03**
F13	Ave	2.52E+01	2.57E+01	**2.50E+01**	1.07E+03	4.10E+09	6.47E+02	1.17E+03	2.58E+01	3.53E+00
	Std	8.30E-01	6.82E-01	**6.02E-01**	4.99E+02	9.52E+08	6.99E+01	1.07E+03	5.46E-01	1.09E+00

TABLE 4. The statistical performance criteria for the proposed hybrid methods and eight other optimisation algorithms for Composition functions.

Func		MPA	HNMPA	HNCMPA	PSO	MFO	MVO	SSA	GWO	WOA
F14	Ave	2.20E+03	2.20E+03	2.20E+03	2.31E+03	2.31E+03	2.31E+03	2.28E+03	2.32E+03	2.32E+03
	Std	2.36E-08	1.94E+01	2.19E-09	5.66E+01	4.59E+01	3.63E+01	5.76E+01	8.72E+00	6.24E+01
F15	Ave	2.26E+03	2.25E+03	2.25E+03	2.30E+03	2.31E+03	2.32E+03	2.33E+03	2.32E+03	2.36E+03
	Std	4.84E+01	4.88E+01	4.57E+01	1.09E+00	1.98E+01	8.32E+01	1.75E+02	7.14E+01	2.89E+02
F16	Ave	2.59E+03	2.61E+03	2.59E+03	2.71E+03	2.63E+03	2.62E+03	2.62E+03	2.62E+03	2.65E+03
	Std	7.83E+01	3.05E+00	3.24E+00	3.59E+01	9.04E+00	8.50E+00	7.66E+00	8.99E+00	1.74E+01
F17	Ave	2.50E+03	2.50E+03	2.50E+03	2.75E+03	2.77E+03	2.74E+03	2.74E+03	2.75E+03	2.78E+03
	Std	2.63E+01	4.72E+01	2.56E+01	1.39E+02	1.27E+01	4.60E+01	4.64E+01	1.05E+01	2.32E+01
F18	Ave	2.89E+03	2.89E+03	2.88E+03	2.92E+03	2.93E+03	2.92E+03	2.92E+03	2.94E+03	2.94E+03
	Std	5.44E+01	5.44E+01	5.24E+01	2.24E+01	2.62E+01	2.35E+01	2.39E+01	2.26E+01	6.35E+01
F19	Ave	2.76E+03	2.81E+03	2.77E+03	3.07E+03	3.09E+03	3.01E+03	2.93E+03	3.24E+03	3.63E+03
	Std	1.07E+02	1.07E+02	1.21E+02	3.96E+02	2.76E+02	3.25E+02	1.85E+02	4.41E+02	5.43E+02
F20	Ave	3.09E+03	3.09E+03	3.09E+03	3.16E+03	3.10E+03	3.09E+03	3.09E+03	3.10E+03	3.14E+03
	Std	7.80E-01	4.79E-01	6.22E-01	6.92E+01	4.82E+00	1.26E+01	2.89E+00	7.27E+00	4.10E+01

for numerical benchmark and truss optimisation issues, respectively. Notably, the Matlab R2020a platform was utilized to execute the proposed approach and other benchmarked algorithms on a computer equipped with Windows 8.1 64-bit and 6 GB of RAM. The determination of parameters was derived from the ones originally employed by the authors of each algorithm or, alternatively, from those frequently utilized by numerous scholars in the current field of study. Furthermore, all iterations and populations for the optimisation algorithms were set at 2000 and 50,

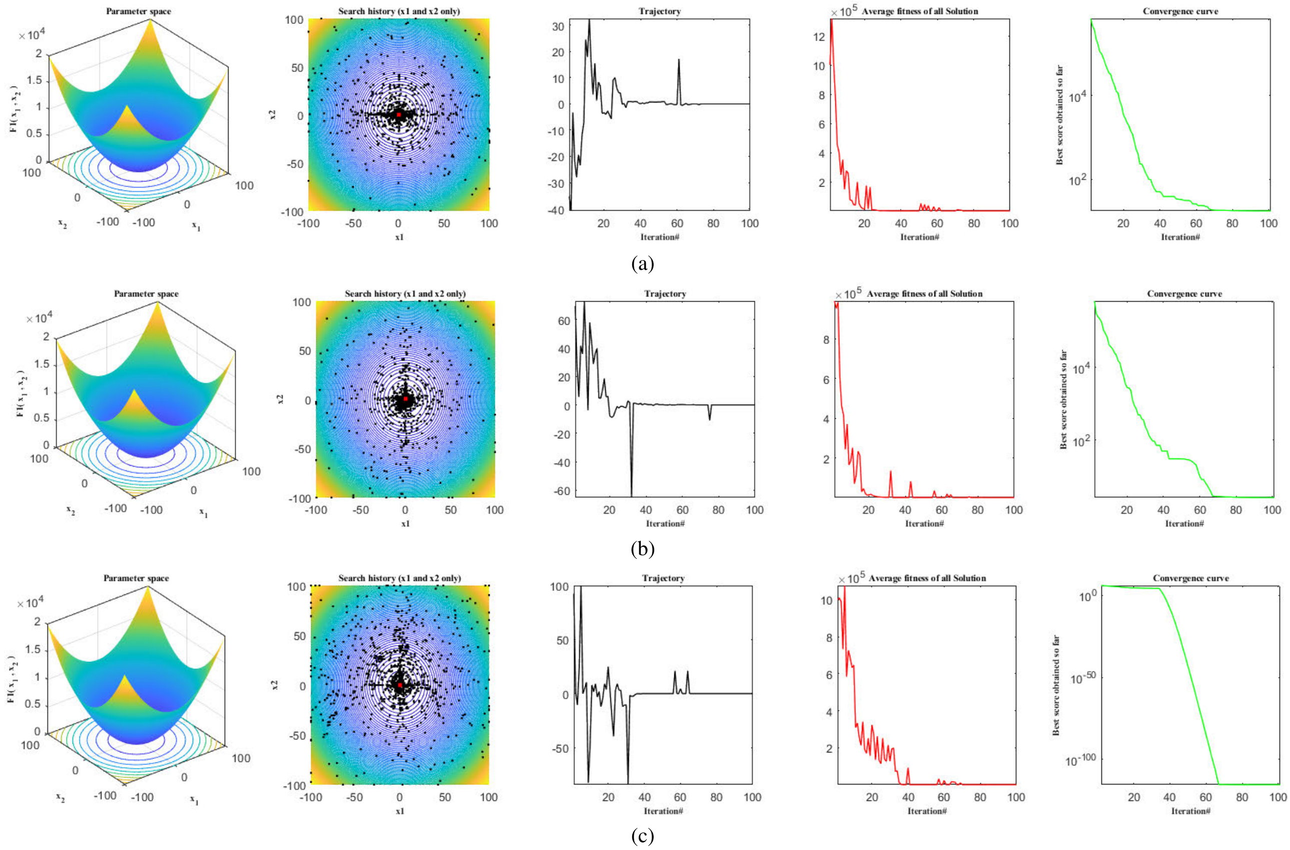


FIGURE 6. The search history, convergence performance of (a) MPA, (b) HNMPA, and (c) HNCMPA on unimodal F1 function.

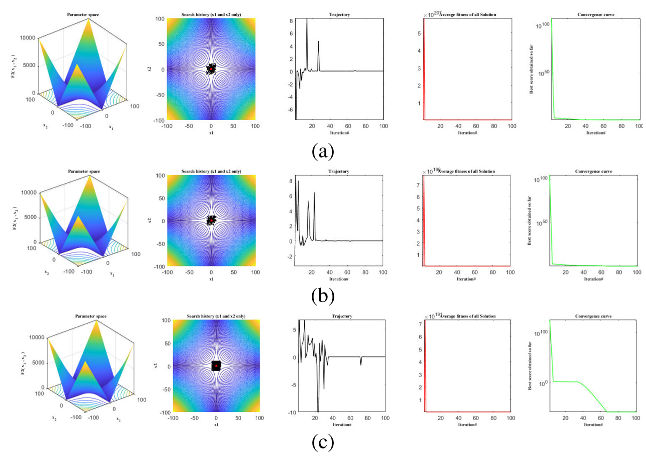


FIGURE 7. The search history, convergence performance of (a) MPA, (b) HNMPA, and (c) HNCMPA on unimodal F2 function.

respectively. Table 1 enumerates the primary parameter configuration for each algorithm implemented in the present study. It is worth noting that the hill-climbing technique for classical and CEC benchmark functions, for which the suggested methods are capable of attaining the global optima in the majority of these functions, was not employed. Source codes of Proposed methods are publicly available at https://github.com/AminDehkordi/Adaptive-Chaotic-Marine-Predators-Hill-Climbing-Algorithm-for-Large-scale-Design-Optimisations.git.

Using HNCMPA and other methods, the test functions are solved using a maximum of 100,000 function evaluations and 2000 iterations (Npop = 50). To achieve significant statistical results, this study ran all optimisation methods 30 times and presented the results, which included the average and standard deviation values of the best-so-far solutions observed in each run. To illustrate the superior performance of the proposed method over other methods, the test is conducted for PSO [3], MFO [49], WOA [7], SSA [50], GWO [6], MVO [51], and MPA [38]. Table 1 summarises the parameter settings for other techniques. These parameters are either highly suggested by their developers or fall within the reference values in order to achieve the ideal performance for each algorithm [52].

1) EXPLOITATION PHASE ANALYSIS

Due to the unimodal functions' definition, they contain only one global optimum. Therefore, they can evaluate the exploitation ability of an algorithm. Table 2 provides the average and standard deviation values for HNCMPA and other techniques on unimodal test functions (F1-F7). The results show that HNCMPA outperformed most methods in almost all test functions. These results demonstrate HNCMPA's exploitation capabilities, which can help HNCMPA converge toward the global optimum and exploit it efficiently. The characterised nonlinear control parameter and small steps of Lévy movements contribute to this ability.

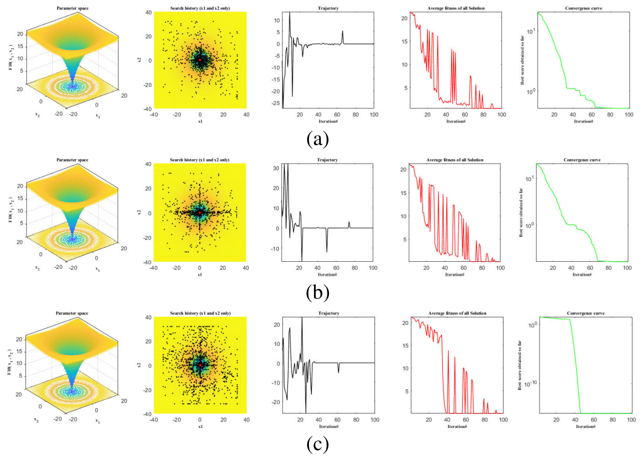


FIGURE 8. The search history, convergence performance of (a) MPA, (b) HNMPA, and (c) HNCMPA on unimodal F10 function.

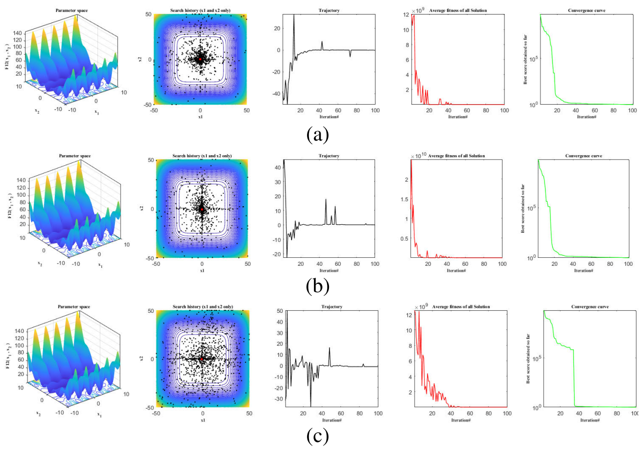


FIGURE 9. The search history, convergence performance of (a) MPA, (b) HNMPA, and (c) HNCMPA on unimodal F12 function.

2) EXPLORATION PHASE ANALYSIS

Multi-modal test functions have many local optima due to their inherent structure, which increases tremendously with the number of function design variables. Having more than one optimum is beneficial when evaluating an algorithm's exploration capability. High and fixed (low) dimensional multimodal functions are found in F8 through F13. Tables 3 demonstrate the results of implementing HNCMPA and various algorithms to these functions. Table 3 indicates that HNCMPA has superior exploration ability when compared to other techniques, particularly in comparison to other HNCMPA surpasses all algorithms on most high-dimensional multimodal functions, particularly MPA and HNMPA, and the results are competitive with high-performance optimisers for the remaining functions. HNCMPA has achieved the global optimum in most problems for fixed-dimensional functions with a high degree of precision (Std) comparable to that of high-performance optimisers. HNCMPA's exploration is due to its various optimisation steps, chaotic value effect, and predator Brownian motion. Furthermore, the proposed method employs a nonlinear control parameter, which results in a proper balance between the exploration and exploitation phases.

3) ANALYSIS OF HNCMPA LOCAL MINIMA EVASION

The composition test functions are obtained by shifting, rotating, and hybridising some primitive unimodal and multimodal functions (F14-F20). These functions are intended to test algorithms' ability to evade local optima while capable of exploration and exploitation. The efficiency of HNCMPA and other techniques on these kinds of functions is shown in Table 4. HNCMPA's results are very competitive in all functions of this type. These findings indicate that HNCMPA has finely tuned capabilities between exploration and exploitation and superb performance in escaping from local optima. The latter is due to the nonlinear control parameter that has been defined, as well as the more extensive displacement associated with the chaotic value. HNCMPA's exploitation, exploration, and local minima evasion abilities were tested in this section. HNCMPA demonstrated its capacity to comprehensively explore the search space and exploit the best solution while seeking to prevent local minimal stagnation. Therefore, the hypothesis that chaotic values and a nonlinear control parameter are used is proven, which improves the MPA performance.

4) HNMPA AND HNCMPA's CONVERGENCE ANALYSIS

This section discusses HNCMPA's numerical and computational convergence assessments. The convergence of HNCMPA is reviewed using qualitative metrics such as variability and trajectories in the experimental procedure. The analytical section demonstrates that HNCMPA eventually converges to a stationary point, implying that HNCMPA has a reasonable convergence rate. Figures 6–10 depict qualitative indicators for HNCMPA convergence and performance evaluation in the mathematical function testing platform compared to MPA and HNMPA. The figure's first column illustrates the structure of the functions in a two-dimensional perspective to provide an overview of the search space topology. The search history is represented in the figure's second column as the first criterion to be explained here. This figure depicts the collective exploration of agents and how the interaction and collective behaviour patterns of the predators and prey result in the structure of this process in MPA.

In unimodal functions, Figure 6 illustrates more accumulation of agents around the optimum points and more dispersed attitudes in multimodal and composition functions [38]. The first feature of the template is characterized as assisting in exploiting the results, which is favourable in unimodal functions, and the latter is described as exploring the domain, which assists MPA in multimodal and composition functions in searching the entire space [38]. The second criterion is the convergence curve, which represents the best solution discovered thus far. Each function type has its own convergence curve model, as shown in Figure 6 and Figure 7. This pattern is fairly smooth in unimodal functions and demonstrates improved performance in results with the number of iterations, but in multimodal and composition functions, this pattern changes into a step-by-step behaviour, which is

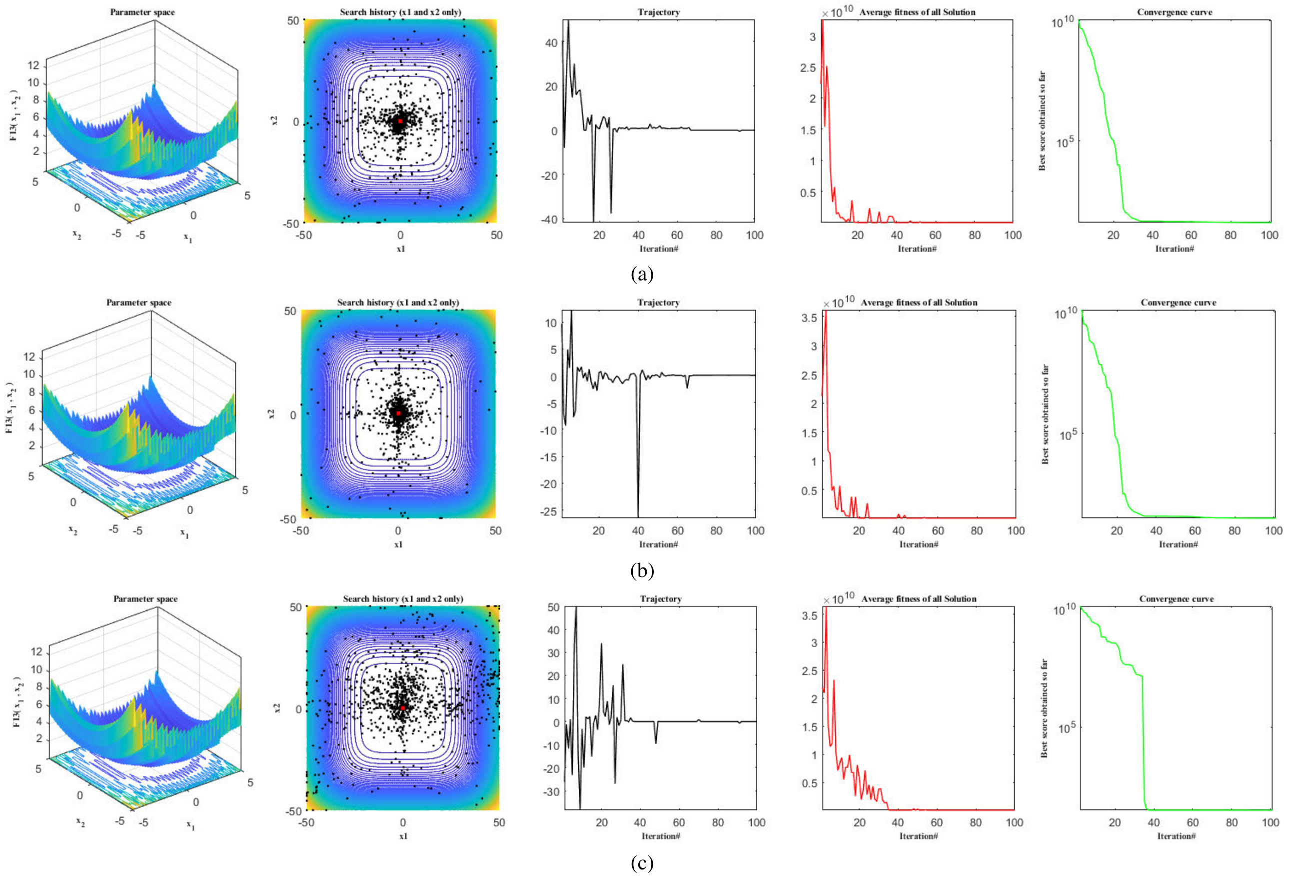


FIGURE 10. The search history, convergence performance of (a) MPA, (b) and (c) HNCMPA's on multimodal F13 function.

TABLE 5. The statistical performance criteria for the proposed hybrid methods and other eight optimisation algorithms for CEC-BC-2017 (Unimodal (F1 and F2) and multimodal functions (F4-F10)).

Func			MPA	HNMPA	HNCMPA	PSO	MFO	MVO	SSA	GWO	WOA
Unimodal	F1	Ave	1.39E+07	2.25E+07	7.26E+06	5.72E+07	1.16E+11	1.17E+07	1.77E+07	5.64E+10	1.24E+10
		Std	7.23E+06	8.72E+06	2.31E+06	9.69E+07	3.92E+10	3.26E+06	1.82E+07	1.14E+10	2.96E+09
	F3	Ave	1.12E+05	1.05E+05	1.01E+05	3.56E+05	8.70E+05	3.14E+05	4.48E+05	3.13E+05	8.73E+05
		Std	1.65E+04	1.66E+04	1.35E+04	5.28E+04	1.58E+05	4.70E+04	1.06E+05	2.80E+04	1.43E+05
Multimodal	F4	Ave	8.50E+02	9.44E+02	8.48E+02	9.48E+02	2.38E+04	9.09E+02	9.28E+02	5.04E+03	5.92E+03
		Std	6.21E+01	9.36E+01	8.73E+01	5.84E+01	1.77E+04	3.87E+01	6.23E+01	1.57E+03	1.18E+03
	F5	Ave	1.15E+03	1.21E+03	1.11E+03	1.26E+03	1.84E+03	1.17E+03	1.36E+03	1.19E+03	1.76E+03
		Std	8.85E+01	7.60E+01	7.52E+01	6.03E+01	1.35E+02	1.27E+02	8.54E+01	1.23E+02	1.33E+02
	F6	Ave	6.24E+02	6.40E+02	6.21E+02	6.58E+02	6.77E+02	6.67E+02	6.69E+02	6.40E+02	6.99E+02
		Std	7.14E+00	8.96E+00	3.70E+00	3.45E+00	6.78E+00	1.28E+01	4.47E+00	4.57E+00	1.24E+01
	F7	Ave	1.66E+03	1.76E+03	1.59E+03	1.47E+03	4.80E+03	1.69E+03	1.94E+03	1.96E+03	3.47E+03
		Std	1.80E+02	1.32E+02	1.14E+02	1.28E+02	9.60E+02	1.44E+02	3.55E+02	1.51E+02	1.52E+02
	F8	Ave	1.29E+03	1.30E+03	1.19E+03	1.59E+03	2.11E+03	1.37E+03	1.60E+03	1.44E+03	2.11E+03
		Std	8.71E+01	7.19E+01	5.68E+01	7.13E+01	1.52E+02	9.90E+01	1.10E+02	6.81E+01	1.22E+02
	F9	Ave	1.59E+04	1.48E+04	1.22E+04	2.39E+04	4.50E+04	4.51E+04	2.74E+04	3.26E+04	5.79E+04
		Std	4.64E+03	5.35E+03	3.56E+03	4.14E+03	6.57E+03	1.61E+04	3.22E+03	1.15E+04	1.29E+04
	F10	Ave	1.39E+04	1.45E+04	1.45E+04	1.40E+04	1.73E+04	1.44E+04	1.61E+04	1.66E+04	2.51E+04
		Std	1.14E+03	1.15E+03	1.34E+03	1.51E+03	1.74E+03	1.23E+03	1.91E+03	4.23E+03	2.43E+03

anticipated in these functions [38]. Another observation in the search history is that the final hybrid shows high exploration that also causes particles being overshoot the search space (black hots that form a rectangle).

From each type, it is essential to recognise that in unimodal functions, HNCMPA can identify and enclose the optimal solution at initial iterations and seek to improve the solutions as iterations continue (see Figure 6 and 7), whereas in

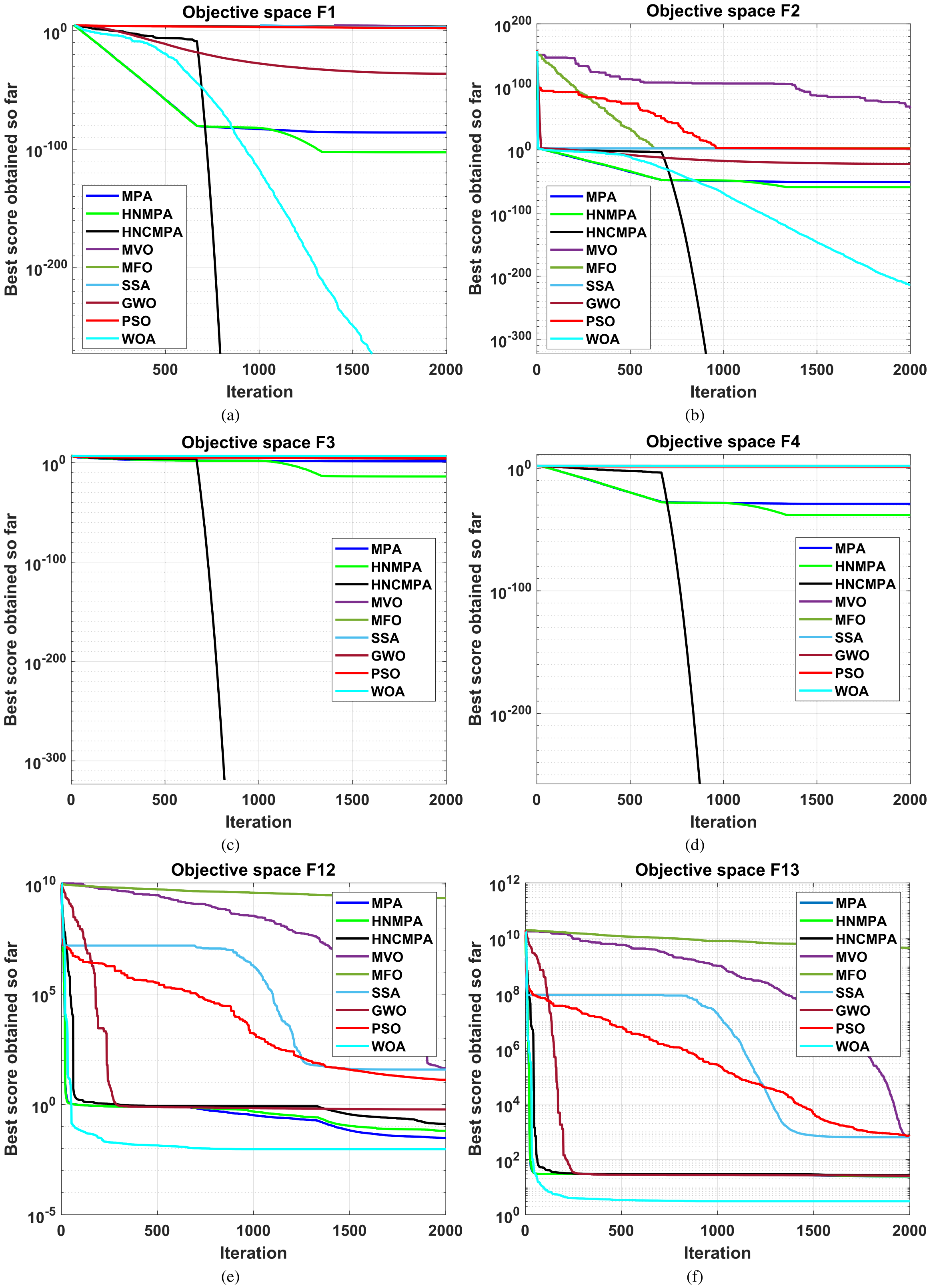


FIGURE 11. **Convergence curves of HNCMPA compared with other optimisation methods on various classical test functions.**

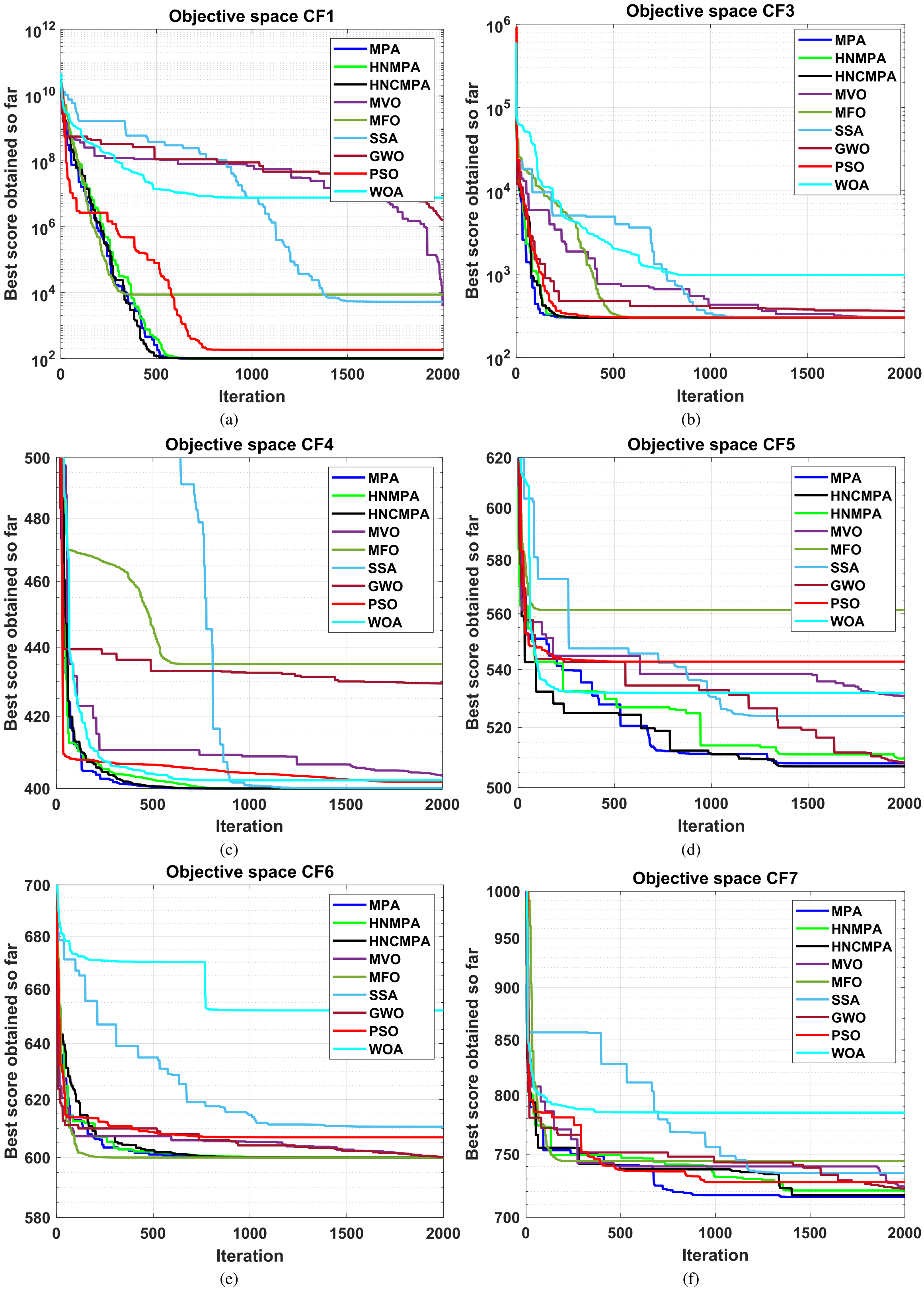


FIGURE 12. Convergence curves of HNCMPA compared with other optimisation methods on various mathematical CEC2017 test functions.

TABLE 6. The statistical performance criteria for the proposed hybrid methods and other eight optimisation algorithms for CEC-2017 Hybrid functions (F11-F20).

Func		MPA	HNMPA	HNCMPA	PSO	MFO	MVO	SSA	GWO	WOA
F11	Ave	3.45E+03	2.96E+03	2.29E+03	2.31E+03	1.31E+05	3.17E+03	5.49E+03	5.74E+04	1.42E+05
	Std	4.45E+02	2.96E+03	2.49E+02	1.70E+02	8.94E+04	3.11E+02	1.37E+03	1.34E+04	7.63E+04
F12	Ave	1.70E+08	2.78E+08	6.81E+07	1.66E+07	3.77E+10	3.02E+08	3.63E+08	8.73E+09	3.01E+09
	Std	1.13E+08	1.84E+08	3.80E+07	7.79E+06	1.42E+10	1.10E+08	1.52E+08	4.74E+09	8.02E+08
F13	Ave	7.49E+04	2.28E+05	5.72E+04	9.11E+03	3.61E+09	1.34E+05	8.99E+04	8.55E+08	2.72E+07
	Std	3.47E+04	5.03E+05	1.91E+04	3.82E+03	2.98E+09	4.11E+04	3.63E+04	1.17E+09	3.68E+07
F14	Ave	1.96E+03	3.96E+03	1.93E+03	7.69E+05	8.93E+06	1.27E+06	1.93E+06	5.36E+06	8.22E+06
	Std	7.51E+01	3.75E+03	1.11E+02	2.83E+05	7.88E+06	6.59E+05	1.05E+06	2.38E+06	3.58E+06
F15	Ave	6.14E+03	3.93E+04	4.55E+03	4.63E+03	1.30E+09	1.17E+05	7.39E+04	1.64E+08	3.75E+06
	Std	2.52E+03	1.37E+04	1.43E+03	3.87E+03	1.08E+09	5.84E+04	3.02E+04	2.19E+08	6.12E+06
F16	Ave	5.19E+03	5.29E+03	4.96E+03	5.40E+03	8.03E+03	5.61E+03	6.51E+03	6.33E+03	1.37E+04
	Std	5.54E+02	5.71E+02	4.25E+02	3.87E+02	8.02E+02	6.96E+02	8.34E+02	1.13E+03	2.36E+03
F17	Ave	4.53E+03	4.06E+03	4.37E+03	5.10E+03	8.47E+03	4.90E+03	5.53E+03	4.77E+03	8.13E+03
	Std	4.53E+02	3.12E+02	3.34E+02	4.73E+02	3.15E+03	4.35E+02	6.47E+02	4.46E+02	1.22E+03
F18	Ave	6.05E+04	1.05E+05	5.77E+04	1.79E+06	1.56E+07	2.75E+06	2.27E+06	5.13E+06	6.60E+06
	Std	2.72E+04	3.80E+04	2.03E+04	9.12E+05	1.63E+07	1.06E+06	1.34E+06	2.72E+06	2.63E+06
F19	Ave	8.27E+03	4.29E+05	6.38E+03	4.16E+03	9.96E+08	1.33E+07	1.23E+07	1.50E+08	3.20E+07
	Std	6.28E+03	3.58E+05	4.82E+03	2.69E+03	1.12E+09	4.73E+06	5.79E+06	2.32E+08	2.39E+07
F20	Ave	4.45E+03	4.85E+03	4.33E+03	4.96E+03	5.81E+03	4.98E+03	5.17E+03	4.89E+03	6.65E+03
	Std	3.39E+02	5.24E+02	2.50E+02	4.15E+02	7.52E+02	5.77E+02	6.81E+02	8.52E+02	5.24E+02

TABLE 7. The statistical performance criteria for the proposed hybrid methods and other eight optimisation algorithms for CEC-2017 Composition functions (F21-F30).

Func		MPA	HNMPA	HNCMPA	PSO	MFO	MVO	SSA	GWO	WOA
F21	Ave	2.66E+03	2.65E+03	2.60E+03	3.48E+03	3.66E+03	2.94E+03	3.11E+03	2.95E+03	4.18E+03
	Std	4.82E+01	5.15E+01	4.52E+01	1.13E+02	1.08E+02	9.57E+01	1.42E+02	1.30E+02	2.05E+02
F22	Ave	1.51E+04	1.85E+04	1.48E+04	1.79E+04	2.04E+04	1.66E+04	1.83E+04	1.93E+04	2.72E+04
	Std	5.18E+03	1.49E+03	6.48E+03	1.58E+03	1.84E+03	1.44E+03	3.57E+03	3.20E+03	1.69E+03
F23	Ave	3.13E+03	3.14E+03	3.12E+03	4.76E+03	3.82E+03	3.43E+03	3.53E+03	3.50E+03	5.00E+03
	Std	5.44E+01	4.74E+01	4.48E+01	3.15E+02	1.08E+02	1.14E+02	1.36E+02	8.52E+01	2.47E+02
F24	Ave	3.67E+03	3.72E+03	3.65E+03	5.46E+03	4.40E+03	3.85E+03	4.02E+03	4.10E+03	6.19E+03
	Std	6.02E+01	5.50E+01	5.96E+01	4.19E+02	1.35E+02	9.89E+01	1.38E+02	1.10E+02	2.56E+02
F25	Ave	3.53E+03	3.56E+03	3.48E+03	3.27E+03	1.46E+04	3.36E+03	3.45E+03	6.20E+03	4.91E+03
	Std	7.47E+01	1.08E+02	6.26E+01	5.80E+01	6.28E+03	5.63E+01	7.71E+01	8.72E+02	2.39E+02
F26	Ave	1.07E+04	1.09E+04	1.02E+04	1.51E+04	1.82E+04	1.16E+04	1.48E+04	1.45E+04	3.43E+04
	Std	6.86E+02	6.57E+02	5.90E+02	8.25E+03	1.43E+03	1.28E+03	1.95E+03	1.09E+03	3.46E+03
F27	Ave	3.49E+03	3.55E+03	3.48E+03	3.51E+03	4.03E+03	3.50E+03	3.81E+03	4.00E+03	5.33E+03
	Std	5.47E+01	9.36E+01	6.08E+01	2.44E+02	2.06E+02	5.79E+01	1.49E+02	1.63E+02	8.17E+02
F28	Ave	3.57E+03	3.55E+03	3.53E+03	3.35E+03	1.83E+04	3.44E+03	3.52E+03	8.15E+03	6.39E+03
	Std	5.38E+01	4.52E+01	4.22E+01	3.27E+01	2.27E+03	4.50E+01	5.06E+01	1.26E+03	5.52E+02
F29	Ave	6.34E+03	6.83E+03	6.21E+03	6.58E+03	1.05E+04	7.71E+03	9.41E+03	8.11E+03	1.63E+04
	Std	3.83E+02	4.46E+02	4.57E+02	5.72E+02	1.58E+03	8.26E+02	1.01E+03	7.64E+02	2.08E+03
F30	Ave	1.88E+06	1.17E+07	9.85E+05	1.15E+04	2.42E+09	9.24E+07	8.72E+07	7.54E+08	7.34E+08
	Std	1.04E+06	6.74E+06	4.01E+05	4.40E+03	1.68E+09	3.89E+07	3.06E+07	5.16E+08	3.09E+08

multimodal and composition functions (see Figure 8 and 9)), the agents attempt to globally browse the solution space even in the final iterations in an endeavour to find an optimal solution still. Therefore, despite the enactment of iterations in some multimodal functions, no advancement in results is caused, eventually leading to the stride template in these curves. The proposed method's exploratory and descriptive attitude is attributed to long moves deduced from the agents' Levy movements, eddy and FAD impacts, and chaotic values that enhanced the HNCMPA's exploration ability. Suppose we take into account the agents (predators and prey) to be collaborators. In that case, the convergence curve depicts the behaviour patterns of the best player in attaining global optimum. Still, it provides no information about the overall team's performance [38]. Therefore, we used another criterion, ''average fitness history,'' to assess HNCMPA's performance during optimisation. This criterion's whole method is similar to the convergence curve, but it reinforces how this interactive attitude improves the outcomes over the initial random population. Some stride characteristics are visible in

TABLE 8. The statistical performance criteria for the proposed hybrid methods and other eight optimisation algorithms for CEC-2022 benchmarks.

Func			MPA	HNMPA	HNCMPA	PSO	MFO	MVO	SSA	GWO	WOA
Unimodal Functions	F1	Ave	3.00E+02	3.00E+02	3.00E+02	3.00E+02	7.47E+03	3.00E+02	3.00E+02	1.96E+03	1.22E+04
		Std	0.00E+00	9.04E-12	0.00E+00	2.99E-14	7.14E+03	2.78E-03	4.30E-10	1.56E+03	5.21E+03
Basic Functions	F2	Ave	4.00E+02	4.01E+02	4.00E+02	4.03E+02	4.26E+02	4.08E+02	4.07E+02	4.24E+02	4.39E+02
		Std	1.22E+00	2.05E+00	7.28E-01	1.28E+01	3.14E+01	1.31E+01	1.30E+01	2.11E+01	6.14E+01
	F3	Ave	6.00E+02	6.00E+02	6.00E+02	6.07E+02	6.04E+02	6.01E+02	6.06E+02	6.01E+02	6.34E+02
		Std	1.31E-04	9.79E-03	1.41E-04	6.32E+00	8.25E+00	8.49E-01	4.74E+00	9.17E-01	1.49E+01
	F4	Ave	8.07E+02	8.08E+02	8.06E+02	8.20E+02	8.34E+02	8.17E+02	8.22E+02	8.14E+02	8.40E+02
		Std	2.33E+00	2.80E+00	2.04E+00	5.90E+00	1.34E+01	1.12E+01	7.81E+00	7.17E+00	1.56E+01
	F5	Ave	9.00E+02	9.00E+02	9.00E+02	9.97E+02	1.08E+03	9.00E+02	9.10E+02	9.23E+02	1.58E+03
		Std	1.63E-02	1.27E-13	0.00E+00	1.87E+02	2.64E+02	1.65E-02	4.22E+01	3.87E+01	5.22E+02
Hybrid Functions	F6	Ave	1.80E+03	1.80E+03	1.80E+03	3.42E+03	5.72E+03	4.82E+03	3.69E+03	5.73E+03	4.05E+03
		Std	1.18E-01	1.13E-01	1.10E-01	2.20E+03	2.20E+03	2.52E+03	1.49E+03	2.33E+03	2.01E+03
	F7	Ave	2.00E+03	2.01E+03	2.00E+03	2.04E+03	2.03E+03	2.03E+03	2.03E+03	2.03E+03	2.06E+03
		Std	5.10E+00	9.41E+00	4.11E+00	1.68E+01	1.20E+01	2.85E+01	1.30E+01	1.33E+01	2.56E+01
	F8	Ave	2.20E+03	2.20E+03	2.20E+03	2.23E+03	2.22E+03	2.23E+03	2.22E+03	2.22E+03	2.23E+03
		Std	3.70E+00	1.39E+00	8.22E-01	3.15E+01	4.68E+00	3.75E+01	4.53E+00	5.56E+00	9.34E+00
Composition Functions	F9	Ave	2.53E+03	2.53E+03	2.53E+03	2.49E+03	2.53E+03	2.53E+03	2.53E+03	2.58E+03	2.57E+03
		Std	2.56E-12	0.00E+00	0.00E+00	3.48E+01	6.31E+00	2.68E+01	1.48E+01	3.48E+01	5.09E+01
	F10	Ave	2.50E+03	2.50E+03	2.50E+03	2.68E+03	2.54E+03	2.55E+03	2.51E+03	2.57E+03	2.64E+03
		Std	5.15E-02	5.32E-02	4.76E-02	2.53E+02	7.65E+01	6.17E+01	3.43E+01	5.28E+01	1.98E+02
	F11	Ave	2.60E+03	2.60E+03	2.60E+03	2.73E+03	2.76E+03	2.77E+03	2.65E+03	2.85E+03	2.82E+03
		Std	1.22E-05	1.95E-11	3.57E-11	1.61E+02	1.21E+02	1.80E+02	1.17E+02	2.00E+02	1.51E+02
	F12	Ave	2.86E+03	2.86E+03	2.86E+03	2.87E+03	2.86E+03	2.86E+03	2.86E+03	2.87E+03	2.89E+03
		Std	1.46E+00	1.30E+00	1.17E+00	4.83E+01	1.51E+00	1.93E+00	2.08E+00	5.24E+00	2.70E+01

TABLE 9. Results of T-test (p-value) overall runs on CEC-2017.

Func.		MPA	HNMPA	MVO	MFO	SSA	GWO	PSO	WOA
Unimodal	F1	9.57E-07	2.19E-13	4.72E-01	2.46E-21	7.37E-20	2.79E-33	1.87E-19	2.32E-38
	F3	7.18E-04	9.32E-06	2.46E-28	1.01E-28	2.62E-27	9.56E-39	4.28E-29	3.21E-41
Multi_Modal	F4	1.15E-01	2.88E-02	6.91E-19	1.64E-11	4.00E-03	5.23E-19	1.24E-19	2.90E-30
	F5	7.43E-01	7.19E-01	4.23E-01	1.57E-27	7.33E-10	5.34E-03	4.22E-06	1.17E-27
	F6	1.30E-12	1.95E-09	1.44E-17	3.47E-30	1.74E-26	5.64E-05	1.04E-23	2.14E-36
	F7	1.98E-08	2.17E-04	2.67E-12	6.88E-29	5.92E-02	1.01E-01	1.30E-22	4.05E-43

TABLE 10. Results of T-test (p-value) overall runs on CEC-2022.

Func.		MPA	HNMPA	MVO	MFO	SSA	GWO	PSO	WOA
Unimodal Func	F1	8.99E-06	8.99E-06	5.94E-14	3.95E-06	1.66E-13	4.85E-04	8.99E-06	2.08E-14
Basic Func	F2	1.97E-01	9.41E-02	1.26E-02	1.12E-03	1.16E-02	6.64E-07	1.10E-01	7.36E-06
	F3	1.11E-02	4.21E-03	4.43E-03	4.41E-03	2.55E-08	3.61E-04	1.46E-07	2.42E-24
	F4	2.75E-03	2.17E-03	3.71E-06	1.41E-16	1.24E-06	5.54E-05	1.03E-14	3.82E-12
	F5	2.62E-02	2.57E-02	2.29E-01	8.20E-03	1.71E-02	1.28E-02	7.16E-02	2.52E-11
Hybrid Func	F6	8.32E-01	3.93E-01	4.90E-11	6.89E-07	3.86E-08	2.72E-11	3.73E-06	2.41E-06
	F7	3.29E-05	6.25E-06	5.82E-03	1.30E-04	5.19E-12	2.60E-05	1.38E-07	5.61E-17
	F8	3.28E-01	4.87E-02	3.71E-05	1.93E-26	1.99E-24	8.00E-20	5.84E-05	1.94E-28
Composition Func	F9	1.00E+00	1.00E+00	8.24E-06	2.11E-02	1.94E-05	1.92E-10	2.09E-07	7.06E-04
	F10	3.14E-01	3.16E-01	2.84E-04	3.60E-02	8.44E-01	1.87E-05	5.01E-04	4.74E-02
	F11	2.36E-09	2.36E-09	5.89E-05	4.09E-10	9.44E-03	2.28E-07	4.05E-05	2.40E-11
	F12	6.67E-01	6.38E-01	9.10E-07	2.29E-15	6.67E-13	1.18E-07	9.45E-02	8.70E-05

these functions in the average fitness history. This happened due to improved performance in all agents' fitness due to a phase transition in the algorithm, which led to overall good agent efficiency. There are slight hillsides in unimodal functions but steep patterns in multimodal and composition functions.

The trajectory of the agents depicted in column 3 of the Figures (6–10) is another criterion. This criterion illustrates an agent's spatial variance from the start to the end of the optimisation procedure. Due to the agents' shifting in many directions in search space, we chose only the first dimension of an agent to reveal its trajectory in order to ensure

TABLE 11. The configuration details of optimisation methods applied to the truss shape and sizing problem. N_{pop} is the initial population size.

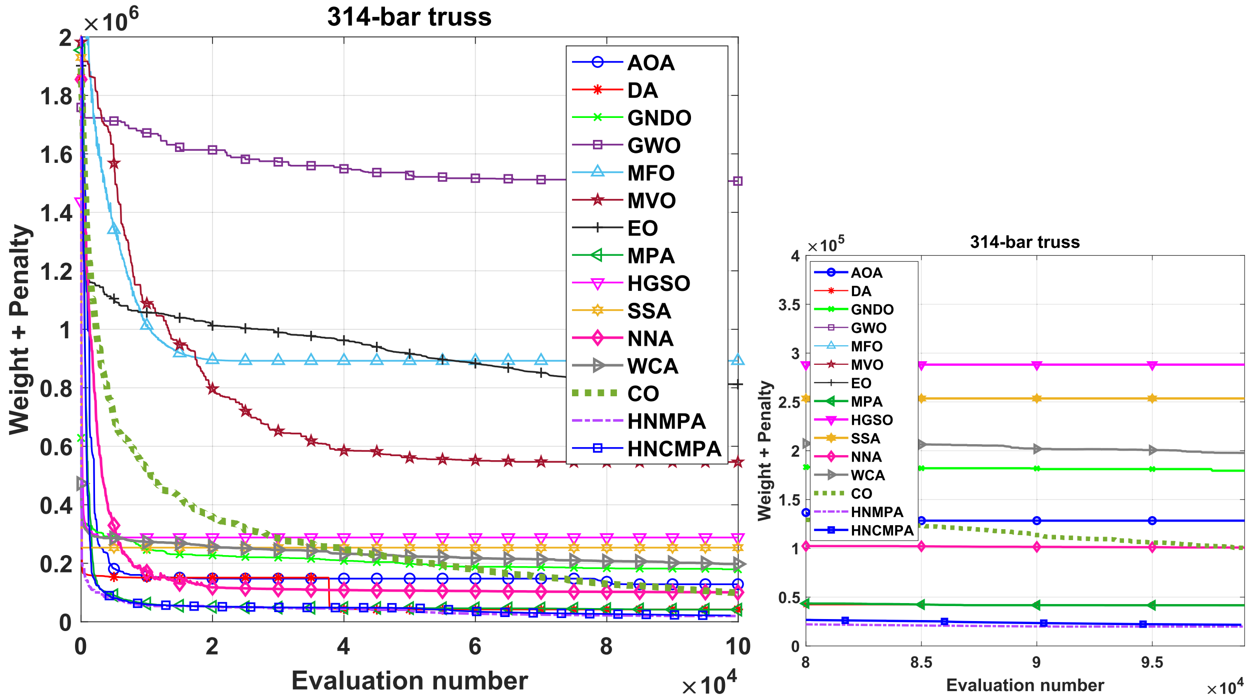
	Abbreviation	full name	N_{pop}	Pre-defined Settings
1	DA [57]	Dragonfly Algorithm	50	$w = 0.9 - 0.2$, $s = 0.1$, $a = 0.1$, $c = 0.7$, $f = 1$, $e = 1$.
2	HGSO [58]	Henry Gas Solubility optimisation	50	$N_g = 5$, $l_1 = 0.05$, $l_2 = 100$, $l_3 = 0.01$, $\alpha = 1$, $\beta = 1$, $c_1 = 0.1$, $c_2 = 0.2$
3	AOA [59]	Arithmetic optimisation Algorithm	50	$MOP_{Max} = 1$, $MOP_{Min} = 0.2$, $C_{iter} = 1$, $\alpha = 5$, $\mu = 0.499$
4	GNDO [60]	Generalized Normal Distribution	50	applied the default settings.
5	SSA [50]	Salp Swarm Algorithm	50	c_1 decreased from 2 to zero. $c_2 = rand$ and $c_3 = rand$
6	MPA [38]	Marine Predators Algorithm	50	$p = 0.5$, $FAD = 0.2$
7	NNA [61]	Neural Network Algorithm	50	pre-defined settings
8	WCA [62]	Water Cycle Algorithm	50	$N_{sr} = 4$, $D_{max} = 10^{-5}$
9	GTO [63]	Artificial Gorilla Troops Optimiser	50	$p = 0.03$, $\beta = 3$, $\omega = 0.8$
10	GWO [6]	Gray Wolf Optimiser	50	$A = 2 \times \alpha \times rand() - \alpha$, $C = 2 \times rand()$, α linearly decreases from 2 to 0
11	MFO [49]	Moth Flame Optimiser	50	Flame no = $N - iter \times ((N-1)/Max_{iter}))$; ,$\alpha$ linearly decreases from -1 to -2
12	MVO [51]	Multi Verse Optimiser	50	minimum and maximum of Wormhole existence probability: $\text{WEP}_{Max} = 1$, $\text{WEP}_{Min} = 0.2$, $\rho = 6$.
13	EO [33]	Equilibrium Optimiser	50	$\omega_1 = 1$, $\omega_2 = 2$, $GP = 0.5$(=generation probability), $V = 1$
14	CO [64]	Cheetah Optimiser	50	predefined settings

TABLE 12. The statistical performance criteria for the proposed hybrid MPA methods compared with other 14 optimisation algorithms for 260-bar truss case study.

	DA	GNDO	EO	AOA	GWO	HGSO	MFO	MVO
Min	279327	131850	1903508	120427	3391504	1141198	1873686	775263
Max	4336301	866948	3830830	180133	10251354	4181235	4555126	2842608
Mean	1756475	422380	2993587	142272	6347008	1861821	2843644	1632285
Median	1352414	392953	3298027	139926	5855308	1545486	2463511	1515654
STD	1482007	237157	743554	18115	2029360	921701	1001899	652826
	SSA	**MPA**	**NNA**	**WCA**	**CO**	**GTO**	**HNMPA**	**HNCMPA**
Min	509119	44524	55371	308566	79210	68061	**20639**	20966
Max	721205	70314	102519	929709	183558	347098	24593	27423
Mean	618163	57767	73054	548484	115795	158200	**22656**	24125
Median	614567	58363	69727	509055	94248	138130	**22394**	24164
STD	63015	7729	13059	178114	41029	89210	**1481**	2103

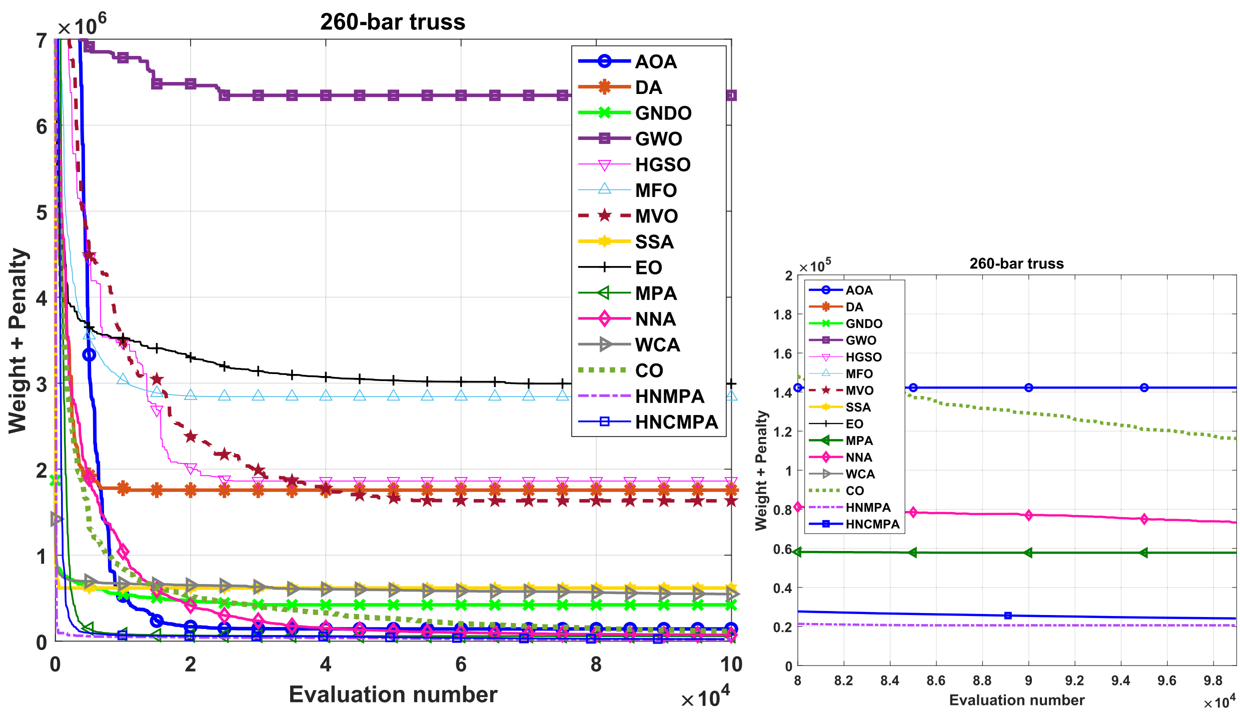
its exact trajectory. These metrics of figures display sudden high amplitude and duration changes in the initial iterations (exploration phase), which will disappear in the final iterations (exploitation phase). This pattern proves the algorithm's exploratory phase in initial iterations while shifting to exploitation in the last ones, ensuring that an algorithm can eventually converge to an optimum global point [53]. Due to the essence of multimodal functions, the intensity and frequency of these shifts are more significant than for unimodal functions, and they usually last longer. Figures 6–10 directly compare HNCMPA to MPA and on two unimodal and three multimodal functions. The search histories (second column) in all functions display that HNCMPA exploration is more extensive than other methods, as several areas of the search space are coated. Nevertheless, as shown in the second-to-last column, this leads to the proposed algorithm for boosting the performance of the population during the optimisation procedure. The convergence of this algorithm is also visible in the last column, which shows the fewest values when compared to MPA.

Figure 11 depicts the convergence curves on some of the test functions for MFO, PSO, GWO, SSA, MVO, WOA, MPA, and HNCMPA. The results of this figure indicate that HNCMPA has a couple of unique, readily identifiable behavioural trends when optimising the test functions. These tendencies are primarily the result of various optimisation steps. The first attitude illustrates a rapid convergence toward the near-global optimum point in the first phase and successive, slight advancements in the second and third phases, proving that a problem can be solved with just one phase.



(a) (b)

FIGURE 13. Convergence rate of 14 optimisation algorithms used to minimize the weight of 314-bar truss. The Maximum number of evaluations is 10^5.



(a) (b)

FIGURE 14. Convergence rate of 14 optimisation algorithms used to minimize the weight of 260-bar truss case study. The Maximum number of evaluations is 10^5.

The first pattern was demonstrated by F1, F2, and F3. To help readers comprehend these behavioural patterns, we will use F1 as an example for other functions; F2-F4.

According to the functions' structure demonstrated in Figure 11, the optimisation process minimises the function's delivered value with a range of parameters (The solution with

TABLE 13. The statistical performance criteria for the proposed hybrid MPA methods compared with other 14 optimisation algorithms for 314-bar truss case study.

	DA	GNDO	EO	AOA	GWO	HGSO	MFO	MVO
Min	39336	103096	457784	122254	1151989	231501	326890	408869
Max	45982	272333	1076032	140836	1737697	386397	1184149	928578
Mean	42170	179515	812210	128341	1506989	288184	892475	546289
Median	41924	165280	784793	127870	1566617	287456	908014	516050
STD	1647	53755	214137	5298	230303	48962	238876	160152
	SSA	**MPA**	**NNA**	**WCA**	**CO**	**GTO**	**HNMPA**	**HNCMPA**
Min	210731	38885	87685	125435	81823	64234	19857	**19398**
Max	288499	44300	114471	251538	121368	195547	21589	29146
Mean	253553	41446	100648	197520	99814	110011	**20559**	21671
Median	258967	41211	99055	204808	101136	93212	20570	20769
STD	27844	1697	8896	45330	11189	43729	**494**	2965

the lowest value is the best). When we applied this function to the group of optimisation techniques, all of them found the best solution close to zero, except for our HNCMPA algorithm, which could go even lower. The use of a nonlinear control parameter, which results in nonlinear behaviour, combined with the chaotic values used by the HNCMPA, may provide the algorithm with more opportunities to diverge from the optimal local solution and converge to the optimal global solution. This has enabled HNCMPA to investigate other areas of the function's environment that may lead to more encouraging minimum solutions as iterations progress. HNCMPA could compete with the MPA and algorithms, precisely F12–13 and CF1–CF7 (Figure 12). Since the structure of these functions is rather complicated and includes many locally optimal solutions, the majority of the proposed algorithms work even harder to reach the global optima. Nonetheless, with all of these functions but apart from F12, our algorithm sustained a satisfactory convergence rate at an initial stage. In contrast, MPA and WOA algorithms could only find relatively improved optimal solutions at the final moment of iterations. However, compared to our proposed HNCMPA algorithm, these methods demonstrate no viable convergence. The slow convergence rate may be quite computationally costly for some applications that desire an accurate solution.

To summarise this section, we can address the rationale for some of the key performance indicators obtained by NMPA in contrast to other cutting-edge algorithms. The essence of the MPA algorithm and the fact that natural marine predators can memorise their prey's regions with broader and deeper food sources are the primary reasons we can emphasise here. Furthermore, the inclusion of Levy and Brownian motions aids the algorithm's performance in various optimisation problems. MPA can hold and use this memory to recall some of the sense of satisfaction in the possible potential area for a globally optimal solution to be investigated or further exploited, depending on such a significant characteristic that other algorithms neglect. This phenomenon has aided our proposed algorithm, which has a suitable mechanism for discovering, on average, superior best solutions to different algorithms.

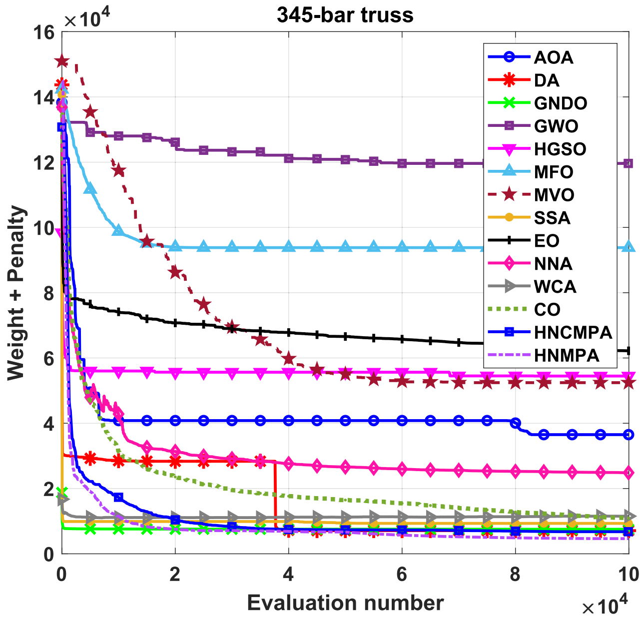


FIGURE 15. Convergence rate of 14 optimisation algorithms used to minimize the weight of 345-bar truss case study. The maximum number of evaluations is 10^5.

The newly presented modifications to the MPA by the nonlinear controller and some of the chaotic behaviour patterns prompted by the chaotic map set of equations led to improved algorithm performance. These new changes are in Section IV have made evident the efficiency of our proposed HNCMPA algorithm in contrast to other benchmark methods.

5) HNMPA AND HNCMPA's PERFORMANCE ANALYSIS ON THE CEC-BC-2017 AND CEC-BC-2022 TEST BENCHMARK FUNCTIONS

To further indicate the proposed method's effectiveness, we chose among the most subsequent and complicated benchmark test functions from the CEC-BC-2017 [48], and CEC-BC-2022 [54] Numerical optimisation competition, which includes 30 functions, at least half of which are complex hybrid and composition functions in CEC-BC-2017 and 12 hybrid and composition functions in the second dataset.

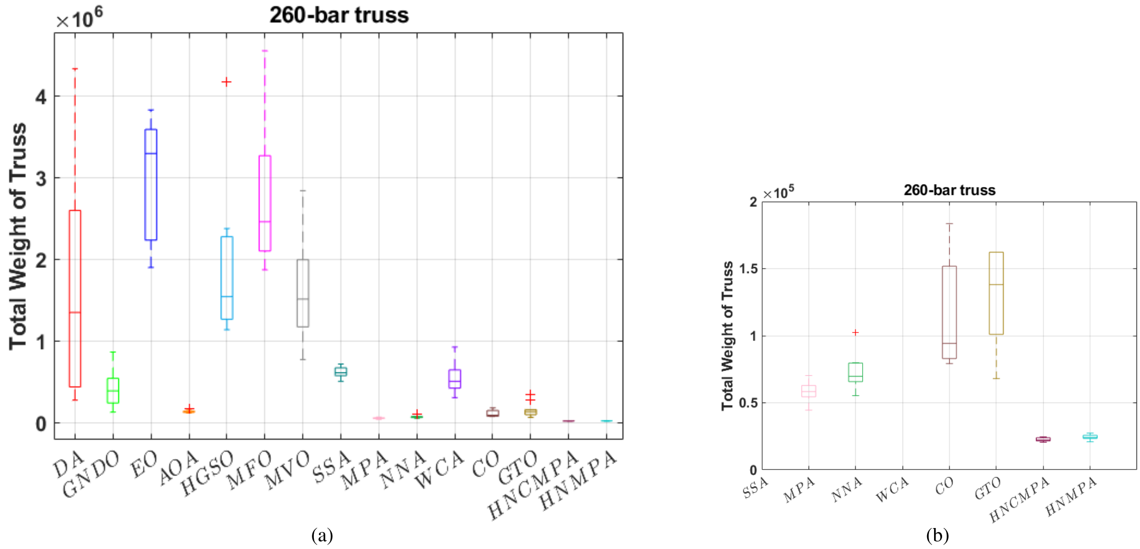


FIGURE 16. a) A box and whisker plot indicates the optimisation summary of 15 meta-heuristics for a 260-bar truss, and the minimum, first quartile, median, third quartile, and maximum findings can be seen. Each box shows the first quartile to the third quartile, and in the following, the vertical line reaches via the box at the median. b) a zoom version of plot a for the last six optimisation methods.

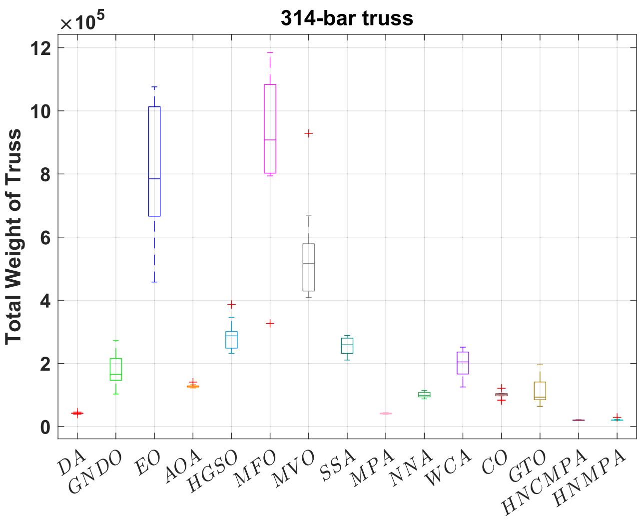


FIGURE 17. A box and whisker plot indicate the optimisation summary of 15 meta-heuristics for 314-bar truss, and the minimum, first quartile, median, third quartile, and maximum findings can be seen. Each box shows the first quartile to the third quartile, and in the following, the vertical line reaches via the box at the median.

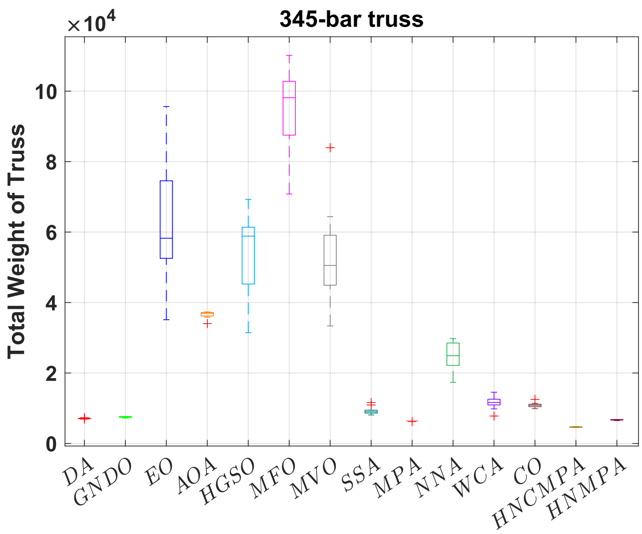


FIGURE 18. A box and whisker plot indicate the optimisation summary of 14 meta-heuristics for 345-bar truss, and the minimum, first quartile, median, third quartile, and maximum findings can be seen.

Appendix A contains the characteristics of the functions. This function's complicated numerical formulation is accessible [48]. We ran the HNCMPA against all these functions with 100 dimensions, and the results were compared to the most state-of-the-art techniques in the literature. For all functions in this dataset, the dimension is fixed to 10. Tables 5 and 6, as in the preceding part, illustrates the average and standard deviation. Each technique is performed 30 times with a 2000 iteration number and total function assessments of 100,000. As results are reported in Tables 5, 6, and 7, the proposed method still has its proper performance on these test suits. The results in Tables 5, 6, and 7 show that the proposed method still performs properly on these test suits. The HNCMPA could outperform other methods and compete with MPA and HNMPA in the majority of test functions. As a result, the hypothesis of using a nonlinear control parameter and chaotic values to improve the performance of the proposed method is proven, as demonstrated by the results.

The findings presented in Table 8 regarding the CEC-2022 functions indicate that HNMPA and HNCMPA exhibit significantly better performance than other optimisation methods across all cases evaluated. These two algorithms demonstrate strong competitiveness and often outperform others in most functions. This highlights the ability of our proposed

TABLE 14. The statistical performance criteria for the proposed hybrid MPA methods compared with other 14 optimisation algorithms for 345-bar truss case study.

	DA	GNDO	EO	AOA	HGSO	MFO	MVO
Min	6928	7190	35123	34022	31450	70787	33356
Max	7297	7665	95617	37322	69283	110163	83957
Mean	7096	7518	62194	36511	54463	93815	52437
Median	7066	7568	58250	36927	58856	98138	50526
STD	100	154	17072	1010	11650	13167	14417
	SSA	**MPA**	**NNA**	**WCA**	**CO**	**HNMPA**	**HNCMPA**
Min	8087	6219	17331	7786	9875	**4751**	4778
Max	11608	6536	29758	14528	12506	5011	5094
Mean	9319	6420	24845	11528	10880	**4918**	4988
Median	8995	6446	24915	11627	10821	4915	5006
STD	1117	113	4056	1841	718	**73**	90

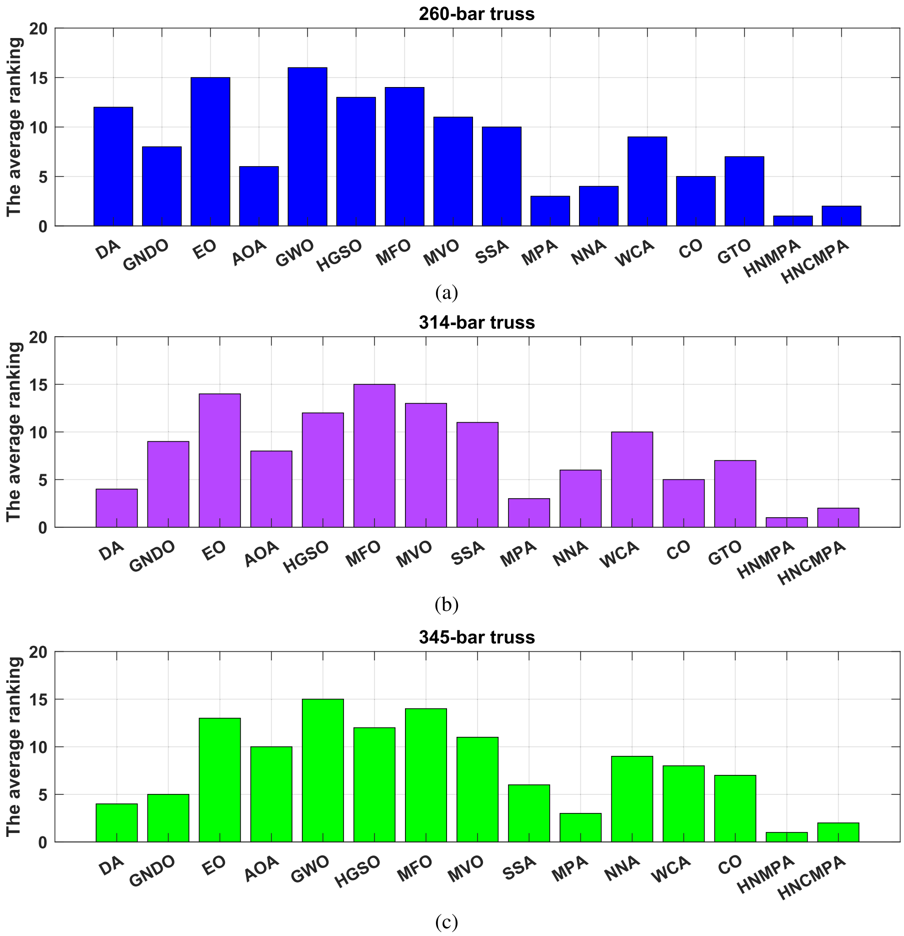


FIGURE 19. a comparison of the proposed hybrid methods average rank with other meta-heuristic algorithms computed by the nonparametric tests *signrank* and *ranksum*.

techniques to identify optimal solutions by leveraging the benefits of nonlinear behaviour with multiple chaotic agents, which can prevent entrapment in local optima.

There is an abundance of statistical techniques available in the academic literature for assessing optimisation algorithms, such as the Wilcoxon rank-sum test, the t-test, and a newly developed test called paradox-free analysis [55], [56]. Nevertheless, this study employed the t-test to evaluate the proposed methods. Based on the p-values presented in Tables 9 and 10, it is evident that both proposed techniques, particularly HNCMPA, exhibit significantly better performance than alternative optimisation methods across all evaluated scenarios. The outcomes attained by our proposed algorithms surpass those of other approaches significantly. Notably, neither MPA nor any other strategy could deliver results comparable to those achieved by the proposed methods. The findings indicate that incorporating chaotic motion values and a nonlinear control parameter can enhance the effectiveness of the proposed methods. Statistical analysis using T-tests, presented in Tables 9 and 10, suggests that both HNCMPA and HNMPA exhibit superior performance compared to alternative approaches. Notably, HNCMPA, followed by HNMPA, consistently achieved lower global optima than other strategies across different fitness functions while also exhibiting higher output relative to MPA.

C. LARGE-SCALE TRUSS STRUCTURES

In this section, we run ten times all optimisation methods independently to solve each large-scale structural case study. Two new boosted MPAs and 15 state-of-the-art meta-heuristics are performed and compared with the same criteria to develop a fair comparative framework. Except for statistical outcomes, Friedman's ranking test based on the ten independent runs is evaluated to ensure that the proposed optimisation algorithm's performance best solves these large-scale real structural problems. The parameters setup for the aforementioned algorithms has been reported in Table 11.

The average convergence rate of 14 meta-heuristic algorithms for the case study of 314-bar can be seen in Figure 13. It can be observed that the HNMPA and HNCMPA converged faster than other algorithms in the initial iterations and handled the dynamic constraints appropriately. Moreover, from Figure 13, most optimisation algorithms faced premature convergence and struggled with local optimums such as AOA, MFO, HGSO, SSA, etc. On the flip side, some algorithms could not converge to a proper solution during this computational runtime (10^5 evaluation number) such as GWO, EO and CO. For the comparative average optimisation developments in Tables 12, 13 and 14, the best-performed algorithms based on both mean and STD value are HNMPA and HNCMPA for three case studies. HNCMPA provided better solutions than HNMPA in three structures, 260-, 314-, and 345-bar at 6.48%, 5.41%, and 44.16%, respectively.

Tables 12– 14, MPA is ranked third in effectiveness in solving truss optimisation problems. In fact, MPA outperforms other advanced algorithms by a significant margin when it comes to solving such issues. As a result of these impressive results on complex multi-dimensional engineering problems, this study's hypothesis regarding the selection and enhancement of MPA's performance has been confirmed.

The convergence rate of optimisation algorithms implemented for the 260-bar truss problem can be shown in Figure 14. Similar to the 314-bar problem, the highest convergence rate is related to HNMPA; HNCMPA and MPA performed considerably as well. The issue of falling into local optimum can be seen in some of the methods in this case study, such as GWO, DA, HGSO, MFO, and EO. Furthermore, The CO and NNA methods need more runtime to find better designs.

Figure 15 indicates a comparison of 15 optimisation algorithms performed for solving the best design of the 345-bar truss problem. For the initial percentage of runtime, GNDO rapidly converged and surpassed other methods; however, the best-found solutions were proposed by the HCMPA finally. The convergence speed of WCA and SSA is considerable in this large case study, but both encountered falling into local optimum.

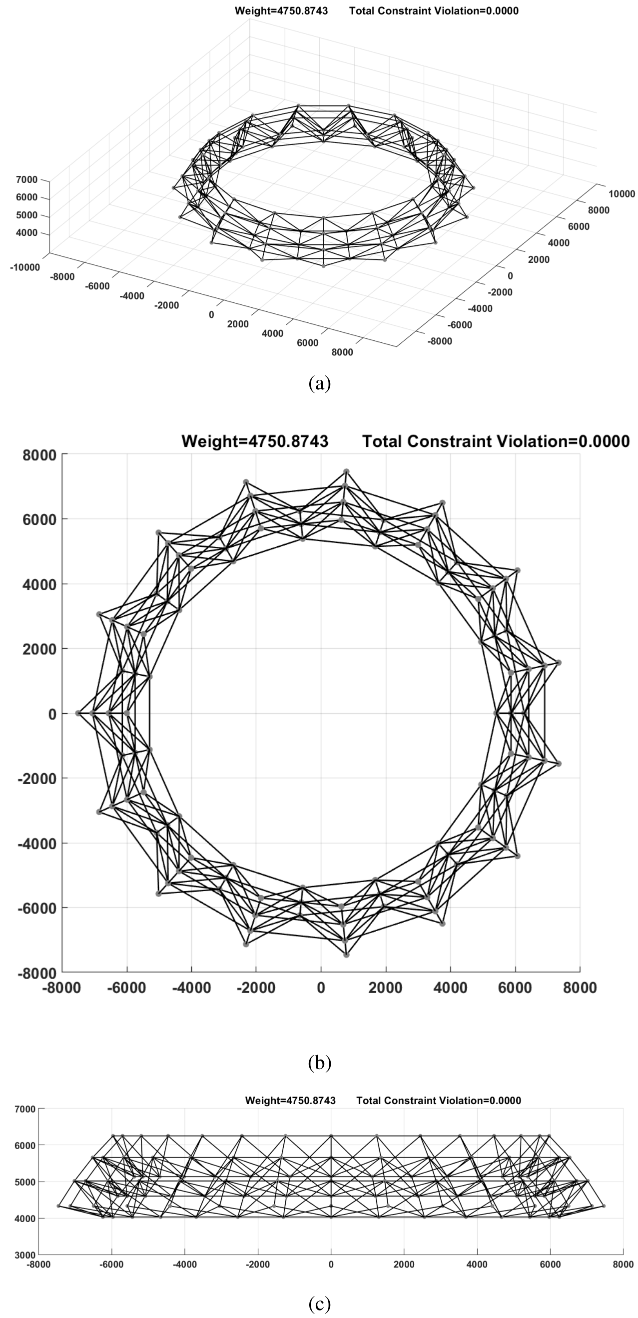


FIGURE 20. Best-found feasible design of 345-bar truss problem proposed by HNMPA. Total weight plus penalty is 4750.87 *kg*.

In order to compare the performance of the proposed novel optimisation algorithm with other modern meta-heuristics, each method runs ten times, and the best-found solutions show in Figure 16. This figure demonstrates the distribution of optimisation methods performance for the 260-bar case study. The box with smaller distribution represents a more robust optimisation method. From Figure 16, the best-performed method is HNCMPA, with the lowest total weight solutions proposed on average. After HNCMPA, we can see that HNMPA, MPA, and NNA performed well. In both large structures, 314 and 345-bar trusses, the best solutions were proposed by HNMPA, which can be seen in Figure 17 and 18. The second rank is related to HNCMPA and MPA in 314-bar and 345-bar trusses, respectively. Furthermore, the DA method could handle the dynamic constraints well and avoid falling into a local optimum. For the comparative average optimisation developments in Tables 12, 13 and 14, the best-performed algorithm based on both mean and STD value is HNMPA for three case studies. HNMPA provided better solutions than HNCMPA in three structures, 260-, 314-, and 345-bar, at 6.48%, 5.41%, and 44.16%, respectively.

Figure 19 shows the average ranking evaluation of 15 optimisation algorithms by a nonparametric test (Friedman rank-sum) for three truss problems. It is clear to observe that HNMPA obtained the first rank in all case studies and HNCMPA, MPA, DA, and GNDO received the second to fifth rank, respectively. Figure 20 shows a 3D and 2D landscape of the best-found design of a 345-bar truss with the minimum weight (4750.87 Kg) found by HNMPA. All displacement and stress constraints are satisfied, and the sum violation is zero.

VI. CONCLUSION

Two novel versions of the Marine Predator Algorithm (MPA) are proposed in this study, which employs a series of non-linear control parameters and chaotic values to assist an adequate equilibrium between the exploration and exploitation phases as well as to boost the exploration phase throughout the optimisation procedure. Our proposed approaches have significantly increased efficiency while looking for the best solutions to large-scale optimisation issues. This enhancement resulted from our proposed approaches' ability to transition from exploration to exploitation phases by utilising our introduced nonlinearity characteristic. Furthermore, the algorithm's chaotic behaviour has enabled it to explore a wider variety of feasible solutions to a specific issue. The algorithm may also profit from its nonlinearity characteristic and devote more emphasis to exploiting promising regions when necessary. Therefore, our algorithms were able to manage an efficient searching approach for locating an optimal solution to a large-scale specified optimisation issue. The proposed algorithms were developed, and their performance was compared to that of the original MPA as well as other current cutting-edge meta-heuristics techniques. Despite minor differences in obtaining results, both proposed strategies in this study outperformed other cutting-edge optimisation algorithms on mathematical benchmark functions, validating them for tackling large-scale challenges.

This study also used thirteen advanced meta-heuristic methods to solve the truss form and sizing optimisation issue. We defined a penalty function, a typical mechanism for dealing with constraint violations. Various penalty variables were assessed in order to determine the optimum value in the context of best-found solutions. This paper employs three distinct truss issues. They all have a vast structure made up of 260, 314, and 345 bars, respectively. It is considered that the truss structure is constant and unchangeable. This problem's main challenge was finding the best truss form and size parameters by lowering load-bearing capacity (structural weight) in proportion to nodal displacement limits, component stress limits, and vibration frequency. This is a complicated optimisation challenge due to its defining mathematical aspects, which are characterised as large-scale, nonlinear, and multi-modal with dynamic constraints. Since meta-heuristics are renowned as efficient global optimisation techniques, we will emphasise their applicability to truss optimisation issues in this paper, particularly novel swarm optimisation approaches. Consequently, we assessed and developed a comparison template for large-scale truss issues using thirteen distinct swarm optimisation strategies. All control variables for each optimisation technique were adjusted based on literature guidelines to ensure a meaningful assessment, considering that no ideal technique exists to achieve the optimal parameter settings. Due to rapid and efficient exploration and exploitation search techniques enhanced by combining chaotic map values with a nonlinear parameter, the suggested approaches outperform existing optimisation methods, particularly the original MPA employed in this study. In terms of the truss optimisation problem, and from an engineering standpoint, we can conclude that integrating the proposed methods with the Hill Climbed approach would increase the performance of the proposed methods in dealing with the truss optimisation problem. Based on the results provided by the proposed techniques, the truss structure indicated by the proposed techniques had the lowest weight, with a substantial difference when compared to the best solutions of other approaches in all three truss case studies. The crucial factor to remember is that in order to achieve the most outstanding efficiency from the proposed methods, the control parameters should be tweaked using these truss issues. The solution space and constraint-handling approach should also be examined. In the future, we intend to improve and create collaborative techniques to handle the multi-objective case of large-scale truss challenges.

The results reported suggest that both HNCMPA and HNMPA exhibited growth rates of 73.31% and 71.94%, respectively, when compared to MPA's final solution in regards to the optimisation of a 260-bar truss. The 314-bar truss optimisation problem results showed a growth rate of 66.87% for HNCMPA and 64.78% for HNMPA in terms of the final solutions. Regarding the third problem of truss optimisation, it was observed that HNCMPA and HNMPA exhibited growth rates of 26.21% and 26.76%, respectively, compared to the optimal outcome obtained through MPA. It can be inferred that integrating the proposed methods with the hill-climbing approach would enhance the performance of the proposed methods when dealing with the truss optimisation problem. The outcomes obtained from the proposed techniques indicate that the truss structure suggested by these methods yielded the lowest weight, with a substantial difference compared to other approaches in all three truss case studies. It is important to note that in order to achieve optimal efficiency from these proposed methods, it is necessary to adjust control parameters using these truss issues. Additionally, the solution space and constraint-handling approach should be analyzed. In future work, we aim to develop collaborative techniques to address multi-objective cases of large-scale truss challenges and improve existing methodologies.

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AMIN ABDOLLAHI DEHKORDI received the M.Sc. degree in artificial intelligence and robotics from Islamic Azad University (IAU), Najafabad, Isfahan, Iran, in 2018. He is a Research Assistant with an extensive experience in the use of analytical and numerical data science techniques, such as machine learning, deep learning, and optimization. He has engaged in a wide range of multi-disciplinary and complicated data modeling projects, such as the IoT, truss optimization, and health systems. He has published multiple research papers in top journals, in order to apply his skills to new real-world engineering problems.

BAHAREH ETAATI received the master's degree in artificial intelligence from the Amirkabir University of Technology, in 2018. She has participated in several engineering optimization projects with the University of Adelaide, the University of Technology Sydney, and Torrens University Australia. Recently, she attended a joint human-computer interaction project between the University of Johannes Kepler Linz and the University of Applied Sciences Upper Austria as a Ph.D. candidate. Her research interests include machine learning, symbolic regression, humancomputer collaboration with a focus on interpretability and explainability of AI, designing novel nature-inspired meta-heuristics, and applying them to real-world problems, such as structural optimisation.

MEHDI NESHAT received the Ph.D. degree in computer science from the University of Adelaide, Australia, in 2020. From 2020 to 2023, he was a Postdoctoral Research Associate in data science, machine learning, and deep learning with the University of South Australia, Australia. He is an Adjunct Research Fellow with the Center for Artificial Intelligence Research and Optimization, Torrens University Australia, Australia. He has published more than 100 papers in top international conferences and journals. His primary research interests include artificial intelligence, optimization, and machine/deep learning. In 2019 and 2020, he received two Best Paper Awards from the most prestigious Genetic and Evolutionary Computation Conference (GECCO).

SEYEDALI MIRJALILI (Senior Member, IEEE) is a Full Professor, a top AI Scientist, and the Director of the Centre for Artificial Intelligence Research and Optimization, Torrens University Australia. He is internationally recognized for his advances in swarm intelligence and optimization, 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 500 publications with over 72000 citations and an H-index of 88. As the most cited researcher in robust optimization, he is in the list of 1% highly-cited researchers and named as one of the most influential researchers in the world by the Web of Science. His research interests include robust optimization, engineering optimization, multi-objective optimization, swarm intelligence, evolutionary algorithms, and artificial neural networks. He is an Editor of several journals, including *Neurocomputing*, *Applied Soft Computing*, *Advances in Engineering Software*, *Applied Intelligence*, and *Engineering Applications of Artificial Intelligence*.