IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 2 November 2023, accepted 17 November 2023, date of publication 20 November 2023, date of current version 28 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3335247

RESEARCH ARTICLE

A Novel Hybrid Prairie Dog Algorithm and Harris Hawks Algorithm for Resource Allocation of Wireless Networks

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ABSTRACT Enhancing the performance of wireless networks and communication systems requires careful resource allocation. Resource allocation optimization, however, is regarded as a mixed-integer non-linear programming (MINLP) problem, which is NP-hard and non-convex. Due to the serious limitations of conventional procedures, solving such optimization problems requires specialized approaches. For instance, no optimal performance can be guaranteed using the heuristic algorithms; besides, the global optimization systems suffer from exponential computation complexity and considerable training duration. This paper introduces an improved version of the Prairie dog optimization (PDO) algorithm by the Harris Hawks optimization (HHO) algorithm. The developed technique, namely HPDO, relies on using the HHO operators to improve the exploitation capability of PDO during the searching procedure. The significance of the presented HPDO is examined and analyzed using 23 mathematical benchmark functions and CEC-2019 with several dimension sizes to show the ability to solve different numerical problems. In addition to the resource allocation problem, the HPDO is evaluated using three engineering problems: The spring design issue, The pressure vessel design issue, and the Welded beam design issue. The experimental and simulation results demonstrated that the exploration and exploitation search method of HPDO and its convergence rate had remarkably increased. The experimental results of the resource allocation of the wireless network with different numbers of users 10, 50, and 100 achieve superior results compared to other algorithms with 0.136, 2.75, and 3.64, respectively.The results showed the supremacy of the HPDO over the traditional HHO, PDO, and several with state-of-the-art algorithms.

INDEX TERMS Wireless networks, 5G, 6G, resource allocation, power allocation, spring design, pressure vessel design, welded beam design.

I. INTRODUCTION

Discovering the ideal values for a particular optimization process' decision parameters while adhering to a set of constraints is the process of optimization [1]. Previously, solving optimization problems required a lot of human interaction and time-consuming trial and error. To reduce or maximize one or more objective functions, a designer must generate values systematically or arbitrarily for the decision parameters [2]. The majority of the metaheuristic

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

optimization algorithms are inspired by nature and can be classified into several approaches based on the origin of motivation [3]. The swarm-based algorithms based on the hunting and cooperation behaviour of fireflies, grasshoppers, wolves, hawks and other nature based algorithms [4].

Recently, various meta-heuristic optimization algorithms have been introduced in the literature to solve various optimization problems. Among these is the Prairie Dog Optimization algorithm (PDO) which mimics the behaviour of prairie dogs [5]. In spite of its successful applications in various fields, the PDO has two drawbacks. The algorithm cannot stalk the current optimal positions, leading to a fast loss of early convergence population variety—further, the algorithm sorrows from a slow convergence rate [6].

Mobile networks are increasingly a significant expansion, as is apparent by continuous growth in the number of subscriber usage and base volumes. Several factors push expansion in the international market, including a more significant uptake of cloud-based video streaming solutions, increasing use of videos as corporate training material, the popularity of video game streaming, and the growing magnitude of live-streamed content [7]. The increasing of mobile users around the globe is leveraging the mobile internet for voice over IP (VoIP) calling, mobile messaging, web browsing, social networks, online learning, and video streaming [8]. Moreover, the market shows profitable opportunities for a higher breakthrough of data traffic in mobile networks. At the same time, the mobile internet is influenced by the advanced implementation of 4g and 5g mobile networks and the growing user base for mobile benefits using different mobile networks.

Wireless networking has witnessed explosive evolution over the past decade. The 4th generation network (4g) improve the bandwidth availability for mobile phone and providing broadband speeds to smartphones. Recently the new mobile network, 5g technology is further improving the cell capability and transmission speeds. Further, 5g network deployed several radio technologies, which is decreasing the latency. Mobile networks continues to extend rapidly, nevertheless, and the following 6th mobile network (6g) is already being visualized. 6g will provide a wide range of applications including telehealth, autonomous vehicles, ubiquitous robotics, holographic telepresence, and smart cities [9].

The Spectrum efficiency (SE) is considered an essential metric for designing the wireless network, which has been studied broadly in the past years [10], [11]. However, as promptly rising power costs of the general application of data rate services and the need for ubiquitous access [12], [13], energy efficiency (EE) has gained more attention recently. For instance, the number of connected devices in 2018 was 18.4 billion; this number will reach 29.3 billion devices by 2023, which indicates that the power consumption will be increased [14]. Moreover, to meet the demand for mobile data and new services like virtual and augmented reality and high-resolution videos are expected to boost energy consumption by mobile networks [15], [16]. Green radio is considered a practical solution focusing on EE and SE and becoming an inevitable direction for the next wireless network design [17].

Optimizing the Energy Efficiency and Spectral Efficiency Tradeoff is typically considered a MINLP problem, which is generally non-convex and NP-hard. There are various effective methods to solve such issues as global optimization, heuristic methods, game-theoretic approaches, machine learning (ML)-based methods, and metaheuristic algorithms [18].

The SE optimal problem is the main focus of research in wireless networks. In term of maximizing the sum rate as an NP-Hard, In [19] show that determining the optimal FDMA spectrum allocation is NP-hard. Kha, H.H et al. propose the difference between two convex functions to develop a practical approach with minimum complexity [20].

There is a remarkable diversity of approaches in the metaheuristic algorithms, each with particular advantages and disadvantages [21], [22]. These strategies, which draw their inspiration from various physical and biological events, can address challenging optimization problems intractable by traditional techniques [23]. They are extensively explored and used to address various issues due to their adaptable and straightforward structure and capacity to avoid local optima through a random search. Consequently, metaheuristic methods have recently swept the scientific community off their feet, becoming a well-known study field for addressing challenging real-world challenges. They have become a preferred tool for various engineering design applications due to their exceptional capacity to deliver the best solutions in a computationally coherent technique and ease of implementation. Considering the problem as a ''black box,'' the algorithm tries solving it without considering its nature. This characteristic makes engineering optimization issues amenable to the use of metaheuristic methods.

In this work, we suggest using metaheuristic algorithms to afford a viable solution to solve the complex resource allocation issue in the wireless network [24]. The metaheuristics approaches are widely used in different applications to several real-word and significant scale engineering optimization problems, e.g., communication networks [25], solar energy [26], electrical engineering [27], mechanical engineering [28] and civil engineering [29].

An enhanced version of the PDO algorithms is suggested in the literature and utilized to solve different issues, demonstrating the feasibility of developing more efficient algorithms. Nevertheless, reaching a balance between exploitation and exploration remains a challenge. Therefore, there is a demand to design an adequate balance approach for optimization issues. Despite their value, metaheuristic algorithms must balance exploration and exploitation to function well. However, the PDO struggles with delayed convergence and being caught in local optima when dealing with high-dimensional issues. After iterations, it frequently only produces modest, comparable solutions, stopping the search from moving forward. No one metaheuristic algorithm can solve every problem regarding the No Free Lunch (NFL) theory [30], [31], [32]. They all have drawbacks, such as early convergence, becoming stuck in local optimal, and the necessity for global search capability [31], [33]. Therefore, this research aims to create a better PDO algorithm to successfully handle various engineering optimization issues. In keeping with this aim, this work offers a practical solution: an enhanced HHO algorithm with a PDO algorithm.The improved version of the PDO algorithm proposed in this study uses HHO algorithm to enhance the exploration and exploitation of the PDO algorithm.

This paper's contributions are outlined in the following points.

- We propose a brand technique named HPDO combining the Prairie dog algorithm (PDO) and Harris Hawks algorithm (HHO) approach inspired by the design of the PDO and HHO algorithm.
- HHO assists the recommended method in improving the variety of the authentic population and its ability to vacate from the falling in the local optimum.
- Improve PDO global and local search to expand convergence accurateness.
- Twenty-three well-known benchmark functions and the CEC-2019 functions are utilized to show the performance of the HPDO algorithm.
- The spring design issue, the pressure vessel, and the Welded beam are implemented to validate the HPDO performance.
- This paper investigates the power allocation problem in wireless networks as a real-world case study using the HPDO algorithm.
- The results reveal the out-performance of HPDO compared to the basic PDO, HHO, and other state-of-art optimization algorithms.

This paper is classified as follows: Section II presents the recent related work. Section III introduces the HHO algorithm. Section IV describes the PDO algorithm. The proposed HPDO algorithm is illustrated in section V. Section VI shows the experimental results of the proposed HPDO. Section VII provides some real-world applications of HPDO, the system model, and the problem formulation of the resource allocation of wireless networks issue is also described in this section. Finally, section 8 summarizes the proposed work.

II. HARRIS HAWKS ALGORITHM

In 2019 Ali Asghar et al. introduce the HHO algorithm, which is a meta-heuristic swarm intelligence approach inspired by the Harris hawk birds [34]. Harris hawk birds try to hunt the prey based on team cooperations. As an algorithm based on the population approach, the initialization stage is a random procedure—two main phases in the HHO algorithm, exploration, and exploitation. Figure 1 illustrates the overall HHO algorithm process.

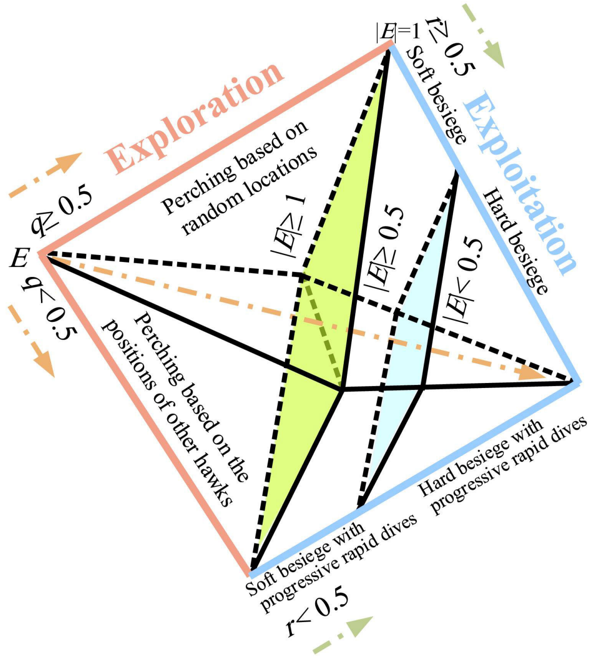

FIGURE 1. Different phases of HHO [34].

A. EXPLORATION STAGE

In HHO, The rabbit position represents the optimal solution, and the Harris hawks positions represent the other solutions. To find their prey, the Harris hawks search randomly in a particular area or remain in specific locations. The Harris hawk's behavior can be implemented in two exploration phases; the first describes the hawk's movement depending on the position of other birds in the population and the prey position in the field. The second one represents the habitation of arbitrary trees by Harris hawks [35]. A random value of q measures the selection of these two phases as the following updating functions:

$$T(t+1) = \begin{cases} T_{random}(t) - r_1 \left|T_{random}(p) - 2r_2 T(p)\right| & q \geq 0.5 \\ (T_{rabbit}(p) - T_m(p)) - r_3(LoB + r_4(UpB - LoB)) & q < 0.5 \end{cases} \tag{1}$$

where $T(p)$ is the current position vector of Harris hawks, $T(p+1)$ represent the vector portions of hawks bird in the following iteration p, and the position of rabbit represent by $T_{rabbit}(p)$, r_1, r_2, r_3, r_4, and q are random numbers between (0,1), LoB and UpB describe the lower and upper bounds of variables, $T_{random}(p)$ show a random value chosen for the bird from the available population, and T_m represent the average of hawks population, and r represents the prey's chance of either failing to escape before a surprise pounce ($r > 0.5$) or succeeding in escape ($r < 0.5$). where the average population position attained by Eq.(2):

$$T_m(p) = \frac{1}{N}\sum_{i=1}^{N} T_i(p) \tag{2}$$

where $T_i(p)$ indicates each bird's position in iteration p and N denotes the total number of birds.

B. EVOLUTION FROM EXPLORATION TO EXPLOITATION

the evolution in the HHO algorithm from exploration to exploitation is achieved using a parameter that indicates the prey's energy. The energy of prey can be obtained via:

$$E = 2E_0(1 - \frac{p}{IT}) \tag{3}$$

where the E, E_0, and IT represent the energy escaping, the initial state of prey energy, and the maximum bound of iterations, respectively. The value of E_0 is selected randomly inside (1,1) for each iteration.

C. EXPLOITATION STAGE

The HHO performs the surprise pounce method to begin an attack on the selected rabbet. However, the prey will escape, and the Harris hawks will try to chase it. To model this behavior, four potential attacking approaches are proposed in the HHO as a following.

1) SOFT BESIEGE

Here rabbits have enough energy; the hawks attempt to exhaust the prey and then execute the surprise pounce. In this phase, the main rule is represented in Eqs. (4) and (5):

$$T(p+1) = \Delta T(p) - E\,|JX_{rabbit}(t) - T(p)| \tag{4}$$

$$\Delta T(t) = T_{rabbit}(p) - T(p) \tag{5}$$

where $\Delta T(p)$ is the difference between the location vector of the prey and the current position in iteration p, r_5 denotes a random number inside (0,1). The $J = 2(1 - r_5)$ describes the arbitrary rabbit movement during the escaping.

2) HARD BESIEGE

In this stage, Harris hawks perform the best solution based on Eq. (6):

$$T(p+1) = T_{rabbit}(p) - E\,|\Delta T(p)| \tag{6}$$

3) SOFT BESIEGE WITH PROGRESSIVE RAPID DIVES

In this stage, the hawks can determine the next move based on the rule shown in Eq. (7)

$$Y = T_{rabbit}(p) - E\,|JT_{rabbit}(p) - T(p)| \tag{7}$$

The Harris Hawks compute the results of rapid dives in this period and compare them with previous dives. The HHO employs the Levy flight operator to simulate these dives, which is achieved by:

$$Z = Y + S \times LF(D) \tag{8}$$

where D represents the number of dimensions, S denotes a random vector, and LF is the levy flight function, which is calculated by:

$$LF(x) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})})}\right)^{\frac{1}{\beta}} \tag{9}$$

where u, v are arbitrary numbers of LF inside (0,1), and β is a constant set to 1.5.

The final approach for updating the positions of Harris hawks in soft besiege with progressively rapid dives can be performed by Eq (10)

$$T(p+1) = \begin{cases} Y & if\ F(Y) < F(T(p)) \\ Z & if\ F(Z) < F(T(p)) \end{cases} \tag{10}$$

where Y and Z are obtained using Eqs. (7) and (8).

4) HARD BESIEGE WITH PROGRESSIVE RAPID DIVES

Here the hawks try to finish the process and decrease the distance with the prey; for this process, the following rule is performed:

$$T(p+1) = \begin{cases} Y & if\ F(Y) < F(T(p)) \\ Z & if\ F(Z) < F(T(p)) \end{cases} \tag{11}$$

where Y and Z are calculated by using new rules in Eqs.(12) and (13). Figure (2) demonstrates a schematic of Hard besieges with progressive rapid dives.

$$Y = T_{rabbit}(p) - E\,|JX_{rabbit}(p) - T_m(p)| \tag{12}$$

$$Z = Y + S \times LF(D) \tag{13}$$

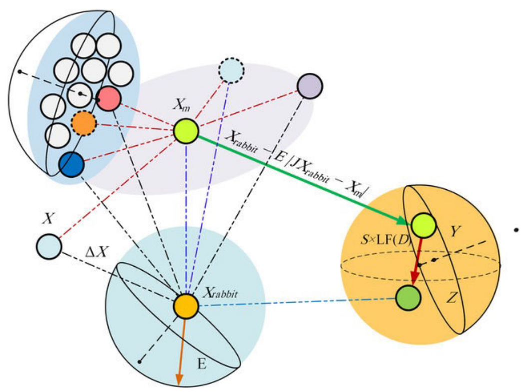

FIGURE 2. **Movements of hawks in HHO in Hard besiege with developed quick dips phase [34].**

III. PRAIRIE DOGS OPTIMIZER (PDO)

Prairie dogs (PrDs) are intelligent rodents that belong to the squirrel family. Prairie dogs dwell in underground burrows in big groups that form a town or colony, sharing food and protecting their burrows [36]. The intricate communication technique used by these species is one of the reasons they are considered clever; they use squeaky sounds to communicate with their colonies and warn them of predators [37]. In a single bark, prairie dogs encode information about the predator's size, color, direction, and speed.

PrDs exhibit a range of actions that are consistent with processes for exploitation and exploration. PrDs move from one location to another throughout the problem search space, effectively searching multiple areas as they eat mostly grasses, small seeds, and some insects throughout the seasons. They use alert messages to exploit particular locations (solutions) in order to find better or nearly ideal solutions (promising areas) [5].

A. INITIALIZATION

Each of the n PrDs that make up a unit is a member of one of the m units. The location of the ith PrD in a spacific type is determined by a vector since PrDs live and work as a unit or group. The matrix presented in Equation 14 displays the locations of all units (UT) in a colony.

$$UT = \begin{bmatrix} UT_{1,1} & UT_{1,2} & \dots & UT_{1,d-1} & UT_{1,d} \\ UT_{2,1} & UT_{2,2} & \dots & UT_{2,d-1} & UT_{2,d} \\ . & . & & . & . \\ . & . & UT_{i,j} & . & . \\ . & . & & . & . \\ UT_{m,1} & UT_{m,2} & \dots & UT_{m,d-1} & UT_{m,d} \end{bmatrix} \tag{14}$$

where $UT_{i;j}$ stands for the colony's jth-dimensional ith-unit. The location of every PrD in a unit is represented by Equation 15:

$$PrD = \begin{bmatrix} PrD_{1,1} & PrD_{1,2} & \dots & PrD_{1,d-1} & PrD_{1,d} \\ PrD_{2,1} & PrD_{2,2} & \dots & PrD_{2,d-1} & PrD_{2,d} \\ . & . & & . & . \\ . & . & PrD_{i,j} & . & . \\ . & . & & . & . \\ PrD_{n,1} & PrD_{n,2} & \dots & PrD_{n,d-1} & PrD_{n,d} \end{bmatrix} \tag{15}$$

where $PrD_{i;j}$ denotes the ith PrDs and jth dimension in a unit, and $n \leq m$. 16 and 17 are used to allocate each unit and PrD position using a uniform distribution:

$$UT_{i;j} = U(0,1) \times (UpperB_j - LowerB_j) + LB_j \tag{16}$$

$$PrD_{i;j} = U(0,1) \times (ub_j - lb_j) + lb_j \tag{17}$$

where $ub_j = UpperB_j$/m and $lb_j = LowerB_j$/m, and U(0,1) is a random value represent a uniform distribution between 0 and 1 and $UpperB_j$ and $LowerB_j$ are the upper and lower bounds of the jth-dimension of the optimization issue, respectively.

B. FITNESS FUNCTION EVALUATION

Depending on where the PrD's is located, a fitness function will be used to assess how close a certain solution is to the optimum solution to the problem. In order to make the best decision, the prairie dog's location is assessed using the fitness function. Each PrD's fitness function has a symbolic value that corresponds to the quality of food offered at a specific source, the capability to excavate further burrows, and the success of anti-predation alarm responses. The values obtained are stored in the array show in Equation 18. These values are sorted and the best solution for the particular minimization problem is stated to be the one with the lowest fitness value. The following three values are taken into consideration together with the best value for several parameters such as burrow development, that help them flee from predators.

$$f(PrD) = \begin{bmatrix} f_1([PrD_{1,1} & PrD_{1,2} & \dots & PrD_{1,d-1} & PrD_{1,d}]) \\ f_2([PrD_{2,1} & PrD_{2,2} & \dots & PrD_{2,d-1} & PrD_{2,d}]) \\ . & . & & . & . \\ . & . & \dots & . & . \\ . & . & & . & . \\ f_n([PrD_{n,1} & PrD_{n,2} & \dots & PrD_{n,d-1} & PrD_{n,d}]) \end{bmatrix} \tag{18}$$

C. EXPLORATION

PrDs scour the entire colony or issue area in search of fresh food or fixes. Based on four factors, the PDO can decide between exploration and exploitation. Exploration and exploitation take up the first two of the four portions of the maximum number of iterations (M_{iter}), which is broken into four sections:

- Criteria 1: $iter < M_{iter}/4$
- Criteria 2: $M_{iter}/4 \leq iter < M_{iter}/2$
- Criteria 3: $M_{iter}/2 \leq iter < 3M_{iter}/4$
- Criteria 4: $3\ M_{iter}/4 \leq iter < M_{iter}$

During the exploration phase, the PrD's movements as they seek for food sources is best represented by the Le'vy flight motion (LV), that is LV(n) distribution [38]. Equation 19 describes location updates for foraging and the Le'vy flight motion in the exploration phase.

$$PrD_{i+1;j+1} = GOptimal_{i,j} - eCOptimal_{i,j} \times p - CPrD_{i,j} \times LV(n) \quad \forall iter < \frac{M_{iter}}{4} \tag{19}$$

Equation 20 shows the location update for forming new caves based on the quality of the detected food sources and the assessment of the digging strength.

$$PrD_{i+1;j+1} = GOptimal_{i,j} \times rPrD \times DS \times LV(n) \forall \frac{M_{iter}}{4} \leq iter < \frac{M_{iter}}{2} \tag{20}$$

where $eCOptimal_i; j$ measures the impact of the best solution currently found and is shown in Equation 21, $GOptimal_i; j$ is the best solution that has been found globally, $rPrD$ is the location of a arbitrary solution, and $CPrD_i; j$ is the arbitrary cumulative effect of all PrDs in the colony and is defined in Equation 22. The unit's digging strength, denoted by DS, is determined by the caliber of the food source and has a random value determined by Equation 23.

$$eCOptimal_{i,j} = GOptimal_{i,j} \times \Delta$$

$$+\frac{PrD_{i,j} \times mean(PrD_{n,m})}{GOptimal_{i,j} \times (UpperB_j - LowerB_j) + \Delta} \tag{21}$$

$$CPrD_{i,j} = \frac{GOptimal_{i,j} - rPD_{i,j}}{GOptimal_{i,j} + \Delta} \tag{22}$$

$$DS = 1.5 \times r \times (1 - \frac{iter}{M_{iter}})^{(2\frac{iter}{M_{iter}})} \tag{23}$$

D stands for a small number that takes into consideration variations in prairie dogs, and r introduces the stochastic property to assure exploration. Depending on the current iteration, r can take the value - 1 or 1, alternating between - 1 and 1 when the current iteration is odd or even.

D. EXPLOITATION

To carry out exploitation phase in the PDO algorithm, PD's disseminate signals similar to alarm sound to notify members of the same unit of food sources or predators locations. This operation is presented in Equations 24 and 25.

$$PrD_{i+1;j+1} = GOptimal_{i,j} - eCOptimal_{i,j} \times \epsilon - CPD_{i,j} \times rand \ \forall \frac{M_{iter}}{2} \leq iter < 3\frac{M_{iter}}{4} \tag{24}$$

$$PrD_{i+1;j+1} = GOptimal_{i,j} - PE \times rand \ \forall\ 3\frac{M_{iter}}{4} \leq iter < M_{iter} \tag{25}$$

$$PE = 1.5 \times (1 - \frac{iter}{M_{iter}})^{(2\frac{iter}{M_{iter}})} \tag{26}$$

where ϵ stands for the food source's quality, equation 26 illustrate the predator effect (PE), and a rand is a random number between 0 and 1.

IV. PROPOSED ALGORITHM

Figure 3 illustrates the general framework of the developed method known as HPDO. Its main goal is to improve the PDO algorithm's capacity to balance the exploration and exploitation process in searching for the best solution. By integrating the HHO algorithm with the PDO's operators, HPDO achieves this balance. The HHO algorithm enhances PDO exploration and speeds up the convergence process toward the optimal solution. This integration between PDO and HHO leads to a better performance of PDO. To start the suggested HPDO algorithm, the initial value of N agents (X) is randomly selected using a specific equation.

$$X_{ij} = rand \times (UpperB - LowerB) + LowerB,\ i = 1, 2, \ldots, N, j = 1, 2, \ldots, Dim. \tag{27}$$

In Eq. (27), Dim represents the size of per parameter X_i. $LowerB$ is the lower boundary, and $UpperB$ is the upper boundary of the search territory. This is tracked by revamping the agents X utilizing the hybrid between PDO and HHO. This is accomplished by operating random parameter $R_n \in [0, 1]$ that swaps between the PDO operators and the HHO. For an instant, The PDO operator is used to update the current solution when $R_n < 0.3$. Otherwise, the HHO algorithm is used to update the solution. This process is formulated as follows:

$$X_i(t+1) = \begin{cases} Use\ PDO\ as\ in\ Eqs.(23) - (26), & R_f < 0.3 \\ Apply\ HHO\ as\ in\ Eq.(10), & otherwise \end{cases} \tag{28}$$

Algorithm 1 illustrates the pseudo code for HPDO algorithm [5]. Initially, PDO creates a set of candidate solutions that are randomly distributed and initializes its parameters. The algorithm then repeats its operations to examine all feasible sites of near-optimal solutions. Based on the fitness evaluation, the algorithm chooses the best answer at the moment and replaces the previously obtained solution each time. To apply exploration, the iterations number should be $iter < Max_{iter}/2$. Furthermore, exploitation is enabled when the iterations number $iter > M_{iter}/2$. PDO terminates when the maximum number of iterations is reached.

V. EXPERIMENTS AND RESULTS

This section presents the experimental findings that support the optimization capabilities of the suggested algorithm. To test the HPDO's performance in this regard, benchmark functions with 23 objective functions (fixed-dimensional, unimodal, and high-dimensional multimodal) are used. The performance of well-known algorithms, including Grey Wolf Optimizer (GWO) [39], Salp Swarm Algorithm (SSA) [40], Whale Optimization Algorithm (WOA) [41], Dragonfly Algorithm (DA) [42], Particle Swarm Optimization (PSO) [43], Marine Predators Algorithm (MPA) [44], Slime Mold Algorithm (SMA) [45], and Harris Hawks Optimization (HHO) is compared to that of HPDO. The HPDO and each competing metaheuristic algorithm are used in five runs, each with 10, 50, and 200 iterations. The markers worst, average, best, and standard deviation (STD) are used to report the outcomes of the algorithms that were used. Additionally, when the p-value is less than 0.05, the Wilcoxon rank-sum is used to acquire statistical data to determine whether HPDO significantly varies from other methods. The values for the crucial parameters of the employed algorithms are shown in Table 1.

A. QUALITATIVE ANALYSIS

The benchmark functions provided in Figure 4 first column, as demonstrated, closely resemble real-world search area problems by yielding a vast number of local optima and a variety of forms for several locations inside the search space. In order to find the global optima, each optimization technique should create a balance for the investigation and application of search strategies. Thus, this set of benchmark functions can be used to assess the relationship between exploration and exploitation. This section investigated the suggested HPDO algorithm convergence behavior. Three primary metrics—the best first-dimension values, average fitness values, and convergence speed—demonstrate the

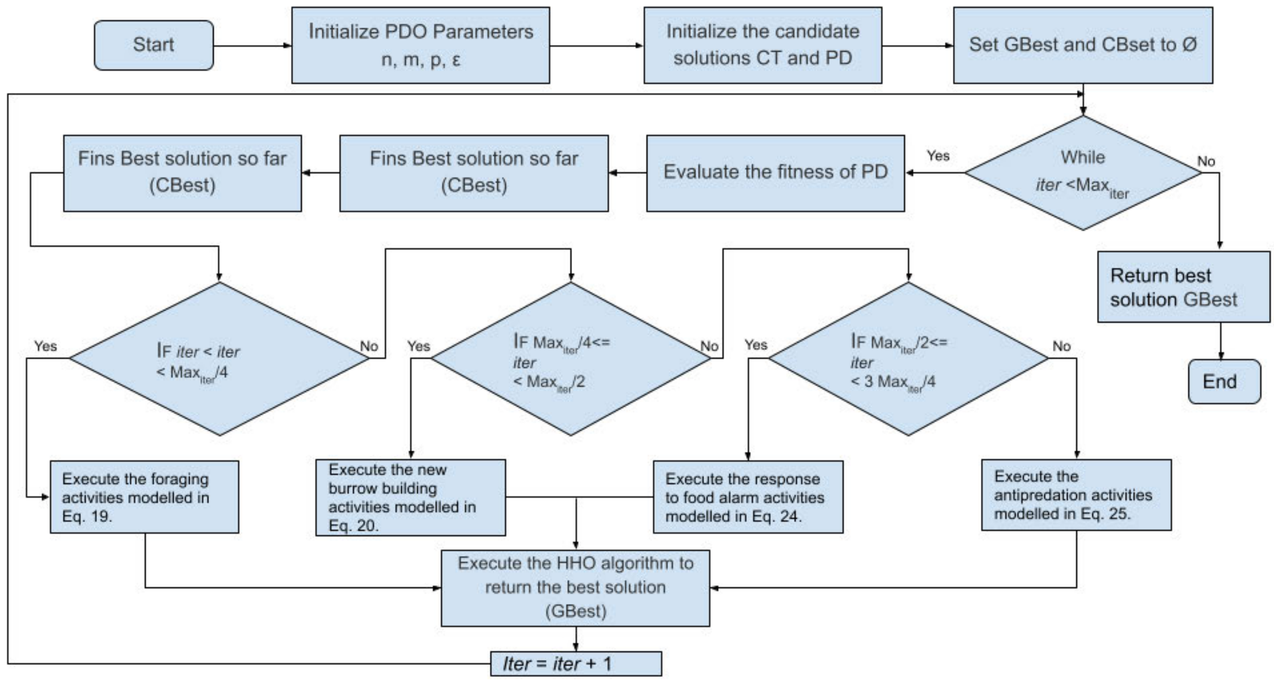

FIGURE 3. **Proposed HPDO algorithm.**

TABLE 1. **Parameter values of the HPDO algorithm and other used algorithms.**

Algorithm	Parameters
MPA	C=[0.2,0.4];
PSO	wMax=0.9; wMin=0.2; c1=2; c2=2
WOA	a1 ∈[0,2]; a2 ∈[2,1]; b = 1
DA	$\beta = 1.5$
SSA	Random values c2 and c3 between 0 and 1
SMA	z = 0.01
HHO	= 1.5
GWO	α =[0,2]
HPDO	$\rho = 0.5$; $\epsilon = 2.220e^{-16}$

HPDO convergence. The tests are run on several benchmark functions (F1, F2, F4, F6, F7, F8, F11, F12, and F13) using 60 iterations using 5 solutions. The second column (first indication) presents the qualitative metric that accounts for the changes in the first solution of the first dimension throughout optimization (enhancement). This indication enables us to identify whether the first solution exhibits moderate shifts in the last repetitions after initially experiencing abrupt or sharp moves. The behavior of the suggested HPDO can verify that a population-based approach locally explores inside the specified search region and converges to a point. It is evident that the modifications progressively become smaller across several iterations, a characteristic that validates the transition from exploration to exploitation. Ultimately, the solution evolves gradually, which forces an exploration search. The average fitness value of every solution throughout the period of repetitions is the qualitative metric represented by the third column (second indication). The average fitness value over the specified repetitions should be developed if an optimization strategy outperforms rival alternatives. The suggested HPDO approach yields lower fitness values on all evaluated functions, as shown by the average fitness trajectory in Figure 4. Another issue that merits an introduction here is the accelerated reduction in the average fitness trajectories, which explains why the development of the existing solutions gets more dependable and faster throughout repetitions. The convergence rate of the optimal solution across a series of repetitions is the qualitative metric represented by the fourth column (third indication). In Figure 4, the convergence curve is a collection of the fitness values of the best solution for each repetition. The suggested HPDO method's convergence is shown by the decline in fitness levels over the specified repetitions. It is also evident that the supplied convergence curve exhibits a reduced convergence rate, which can be attributed to the previously mentioned reason. Additionally, the suggested approach quickly produced the most significant results in several functions, including F6, F7, F8, F11, and F13.

B. SIMULATION RESULTS OF BENCHMARK FUNCTIONS

The performance of HPDO is demonstrated in this section. The implementation is evaluated using average, best, worst,

Algorithm 1 HPDO Algorithm Pseudo Code

$initialize : n, p, m, \epsilon$
$initialize : UT, PrD$
$GOptimal \leftarrow \phi$
$COptimal \leftarrow \phi$
while $iter<M_{iter}$ **do**
  for ($i = 1$ to m) **do**
    for ($j = 1$ to n) **do**
      $Calculate : f(PrD)$
      $Find : COptimal$
      $Update : GOptimal$
      $Update : DS, PE$
      $Update : CPrD_{i,j}$
      if ($iter<\frac{M_{iter}}{4}$) **then**
        $PrD_{i+1;j+1} = GOptimal_{i,j} - eCOptimal_{i,j} \times p - CPrD_{i,j} \times Levy(n)$
      else
        if ($\frac{M_{iter}}{4} \leq iter<\frac{M_{iter}}{2}$) **then**
          $PrD_{i+1;j+1} = GOptimal_{i,j} \times eCOptimal_{i,j} \times DS \times Levy(n)$
        else
          if ($\frac{M_{iter}}{2} \leq iter<3\frac{M_{iter}}{4}$) **then**
            $PrD_{i+1;j+1} = GOptimal_{i,j} - eCOptimal_{i,j} \times \epsilon - CPrD_{i,j} \times rand$
          else
            $PrD_{i+1;j+1} = GOptimal_{i,j} \times PE \times rand$
          end if
        end if
      end if
    end for
  end for
  Execute the HHO algorithm
  return $return : GOptimal$
  $iter = iter + 1$
end while
return $return : GOptimal$
End

and standard deviation (STD) values. Additionally, we'll be conducting the Wilcoxon rank-sum test with a significant differential of 0.05 to determine if there's a substantial difference between the proposed variant and its equivalents. After running the tests, we found that the HPDO is capable of handling most of the employed benchmark functions compared to other state-of-the-art counterparts. To determine the final ranking of the proposed HPDO, we used the Friedman ranking test. This allowed us to show that the HPDO is a powerful tool that can deliver results that are on par with the best in the industry.

1) SCALABILITY ANALYSIS

The proposed HPDO algorithm's convergence solutions are preliminary field investigated to evaluate the impact of incorporating the operators of HHA and PDO distribution while finding the optimal solutions for high-dimensional optimization issues. Consequently, the HPDO convergence curves compared to other algorithms are depicted in Figure 5 for selected results from 23 implemented functions. The results show that the HPDO converges to the optimal results at the beginning of the iterations; on the other hand, the SSA, GOA, and MPA have piled the local solutions.

Tables 2 and 3 describes the HPDO achieved results compared to DA, HHO, GWO, WOA, PSO, SSA, MPA, and SMA. The results of the average, best, worst, and STD achieved by HPDO show an outperformance of the HPDO algorithm among most of the algorithms versus 23 functions, such as the following functions: 1, 2, 5, 6, 12, 14, and 15. Furthermore, the Wilcoxon rank-sum results show an excellent performance of HPDO, the P-value with considerable amiability of 0.05. Therefore, for example, the HPDO outperforms the SSA algorithm in 18 functions; thus, the null hypothesis test is denied, and h=1 means a noteworthy distinction between the HPDO and SSA. Similarly, the null hypothesis test is denied because the performance of the HPDO for the P-value is considerable and outperforms other algorithms (WOA, PSO, HHO, GOW, and SMA).

The Friedman-ranking test is implemented for additional experimentation and to determine the rank of HPDO among the benchmark functions. The acquired solutions are shown in Table 4. The rank solutions reveal that the HPDO reaches a comparative rank regarding other algorithms. The HPDO average rank is 1, which is the most minor achieved solutions, and settled on the first position among the 23 benchmark functions. With an average of 3.74, the MPA algorithm was in second place. We conclude that the HPDO statistically exceeds the current state-of-the-art after looking at the data in Tables 2,3 and 4.

2) CEC-2019

Ten CEC-2019 problems are used in this part to evaluate the proposed HPDO. Table 5 lists the specifics of these problems.

The outcomes of the CEC2019 comparing techniques are shown in Table 6, along with the fitness function values for the worst, mean, and best results. It is obvious that the suggested method, almost for all of the investigated problems, produced superior results than other comparison methods. The Wilcoxon signed-rank test indicated that in F2, the suggested HPDO exceeded the SMA, HHO, SSA, WOA, DA, GOA, GWO, ALO, SCA, MPA, PSO, and PDO. Another case (F10) over-whelmed ALO, GWO, PSO, GOA, and SMA. The Friedman ranking test ranks the demonstrated HPDO as the best method, with MPA coming in second, HHO coming in third, MPA coming in fourth, GWO coming in fifth, DA coming in sixth, PSO coming in seventh, WOA coming in eighth, and SSA coming in ninth. Additionally, Figure 6 provides the convergence behavior of the comparison approaches on the CEC-2019 test functions. This graphic demonstrates that the performance of the suggested strategy outperforms alternative methods.

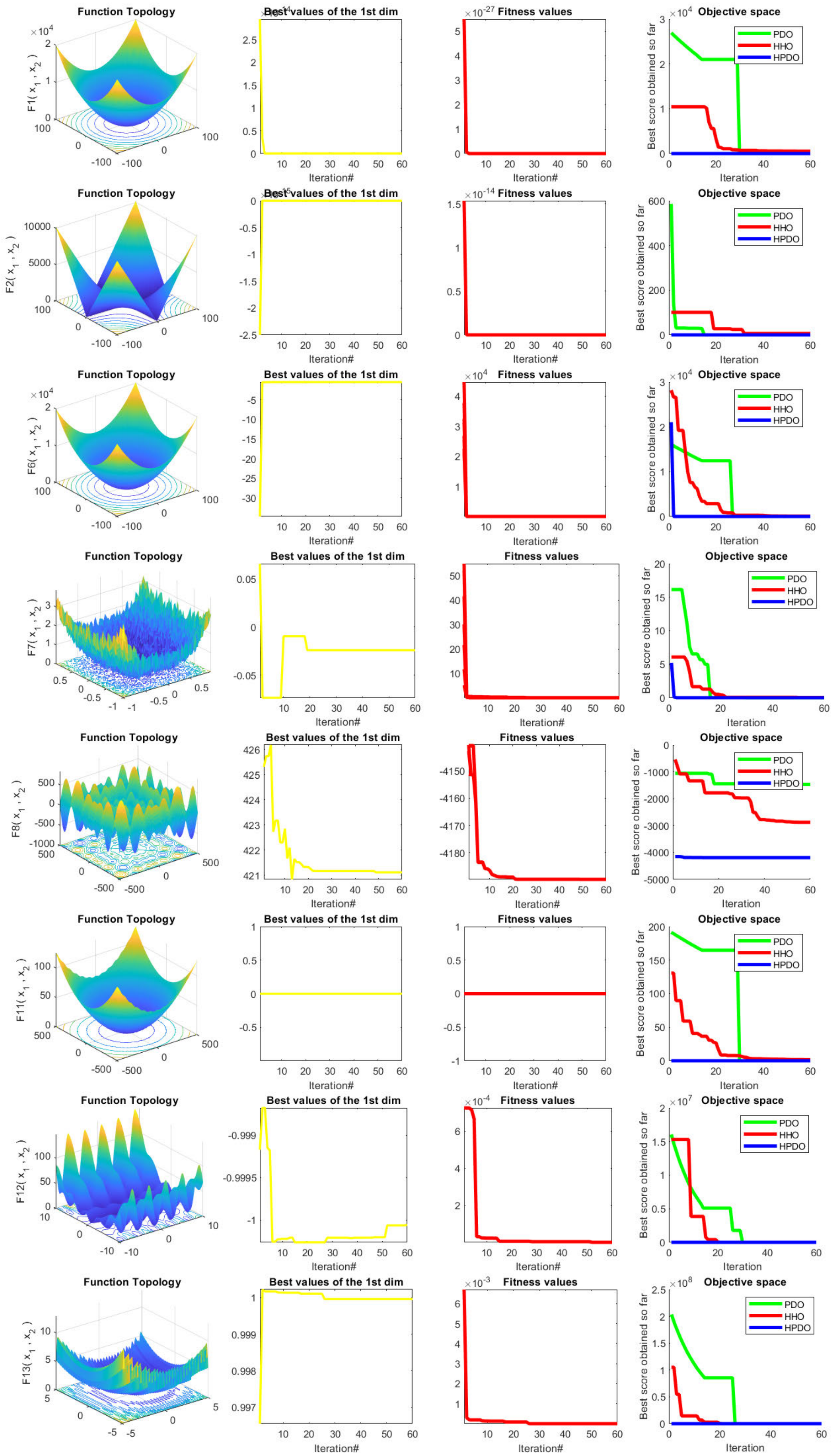

FIGURE 4. Qualitative results for the some tested problems.

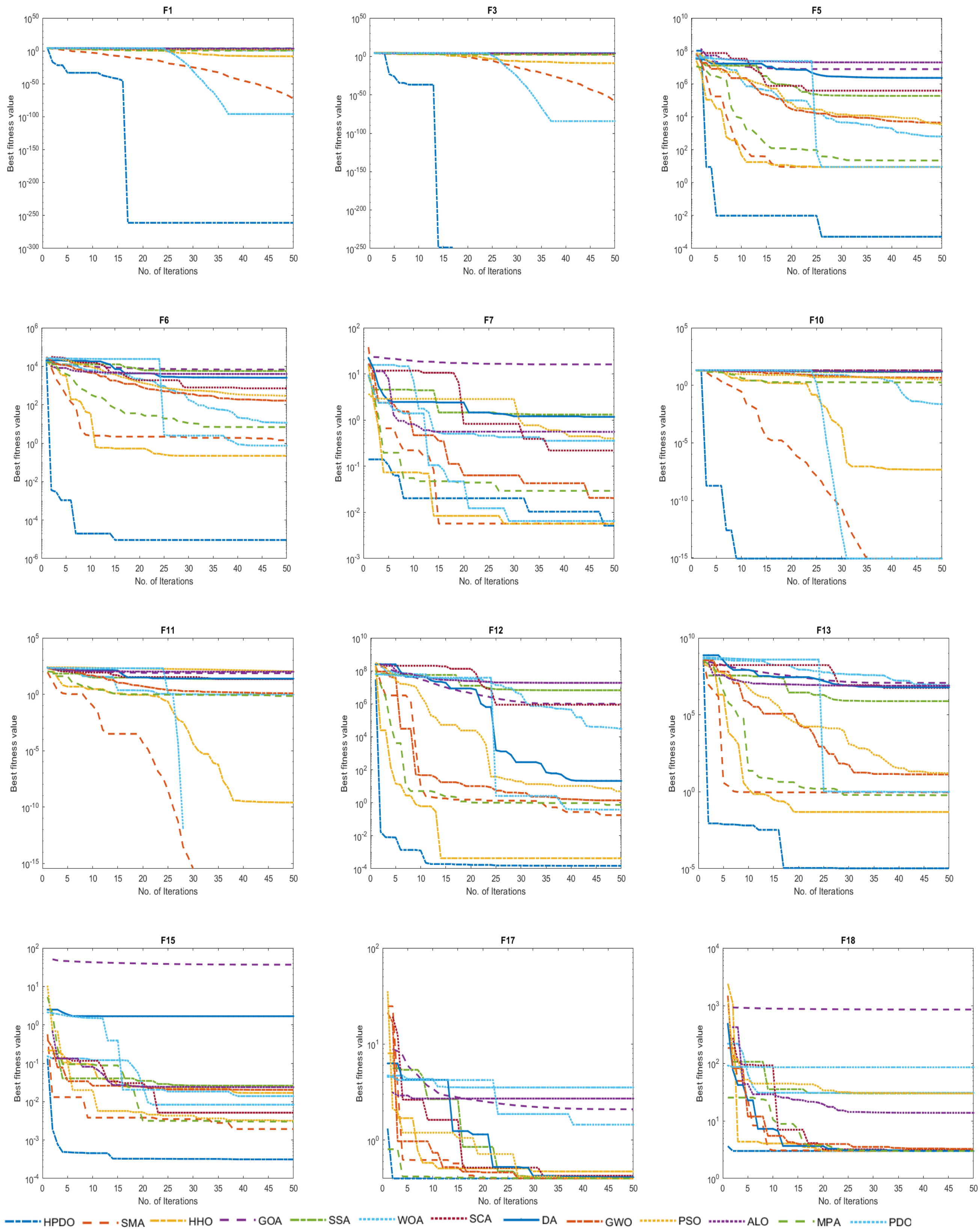

FIGURE 5. Qualitative analysis 50 iteration.

TABLE 2. The outcomes of 10 benchmark functions (F1–F23) using comparison approaches, with a dimension of 10.

Function	Measure	Comparative methods								
		HHO	SSA	WOA	DA	GWO	PSO	MPA	SMA	HPDO
1	Best	5.590E+00	2.085E+04	1.699E+04	1.714E+04	9.871E+03	9.550E+03	2.655E+03	1.024E-07	1.785E-40
	Average	2.537E+00	9.968E+03	8.253E+03	6.445E+03	5.808E+03	8.478E+03	2.195E+03	3.183E-08	3.570E-41
	Worst	1.953E-01	2.831E+03	2.609E+03	1.084E+03	3.831E+03	5.732E+03	1.461E+03	9.190E-10	1.078E-239
	STD	1.974E+00	6.756E+03	6.159E+03	6.540E+03	2.705E+03	1.554E+03	4.937E+02	4.265E-08	7.982E-41
	p-value	2.070E-02	1.088E-02	1.717E-02	5.866E-02	1.354E-03	1.887E-06	8.877E-06	1.337E-01	1.000E+00
	h	1	1	1	0	1	1	1	0	0
2	Best	5.249E+00	6.108E+01	3.811E+01	3.075E+01	2.799E+01	3.206E+01	2.069E+01	2.966E-02	7.538E-24
	Average	2.131E+00	3.098E+01	2.136E+01	2.080E+01	1.918E+01	2.326E+01	1.390E+01	5.973E-03	2.331E-24
	Worst	2.740E-02	1.611E+01	1.443E+01	1.292E+01	1.409E+01	1.318E+01	7.248E+00	6.538E-06	4.051E-98
	STD	2.831E+00	1.757E+01	9.541E+00	6.462E+00	5.501E+00	8.951E+00	5.378E+00	1.324E-02	3.413E-24
	p-value	1.308E-01	4.275E-03	1.046E-03	9.286E-05	5.255E-05	4.009E-04	4.140E-04	3.427E-01	1.000E+00
	h	0	1	1	1	1	1	1	0	0
3	Best	1.300E+04	3.679E+04	2.480E+04	1.185E+04	1.356E+04	5.911E+04	3.605E+03	1.155E-03	3.212E-29
	Average	3.298E+03	2.047E+04	1.518E+04	7.633E+03	6.873E+03	2.804E+04	2.580E+03	2.862E-04	6.426E-30
	Worst	9.916E+01	1.058E+04	3.845E+03	3.490E+03	3.553E+03	8.188E+03	1.055E+03	8.210E-07	7.885E-169
	STD	5.532E+03	1.014E+04	9.131E+03	3.695E+03	4.106E+03	1.971E+04	1.019E+03	4.922E-04	1.437E-29
	p-value	2.192E-01	1.962E-03	5.889E-03	1.713E-03	5.685E-03	1.299E-02	4.750E-04	2.297E-01	1.000E+00
	h	0	1	1	1	1	1	1	0	0
4	Best	1.690E+01	7.527E+01	8.515E+01	5.078E+01	6.247E+01	5.623E+01	4.918E+01	8.877E-04	7.883E-23
	Average	4.670E+00	6.171E+01	6.276E+01	4.106E+01	3.939E+01	5.010E+01	2.917E+01	3.562E-04	2.031E-23
	Worst	6.902E-01	5.164E+01	3.554E+01	3.508E+01	2.264E+01	4.503E+01	1.922E+01	3.841E-05	6.377E-130
	STD	6.881E+00	8.964E+00	1.920E+01	5.885E+00	1.772E+01	4.544E+00	1.243E+01	3.539E-04	3.416E-23
	p-value	1.676E-01	3.152E-07	8.324E-05	2.841E-07	1.094E-03	7.820E-09	7.747E-04	5.455E-02	1.000E+00
	h	0	1	1	1	1	1	1	0	0
5	Best	7.191E+03	1.557E+07	3.249E+07	6.055E+06	1.082E+07	6.598E+06	4.819E+06	9.059E+00	8.379E-02
	Average	2.832E+03	7.088E+06	1.040E+07	2.502E+06	4.168E+06	1.725E+06	1.721E+06	9.005E+00	2.798E-02
	Worst	2.179E+01	2.250E+06	2.977E+04	4.331E+05	1.756E+06	1.351E+05	9.442E+04	8.984E+00	4.778E-04
	STD	3.776E+03	5.728E+06	1.345E+07	2.538E+06	3.812E+06	2.759E+06	1.903E+06	3.095E-02	3.669E-02
	p-value	1.321E-01	2.441E-02	1.222E-01	5.859E-02	4.023E-02	1.997E-01	7.770E-02	1.197E-18	1.000E+00
	h	0	1	0	0	1	0	0	1	0
6	Best	1.374E+02	1.392E+04	1.278E+04	1.470E+04	9.930E+03	1.295E+04	5.132E+03	2.696E+00	2.061E-03
	Average	4.461E+01	7.462E+03	8.284E+03	7.893E+03	6.189E+03	9.886E+03	2.293E+03	2.320E+00	9.085E-04
	Worst	6.036E-02	3.014E+03	4.000E+03	2.747E+03	2.225E+03	7.779E+03	3.077E+02	1.946E+00	1.585E-04
	STD	6.128E+01	4.056E+03	3.708E+03	5.262E+03	2.857E+03	2.031E+03	1.978E+03	2.790E-01	8.117E-04
	p-value	1.422E-01	3.374E-03	1.059E-03	1.003E-02	1.282E-03	4.499E-06	3.199E-02	7.231E-08	1.000E+00
	h	0	1	1	1	1	1	1	1	0
7	Best	1.868E-01	3.693E+00	9.265E+00	5.979E+00	7.512E+00	9.131E+00	5.434E-01	1.069E-01	5.213E-02
	Average	7.448E-02	2.055E+00	4.297E+00	2.181E+00	2.747E+00	7.476E+00	2.900E-01	5.311E-02	2.934E-02
	Worst	2.156E-02	1.165E+00	7.549E-01	3.604E-01	6.203E-01	5.514E+00	1.658E-01	2.736E-02	7.283E-03
	STD	6.667E-02	1.172E+00	4.340E+00	2.233E+00	2.806E+00	1.639E+00	1.511E-01	3.306E-02	1.746E-02
	p-value	1.813E-01	4.778E-03	5.909E-02	6.335E-02	6.229E-02	7.540E-06	5.009E-03	1.931E-01	1.000E+00
	h	0	1	0	0	0	1	1	0	0
8	Best	-5.648E+02	-9.596E+02	-9.300E+02	-1.043E+03	-9.421E+02	-7.404E+02	-9.991E+02	-1.706E+03	-4.186E+03
	Average	-1.457E+03	-1.178E+03	-1.835E+03	-1.201E+03	-1.211E+03	-1.194E+03	-1.467E+03	-2.718E+03	-4.189E+03
	Worst	-2.169E+03	-1.340E+03	-2.426E+03	-1.417E+03	-1.682E+03	-2.035E+03	-1.973E+03	-4.075E+03	-4.190E+03
	STD	6.604E+02	1.383E+02	5.689E+02	1.421E+02	3.079E+02	5.091E+02	4.080E+02	1.153E+03	1.368E+00
	p-value	1.513E-05	3.511E-11	1.511E-05	4.637E-11	2.202E-08	1.062E-06	4.023E-07	2.139E-02	1.000E+00
	h	1	1	1	1	1	1	1	1	0
9	Best	4.803E+01	1.056E+02	1.516E+02	9.270E+01	1.029E+02	1.024E+02	8.158E+01	3.094E-03	0.000E+00
	Average	1.298E+01	8.073E+01	1.028E+02	8.005E+01	9.096E+01	9.352E+01	6.768E+01	6.188E-04	0.000E+00
	Worst	2.891E-01	6.865E+01	7.194E+01	6.769E+01	7.311E+01	8.465E+01	5.186E+01	1.726E-10	0.000E+00
	STD	2.014E+01	1.599E+01	3.082E+01	9.053E+00	1.104E+01	7.971E+00	1.101E+01	1.384E-03	0.000E+00
	p-value	1.877E-01	3.401E-06	7.189E-05	4.459E-08	7.754E-08	4.788E-09	7.586E-07	3.466E-01	NaN
	h	0	1	1	1	1	1	1	0	NaN
10	Best	5.707E+00	1.932E+01	2.001E+01	1.970E+01	1.791E+01	1.759E+01	1.695E+01	2.283E-03	8.882E-16
	Average	3.965E+00	1.837E+01	1.799E+01	1.472E+01	1.706E+01	1.562E+01	1.498E+01	4.922E-04	8.882E-16
	Worst	4.911E-01	1.788E+01	1.320E+01	1.129E+01	1.511E+01	1.346E+01	1.371E+01	2.897E-05	8.882E-16
	STD	2.047E+00	5.517E-01	2.768E+00	3.092E+00	1.137E+00	1.693E+00	1.433E+00	1.001E-03	0.000E+00
	p-value	2.505E-03	1.178E-12	4.933E-07	5.306E-06	6.832E-10	3.192E-08	1.194E-08	3.035E-01	NaN
	h	1	1	1	1	1	1	1	0	NaN
11	Best	1.472E+00	1.183E+02	1.314E+02	6.884E+01	9.260E+01	2.117E+02	3.951E+01	1.217E-05	0.000E+00
	Average	1.002E+00	9.434E+01	6.166E+01	4.453E+01	5.897E+01	1.833E+02	2.153E+01	4.070E-06	0.000E+00
	Worst	2.558E-01	6.229E+01	2.897E+01	2.348E+01	4.024E+01	1.289E+02	1.556E+01	2.639E-08	0.000E+00
	STD	4.560E-01	2.519E+01	4.088E+01	1.809E+01	2.118E+01	3.207E+01	1.011E+01	4.958E-06	0.000E+00
	p-value	1.174E-03	3.137E-05	9.744E-03	5.714E-04	2.522E-04	1.327E-06	1.427E-03	1.037E-01	NaN
	h	1	1	1	1	1	1	1	0	NaN
12	Best	2.617E+01	6.020E+07	1.553E+07	2.174E+07	3.453E+06	4.300E+05	1.772E+07	2.610E+00	1.128E-03
	Average	5.715E+00	1.775E+07	6.294E+06	8.160E+06	1.066E+06	1.619E+05	3.980E+06	1.720E+00	4.510E-04
	Worst	7.456E-02	6.025E+05	9.297E+05	2.239E+05	4.332E+03	1.332E+03	1.665E+01	7.763E-01	5.612E-07
	STD	1.144E+01	2.523E+07	6.038E+06	1.083E+07	1.521E+06	2.137E+05	7.703E+06	6.859E-01	4.979E-04
	p-value	2.963E-01	1.545E-01	4.811E-02	1.307E-01	1.556E-01	1.286E-01	2.813E-01	5.061E-04	1.000E+00
	h	0	0	1	0	0	0	0	1	0

TABLE 3. **(Cont.) The outcomes of 10 benchmark functions (F1–F23) using comparison approaches, with a dimension of 10.**

Function	Measure	Comparative methods								
		HHO	SSA	WOA	DA	GWO	PSO	MPA	SMA	HPDO
13	Best	1.441E+00	2.288E+08	3.792E+07	3.778E+07	2.806E+07	2.540E+07	7.817E+06	9.995E-01	1.992E-03
	Average	7.608E-01	7.414E+07	1.416E+07	2.269E+07	1.084E+07	7.506E+06	3.305E+06	7.666E-01	5.032E-04
	Worst	2.156E-01	4.773E+06	6.098E+05	5.245E+06	9.892E+05	1.703E+05	4.036E+05	1.634E-01	6.356E-05
	STD	4.744E-01	8.955E+07	1.405E+07	1.504E+07	1.188E+07	1.029E+07	2.747E+06	3.655E-01	8.362E-04
	p-value	7.148E-03	1.013E-01	5.435E-02	9.755E-03	7.559E-02	1.416E-01	2.747E-02	1.568E-03	1.000E+00
	h	1	0	0	1	0	0	1	1	0
14	Worst	7.854E+01	1.802E+02	2.123E+01	7.215E+01	2.317E+02	2.520E+01	1.737E+01	1.924E+01	5.929E+00
	Average	2.574E+01	8.234E+01	1.652E+01	2.622E+01	5.459E+01	1.110E+01	8.294E+00	1.302E+01	2.183E+00
	Best	3.331E+00	1.456E+01	1.267E+01	5.955E+00	2.368E+00	1.015E+00	3.968E+00	7.874E+00	9.980E-01
	STD	3.005E+01	8.857E+01	3.417E+00	2.634E+01	9.916E+01	8.773E+00	5.745E+00	4.046E+00	2.138E+00
	p-value	1.184E-01	7.768E-02	4.542E-05	7.631E-02	2.713E-01	5.824E-02	5.636E-02	7.309E-04	1.000E+00
	h	0	0	1	0	0	0	0	1	0
15	Worst	2.426E-02	6.797E+00	1.266E-01	1.270E-01	2.462E-01	7.455E-02	1.035E-01	1.413E-01	6.908E-04
	Average	1.216E-02	1.383E+00	5.385E-02	8.752E-02	1.119E-01	3.015E-02	4.346E-02	4.950E-02	5.031E-04
	Best	1.648E-03	4.866E-03	6.096E-03	6.711E-03	2.229E-03	5.355E-03	1.694E-03	1.572E-02	3.393E-04
	STD	8.740E-03	3.027E+00	4.989E-02	4.689E-02	1.088E-01	3.101E-02	4.107E-02	5.312E-02	1.286E-04
	p-value	1.757E-02	3.371E-01	4.379E-02	3.210E-03	5.137E-02	6.498E-02	4.750E-02	7.310E-02	1.000E+00
	h	1	0	1	1	0	0	1	0	0
16	Worst	-5.509E-03	2.960E+00	1.940E-01	-8.456E-01	-7.387E-02	-3.257E-01	-5.695E-01	-8.762E-02	-1.032E+00
	Average	-7.278E-01	2.875E-01	-5.114E-01	-9.418E-01	-8.019E-01	-7.040E-01	-8.335E-01	-6.588E-01	-1.032E+00
	Best	-1.032E+00	-9.232E-01	-1.023E+00	-1.010E+00	-1.011E+00	-9.853E-01	-1.031E+00	-1.001E+00	-1.032E+00
	STD	4.245E-01	1.600E+00	4.595E-01	8.292E-02	4.080E-01	2.913E-01	2.271E-01	4.505E-01	6.312E-07
	p-value	1.481E-01	1.025E-01	3.517E-02	4.168E-02	2.434E-01	3.610E-02	8.689E-02	1.014E-01	1.000E+00
	h	0	0	1	1	0	1	0	0	0
17	Worst	2.213E+00	1.383E+01	2.706E+00	8.522E-01	1.097E+00	3.027E+00	9.002E-01	3.423E+00	3.980E-01
	Average	9.301E-01	4.402E+00	1.317E+00	5.397E-01	5.877E-01	1.089E+00	6.914E-01	1.313E+00	3.979E-01
	Best	4.361E-01	5.070E-01	5.037E-01	4.053E-01	3.985E-01	4.163E-01	3.994E-01	4.353E-01	3.979E-01
	STD	7.550E-01	5.376E+00	8.401E-01	1.886E-01	2.887E-01	1.090E+00	1.961E-01	1.236E+00	3.193E-05
	p-value	1.537E-01	1.343E-01	4.021E-02	1.312E-01	1.797E-01	1.937E-01	1.012E-02	1.365E-01	1.000E+00
	h	0	0	1	0	0	0	1	0	0
18	Worst	3.907E+01	3.731E+02	4.158E+02	9.223E+01	9.838E+01	4.108E+01	3.841E+01	8.310E+01	3.000E+00
	Average	2.051E+01	1.096E+02	1.093E+02	2.803E+01	2.954E+01	1.808E+01	1.647E+01	4.615E+01	3.000E+00
	Best	3.547E+00	8.968E+00	3.420E+00	4.014E+00	3.175E+00	3.252E+00	3.002E+00	2.389E+01	3.000E+00
	STD	1.540E+01	1.492E+02	1.743E+02	3.785E+01	3.956E+01	1.659E+01	1.657E+01	2.302E+01	1.356E-05
	p-value	3.459E-02	1.490E-01	2.098E-01	1.775E-01	1.719E-01	7.648E-02	1.066E-01	3.036E-03	1.000E+00
	h	1	0	0	0	0	0	0	1	0
19	Worst	-2.665E+00	-2.352E+00	-2.538E+00	-2.748E+00	-2.931E+00	-2.848E+00	-2.503E+00	-2.980E+00	-3.826E+00
	Average	-3.262E+00	-3.522E+00	-3.208E+00	-3.419E+00	-3.537E+00	-3.377E+00	-3.268E+00	-3.507E+00	-3.851E+00
	Best	-3.672E+00	-3.850E+00	-3.827E+00	-3.854E+00	-3.852E+00	-3.810E+00	-3.825E+00	-3.860E+00	-3.861E+00
	STD	4.447E-01	6.565E-01	4.797E-01	5.213E-01	3.575E-01	4.198E-01	5.426E-01	4.464E-01	1.407E-02
	p-value	1.812E-02	2.960E-01	1.722E-02	1.015E-01	8.579E-02	3.566E-02	4.322E-02	1.238E-01	1.000E+00
	h	1	0	1	0	0	1	1	0	0
20	Worst	-9.865E-01	-1.259E+00	-4.019E-01	-5.542E-01	-2.246E+00	-9.801E-01	-1.620E+00	-6.600E-01	-2.851E+00
	Average	-1.599E+00	-1.926E+00	-1.431E+00	-1.471E+00	-2.646E+00	-1.744E+00	-2.635E+00	-1.345E+00	-2.988E+00
	Best	-2.226E+00	-2.249E+00	-2.571E+00	-2.483E+00	-3.111E+00	-2.476E+00	-2.965E+00	-1.890E+00	-3.198E+00
	STD	4.669E-01	4.036E-01	7.730E-01	8.561E-01	4.369E-01	6.133E-01	5.726E-01	5.282E-01	1.380E-01
	p-value	2.132E-04	5.293E-04	2.181E-03	4.467E-03	1.336E-01	2.213E-03	2.169E-01	1.482E-04	1.000E+00
	h	1	1	1	1	0	1	0	1	0
21	Worst	-4.965E-01	-1.926E-01	-5.807E-01	-8.871E-01	-9.818E-01	-4.591E-01	-8.701E-01	-5.654E-01	-4.903E+00
	Average	-9.886E-01	-1.199E+00	-1.389E+00	-1.991E+00	-1.409E+00	-9.058E-01	-1.632E+00	-1.763E+00	-5.006E+00
	Best	-1.990E+00	-4.326E+00	-3.718E+00	-3.066E+00	-1.857E+00	-1.829E+00	-3.174E+00	-6.270E+00	-5.050E+00
	STD	6.036E-01	1.754E+00	1.318E+00	9.810E-01	4.354E-01	5.379E-01	9.742E-01	2.520E+00	5.884E-02
	p-value	4.253E-07	1.274E-03	2.794E-04	1.299E-04	8.156E-08	1.494E-07	5.583E-05	2.063E-02	1.000E+00
	h	1	1	1	1	1	1	1	1	0
22	Worst	-1.804E+00	-3.707E-01	-8.711E-01	-3.123E-01	-9.655E-01	-1.066E+00	-4.677E-01	-3.737E-01	-5.058E+00
	Average	-2.981E+00	-7.045E-01	-1.891E+00	-1.000E+00	-2.571E+00	-1.426E+00	-1.326E+00	-7.981E-01	-5.071E+00
	Best	-4.199E+00	-9.835E-01	-4.927E+00	-1.459E+00	-6.741E+00	-1.896E+00	-2.618E+00	-1.759E+00	-5.087E+00
	STD	9.629E-01	2.290E-01	1.705E+00	4.803E-01	2.401E+00	3.421E-01	8.559E-01	5.636E-01	1.184E-02
	p-value	1.268E-03	1.022E-10	3.123E-03	6.234E-08	4.832E-02	1.032E-08	9.988E-06	1.491E-07	1.000E+00
	h	1	1	1	1	1	1	1	1	0
23	Worst	-5.880E-01	-5.325E-01	-3.573E-01	-5.808E-01	-9.504E-01	-1.426E+00	-9.927E-01	-5.101E-01	-4.975E+00
	Average	-2.219E+00	-7.710E-01	-1.089E+00	-1.312E+00	-2.020E+00	-2.035E+00	-1.356E+00	-1.952E+00	-5.086E+00
	Best	-4.964E+00	-9.152E-01	-1.845E+00	-3.117E+00	-3.907E+00	-2.775E+00	-1.781E+00	-5.128E+00	-5.123E+00
	STD	1.813E+00	1.486E-01	6.194E-01	1.042E+00	1.187E+00	6.047E-01	2.960E-01	2.029E+00	6.270E-02
	p-value	7.694E-03	6.777E-12	5.411E-07	4.034E-05	4.204E-04	3.568E-06	3.234E-09	8.670E-03	1.000E+00
	h	1	1	1	1	1	1	1	1	0

It is also obvious that the suggested method avoids the primary flaws listed in the original HHO method, such as the search process imbalance, by avoiding local optima and premature convergence. We came to the conclusion that the suggested HPDO clearly has the capacity to outperform the other approaches in a number of benchmark problems from CEC-2019. The major goal of this work was achieved by the presented approach, which outperformed the original method

TABLE 4. The results of the comparative methods on 10 benchmark functions (F1-F23), where the dimension is 10.

Function	Comparative methods								
	HHO	SSA	WOA	DA	GWO	PSO	MPA	SMA	HPDO
1	3	9	7	6	5	8	4	2	1
2	3	9	7	6	5	8	4	2	1
3	4	8	7	6	5	9	3	2	1
4	3	8	9	6	5	7	4	2	1
5	3	8	9	6	7	5	4	2	1
6	3	6	8	7	5	9	4	2	1
7	3	5	8	6	7	9	4	2	1
8	5	9	3	7	6	8	4	2	1
9	3	6	9	5	7	8	4	2	1
10	3	9	8	4	7	6	5	2	1
11	3	8	7	5	6	9	4	2	1
12	3	9	7	8	5	4	6	2	1
13	2	9	7	8	6	5	4	3	1
14	6	9	5	7	8	3	2	4	1
15	2	9	6	7	8	3	4	5	1
16	5	9	8	2	4	6	3	7	1
17	5	9	8	2	3	6	4	7	1
18	4	9	8	5	6	3	2	7	1
19	8	3	9	5	2	6	7	4	1
20	6	4	8	7	2	5	3	9	1
21	8	7	6	2	5	9	4	3	1
22	2	9	4	7	3	5	6	8	1
23	2	9	8	7	4	3	6	5	1
Summation	89	180	166	131	121	144	95	86	23
Mean	3.87	7.83	7.22	5.70	5.26	6.26	4.13	3.74	1.00
final Rank	3	9	8	6	5	7	4	2	1

and other cutting-edge methods in terms of its ability to solve a variety of issues. The results refute the authors' assertions; the upgraded method used a variety of search techniques to find better answers. Figure 7 explains the ultimate outcomes of the comparison techniques. The proposed method achieved improved results in terms of the execution time for all of the examined issues, as shown in the figure. The suggested HPDO places the first on the reduced execution time.

VI. REAL-WORLD APPLICATION

The HPDO algorithm in this section is implemented to solve three engineering design problems to show the algorithm's validity: The spring design issue, the pressure vessel, and the Welded beam. In addition, the power allocation problem in wireless networks is studied in subsection VI-D. The size of the population is set to 30 for the HPDO simulation and runs 20 times. The maximum number of iterations is 200. These specifics are widely known for resolving this particular issue.

A. SPRING DESIGN ISSUE

As shown in Figure 8, this task aims to reduce the weight of a spring. There are certain limitations to the minimization procedure, such as shear stress, surge frequency, and minimum deflection. The wire diameter (d), mean coil diameter (D), and number of active coils (N) are the three variables in this problem. This problem's mathematical formulation is as follows:

$$\textit{Consider}: \quad \vec{\sigma} = [\sigma_1, \sigma_2, \sigma_3] = [dDN], \tag{29}$$

$$\textit{Minimize}: \quad f(\vec{\sigma}) = (\sigma_3 + 2)\sigma_2\sigma_1^2, \tag{30}$$

$$\textit{Subject to}: \quad g_1(\vec{\sigma}) = 1 - \frac{\sigma_2^3\sigma_3}{71785\sigma_1^4} \leq 0, \tag{31}$$

$$g_2(\vec{\sigma}) = \frac{4\sigma_2^2 - \sigma_1\sigma_2}{12,566(\sigma_2\sigma_1^3 - \sigma_1^4)} + \frac{1}{5108\sigma_1^2} \leq 0, \tag{32}$$

$$g_3(\vec{\sigma}) = 1 - \frac{140.45\sigma_1}{\sigma_2^2\sigma_3} \leq 0, \tag{33}$$

$$g_4(\vec{\sigma}) = \frac{\sigma_1 + \sigma_2}{1.5} - 1 \leq 0,$$

$$\textit{Variable Range}:$$

$$0.05 \leq \sigma_1 \leq 2.00, \ 0.25 \leq \sigma_2 \leq 1.30, \tag{34}$$

and $2.00 \leq \sigma_3 \leq 15.00$.

The findings of all comparison algorithms and the suggested HPDO to address the spring design problem are shown in Table 8. The ideal parameter values are shown in Table 8, along with the top outcomes for all comparison algorithms. The best variables at σ = (d = 0.051599, D = 0.356488, N = 11.2501198) with the optimal objective's value: F(σ) = 0.0126654 show that the suggested HPDO is a better approach compared to other state-of-the-art methods by providing a more dependable solution.

B. THE PRESSURE VESSEL DESIGN ISSUE

The hemispherically capped cylindrical pressure vessel (see Figure 9) must be constructed at a low cost. The compressed air tank must be built following the American Society of Mechanical Engineers (ASME) code on boilers and pressure vessels and has an operating pressure of 3K psi and a lowest volume of 750 ft3. The sum of the welding, material, and forming charges determines the final price. As optimization factors, it was decided to include the length of the cylindrical segment of the vessel, the inner radius, the thickness of the cylinder skin, the thickness of the spherical head, and the inner radius. Only discrete values with integer multiples of 0.0625 can be used for thickness. This problem's mathematical formulation is as follows:

$$\textit{Minimize}: \quad f(\sigma) = 0.6224\sigma_1\sigma_3\sigma_4 + 1.7781\sigma_2\sigma_3^2 + 3.1661\sigma_1^2\sigma_4 + 19.84\sigma_1^2\sigma_3 \tag{35}$$

$$\textit{Subjectto}: \quad g_1(\sigma) = -\sigma_1 + 0.0193\sigma_3 \leq 0 \tag{36}$$

$$g_2(\sigma) = -\sigma_2 + 0.00954\sigma_3 \leq 0 \tag{37}$$

$$g_3(\sigma) = -\pi\sigma_3^2\sigma_4 - \frac{4}{3}\pi\sigma_3^3 + 1296000 \leq 0 \tag{38}$$

$$g_4(\sigma) = \sigma_4 - 240 \leq 0 \tag{39}$$

where:

$1 \times 0.0625 \leq \sigma_1, \sigma_2 \leq 99 \times 0.0625, \ 10 \leq \sigma_3 \leq 200 \, and \, 10 \leq \sigma_4 \leq 240$.

Table 9 demonstrate the comparative algorithms and the HPDO algorithm to solve the vessel design issue. The superior parameter values are shown in Table 9, along with

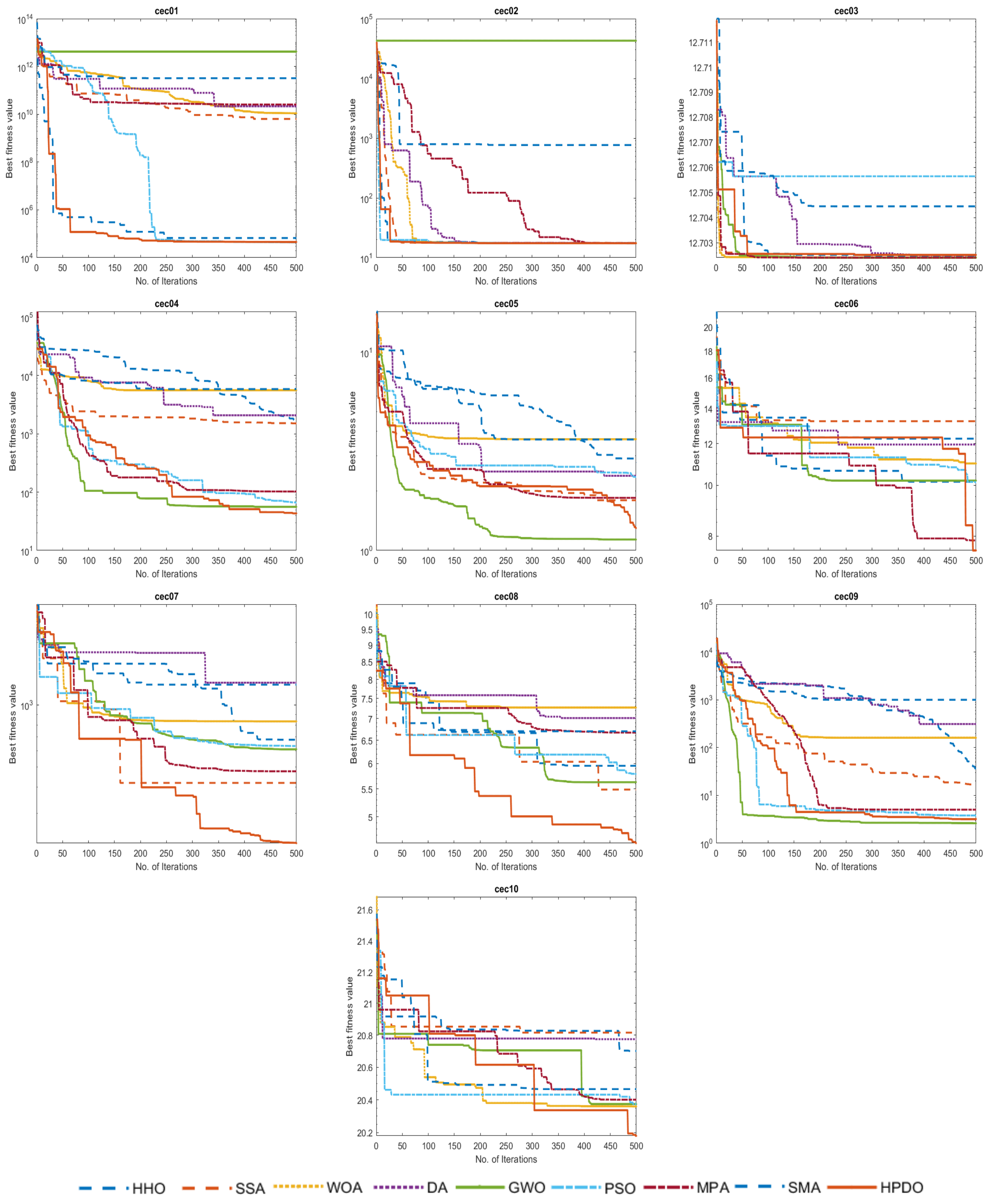

FIGURE 6. The outcomes of 10 benchmark functions (cec1 to cec10) using comparison approaches.

the top outcomes for all compared algorithms. Table 9 clarifies that the suggested HPDO is superior to other state-of-the-art methods because it provides a more dependable solution that places the ideal variables at $\sigma = (\sigma_1 = 0.8125, \sigma_2 = 0.4381, \sigma_3 = 42.098353, \sigma_4 = 176.626642)$ with the best objective's value $f(\sigma) = 6060.7245$.

TABLE 5. CEC-2019 functions.

No.	Function name	Search domain	Dim
cec1	Storn's-Chebyshev polynomial fitting problem	[–8192,8192]	9
cec2	Inverse-Hilbert matrix	[–16384,16384]	16
cec3	Lennard–Jones minimum energy cluster	[–4,4]	18
cec4	Rastrigin's	[–100,100]	10
cec5	Griewangk's	[–100,100]	10
cec6	Weierstrass	[–100,100]	10
cec7	Modified-Schwefel's	[–100,100]	10
cec8	Expanded-Schaffer's F6 function	[–100,100]	10
cec9	Happy-Cat	[–100,100]	10
cec10	Ackley	[–100,100]	10

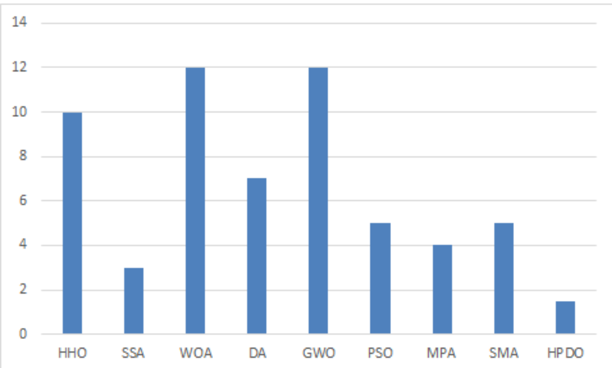

FIGURE 7. Execution time.

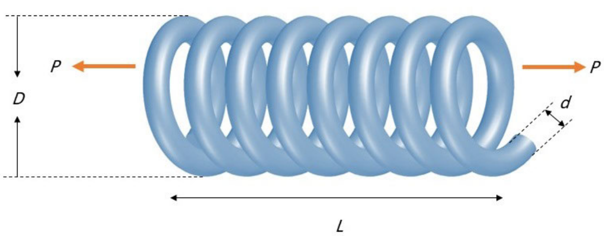

FIGURE 8. Spring design issue.

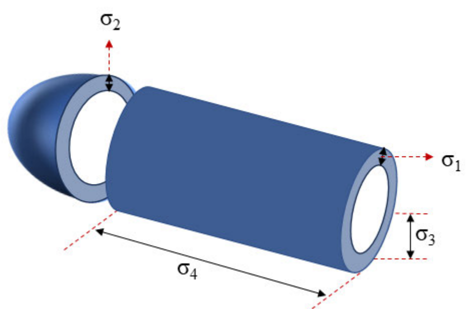

FIGURE 9. Pressure vessel design issue.

C. WELDED BEAM DESIGN ISSUE

The welded beam in Figure 10 needs to be constructed with the least amount of materials possible [46]. Low carbon steel (C-1010) is used to make the beam, which is welded to stiff support and loaded by the shear load P operating at the free tip. Design variables included:

- The width of the beam (t).
- The thickness of the beam (b).
- The thickness of the weld (h).
- The length of the welded junction (l).

H and L must have integer values that are multiples of 0.0065 in. The problem's goal function is stated as follows:

$$\text{Consider} \quad \vec{\sigma} = [\sigma_1, \sigma_2, \sigma_3, \sigma_4] = [h, l, t, b] \tag{40}$$

$$\text{Minimize} \quad f(\vec{\sigma}) = 1.10471\sigma_1^2\sigma_2 + 0.04811\sigma_3\sigma_4(14.0 + \sigma_2) \tag{41}$$

$$\text{Subject to} \quad g1(\vec{\sigma}) = \tau(\sigma) - \tau_{max} \le 0 \tag{42}$$

$$g2(\vec{\sigma}) = \lambda - \lambda_{max} \le 0 \tag{43}$$

$$g3(\vec{\sigma}) = \delta - \delta_{max} \le 0 \tag{44}$$

$$g4(\vec{\sigma}) = \sigma_1 - \sigma_4 \le 0 \le 0 \tag{45}$$

$$g5(\vec{\sigma}) = P - P_C(\vec{\sigma}) \le 0 \tag{46}$$

$$g6(\vec{\sigma}) = 0.125 - \sigma_1 \le 0 \tag{47}$$

$$g7(\vec{\sigma}) = 1.10471\sigma_1^2 + 0.04811\sigma_3\sigma_4(14 + \sigma_2) - 5 \le 0$$

Variable range

$$0.125 \le \sigma_1 \le 5,\ 0.1 \le \sigma_2,\ \sigma_3 \le 10,\ \text{and}\ 0.1 \le \sigma_4 \le 5. \tag{48}$$

where

$$\tau(\vec{\sigma}) = \sqrt{(\tau')^2 + 2\tau'\tau''\frac{\sigma_2}{2R} + (\tau'')^2},\ \tau' = \frac{P}{\sqrt{2}\sigma_1\sigma_2},$$

$$\tau' = \frac{MR}{J}, M = P\left(L + \frac{\sigma_2}{2}\right) \tag{49}$$

$$R = \sqrt{\frac{\sigma_1^2}{4} + \left(\frac{\sigma_1 + \sigma_3}{2}\right)^2}, J = 2\left\{\sqrt{2}\sigma_1\sigma_2\left[\frac{\sigma_2^2}{4} + \left(\frac{\sigma_1 + \sigma_3}{2}\right)^2\right]\right\}, \tag{50}$$

$$\sigma(\vec{\sigma}) = \frac{6PL}{E\sigma_3^2\sigma_4},\ \delta(\vec{\sigma}) = \frac{6PL^3}{E\sigma_3^2\sigma_4}, \tag{51}$$

TABLE 6. The results of the comparative methods on cec2019.

Function	Measure	Comparative methods								
		HHO	SSA	WOA	DA	GWO	PSO	MPA	SMA	HPDO
cec01	Best	2.754E+11	1.278E+14	8.732E+11	1.560E+12	3.012E+11	2.795E+05	9.913E+05	4.924E+12	8.249E+05
	Average	1.575E+11	4.308E+13	4.819E+11	7.426E+11	1.013E+11	1.889E+05	5.077E+05	1.328E+12	3.498E+05
	Worst	2.835E+10	5.719E+12	8.588E+10	7.282E+10	7.471E+09	1.170E+05	8.931E+04	8.777E+10	9.257E+04
	STD	9.753E+10	5.276E+13	2.810E+11	5.894E+11	1.221E+11	7.083E+04	3.785E+05	2.021E+12	2.824E+05
	p-value	2.320E-01	1.150E-01	3.811E-01	5.516E-01	2.126E-01	1.800E-01	1.800E-01	1.000E+00	1.800E-01
	h	0	0	0	0	0	0	0	0	0
cec02	Best	1.354E+04	3.646E+04	1.663E+03	2.226E+02	4.223E+02	1.811E+01	1.881E+01	2.590E+04	1.873E+01
	Average	5.429E+03	2.617E+04	6.043E+02	6.094E+01	2.075E+02	1.776E+01	1.833E+01	9.915E+03	1.815E+01
	Worst	6.374E+02	1.561E+04	2.039E+01	1.897E+01	3.774E+01	1.746E+01	1.776E+01	3.899E+03	1.777E+01
	STD	4.818E+03	9.490E+03	6.904E+02	9.042E+01	1.437E+02	2.693E-01	5.133E-01	9.055E+03	4.314E-01
	p-value	3.568E-01	2.422E-02	5.108E-02	4.101E-02	4.340E-02	4.032E-02	4.033E-02	1.000E+00	4.033E-02
	h	0	1	0	1	1	1	1	0	1
cec03	Best	1.271E+01	1.270E+01	1.271E+01	1.271E+01	1.270E+01	1.270E+01	1.271E+01	1.271E+01	1.271E+01
	Average	1.271E+01	1.270E+01	1.270E+01	1.270E+01	1.270E+01	1.270E+01	1.271E+01	1.271E+01	1.271E+01
	Worst	1.270E+01	1.270E+01	1.270E+01	1.270E+01	1.270E+01	1.270E+01	1.270E+01	1.271E+01	1.270E+01
	STD	1.555E-03	1.076E-03	1.189E-03	2.289E-03	8.704E-04	3.996E-04	2.156E-03	6.964E-04	1.770E-03
	p-value	1.187E-02	7.694E-05	1.169E-03	1.207E-02	2.226E-05	1.255E-06	2.060E-01	1.000E+00	4.852E-02
	h	1	1	1	1	1	1	0	0	1
cec04	Best	2.458E+04	3.501E+04	1.592E+04	1.876E+04	9.598E+03	3.533E+04	5.439E+03	5.358E+04	7.991E+03
	Average	1.398E+04	1.284E+04	8.116E+03	1.449E+04	5.772E+03	2.214E+04	3.134E+03	3.295E+04	4.260E+03
	Worst	5.214E+03	1.227E+03	4.624E+03	1.118E+04	2.406E+03	6.815E+03	1.074E+03	1.909E+04	1.901E+03
	STD	7.830E+03	1.313E+04	4.594E+03	3.063E+03	2.884E+03	1.214E+04	2.107E+03	1.475E+04	2.347E+03
	p-value	3.471E-02	5.225E-02	7.034E-03	2.544E-02	3.715E-03	2.415E-01	2.069E-03	1.000E+00	2.631E-03
	h	1	0	1	1	1	0	1	0	1
cec05	Best	8.577E+00	1.433E+01	4.608E+00	4.419E+00	4.030E+00	6.722E+00	3.547E+00	9.156E+00	3.332E+00
	Average	5.119E+00	6.224E+00	3.869E+00	4.049E+00	3.378E+00	5.127E+00	2.866E+00	6.711E+00	2.746E+00
	Worst	2.966E+00	3.547E+00	3.223E+00	3.655E+00	2.560E+00	4.538E+00	2.380E+00	4.857E+00	1.998E+00
	STD	2.131E+00	4.545E+00	5.071E-01	3.234E-01	5.554E-01	9.033E-01	4.457E-01	1.976E+00	5.484E-01
	p-value	2.556E-01	8.317E-01	1.435E-02	1.781E-02	6.682E-03	1.418E-01	2.824E-03	1.000E+00	2.535E-03
	h	0	0	1	1	1	0	1	0	1
cec06	Best	1.415E+01	1.393E+01	1.533E+01	1.380E+01	1.467E+01	1.390E+01	1.340E+01	1.280E+01	1.472E+01
	Average	1.284E+01	1.297E+01	1.395E+01	1.277E+01	1.380E+01	1.298E+01	1.303E+01	1.193E+01	1.330E+01
	Worst	1.118E+01	1.234E+01	1.274E+01	1.181E+01	1.227E+01	1.173E+01	1.271E+01	1.043E+01	1.080E+01
	STD	1.110E+00	7.064E-01	1.044E+00	7.700E-01	1.093E+00	1.066E+00	3.140E-01	1.010E+00	1.537E+00
	p-value	2.122E-01	9.551E-02	1.442E-02	1.775E-01	2.278E-02	1.471E-01	4.806E-02	1.000E+00	1.344E-01
	h	0	0	1	0	1	0	1	0	0
cec07	Best	1.717E+03	1.505E+03	1.982E+03	2.087E+03	1.633E+03	1.390E+03	8.949E+02	1.639E+03	1.133E+03
	Average	1.364E+03	9.637E+02	1.542E+03	1.804E+03	1.405E+03	1.153E+03	6.294E+02	1.080E+03	7.327E+02
	Worst	1.032E+03	3.336E+02	9.565E+02	1.652E+03	9.126E+02	7.363E+02	3.652E+02	7.951E+02	3.062E+02
	STD	3.044E+02	4.448E+02	4.105E+02	1.710E+02	2.964E+02	2.489E+02	2.246E+02	3.247E+02	3.293E+02
	p-value	1.923E-01	6.485E-01	8.377E-02	2.257E-03	1.369E-01	7.019E-01	3.393E-02	1.000E+00	1.313E-01
	h	0	0	0	1	0	0	1	0	0
cec08	Best	7.211E+00	7.338E+00	8.096E+00	8.317E+00	8.349E+00	7.653E+00	7.539E+00	8.046E+00	7.871E+00
	Average	7.054E+00	6.859E+00	7.631E+00	7.583E+00	7.537E+00	7.024E+00	7.009E+00	7.469E+00	7.082E+00
	Worst	6.759E+00	6.003E+00	7.301E+00	6.677E+00	6.406E+00	6.204E+00	6.310E+00	6.288E+00	6.751E+00
	STD	1.893E-01	5.353E-01	3.440E-01	6.283E-01	7.412E-01	5.506E-01	4.860E-01	7.231E-01	4.506E-01
	p-value	2.499E-01	1.684E-01	6.623E-01	7.959E-01	8.854E-01	3.056E-01	2.720E-01	1.000E+00	3.397E-01
	h	0	0	0	0	0	0	0	0	0
cec09	Best	4.820E+03	2.671E+03	4.372E+03	4.912E+03	2.058E+03	2.860E+03	8.349E+02	9.370E+03	1.131E+03
	Average	1.788E+03	1.884E+03	1.993E+03	2.911E+03	7.478E+02	2.102E+03	3.456E+02	4.264E+03	4.499E+02
	Worst	1.923E+02	9.021E+02	7.742E+02	1.427E+03	3.177E+01	1.435E+03	7.535E+01	1.712E+03	3.079E+01
	STD	1.786E+03	6.362E+02	1.501E+03	1.284E+03	9.208E+02	6.464E+02	2.962E+02	3.175E+03	4.490E+02
	p-value	1.670E-01	1.389E-01	1.862E-01	4.028E-01	4.464E-02	1.739E-01	2.514E-02	1.000E+00	2.880E-02
	h	0	0	0	0	1	0	1	0	1
cec10	Best	2.090E+01	2.097E+01	2.105E+01	2.095E+01	2.096E+01	2.085E+01	2.110E+01	2.100E+01	2.089E+01
	Average	2.073E+01	2.081E+01	2.098E+01	2.076E+01	2.083E+01	2.079E+01	2.084E+01	2.065E+01	2.076E+01
	Worst	2.044E+01	2.061E+01	2.083E+01	2.059E+01	2.060E+01	2.066E+01	2.056E+01	2.039E+01	2.053E+01
	STD	1.779E-01	1.773E-01	8.803E-02	1.424E-01	1.329E-01	7.935E-02	2.188E-01	2.260E-01	1.462E-01
	p-value	5.428E-01	2.349E-01	1.598E-02	3.559E-01	1.637E-01	2.015E-01	1.956E-01	1.000E+00	3.658E-01
	h	0	0	1	0	0	0	0	0	0

$$P_C(\vec{\sigma}) = \frac{4.013E\sqrt{\frac{\sigma_3^2\sigma_4^6}{36}}}{L^2}\left(1-\frac{z_3}{2L}\sqrt{\frac{E}{4G}}\right) \tag{52}$$

$$\lambda_{max} = 3000psi,\ \delta_{max} = 0.25in,\ \tau_{max} = 30,000psi. \tag{53}$$

$$E = 30\times 10^6 psi,\ G = 12\times 10^6 psi \tag{54}$$

$$L = 14in,\ P = 6000lb, \tag{55}$$

The suggested HPDO is put into practice on the welded beam issue, and the outcomes are contrasted with those of various metaheuristic methods, including MPA, DA, SSA, PSO, GWO, SMA, WOA, and HHO. The HPDO algorithm achieves superior results compared to other algorithms and reliable results with the best variables at $\sigma=$ (h=*0.25306111*, l=*1.8423029*, t=*8.27022978*, b=*0.253219*) and with the optimal cost at $f(\sigma)$=*1.725701*. This shows

TABLE 7. The results of the comparative methods on cec2019.

Function	Comparative methods								
	HHO	SSA	WOA	DA	GWO	PSO	MPA	SMA	HPDO
cec01	5	9	6	7	4	1	3	8	2
cec02	7	9	6	4	5	1	3	8	2
cec03	6	3	5	4	2	1	8	9	7
cec04	6	5	4	7	3	8	1	9	2
cec05	6	8	4	5	3	7	2	9	1
cec06	3	4	9	2	8	5	6	1	7
cec07	6	3	8	9	7	5	1	4	2
cec08	4	1	9	8	7	3	2	6	5
cec09	4	5	6	8	3	7	1	9	2
cec10	2	6	9	4	7	5	8	1	3
Sum	49	53	66	58	49	43	35	64	33
Mean	4.9	5.3	6.6	5.8	4.9	4.3	3.5	6.4	3.3
Rank	4	6	9	7	4	3	2	8	1

TABLE 8. The HPDO results for solving the spring design issue.

	Optimal results for variables			
Algorithm	d	D	N	**Best cost**
MPA	0.05173	0.357646	11.255543	0.012776
PSO	0.051155	0.349876	12.080432	0.0127706
SMA	0.05	0.316	14.22	0.0129443
GWO	0.051646	0.3554	11.407926	0.012711
DA	0.05199455	0.3641098	10.90842186	0.012686
WOA	0.0517	0.35675	11.3085	0.012686
SSA	0.05141	0.349096	11.80279	0.012682
HHO	0.05173	0.357044	11.255543	0.012673
HPDO	0.051599	0.356488	11.2501198	0.012669

TABLE 9. The HPDO results for solving the The pressure vessel design issue.

	Optimal results for variables				
Algorithm	σ_1	σ_2	σ_3	σ_4	Best cost
MPA	1.126	0.626	49.01	107.11	7979.1
PSO	1.27	0.0626	59.1603	71.7221	5845.9782
SMA	1.126	0.626	58.30016	44.68155	7287.75
GWO	0.8131	0.4381	42.098412	175.63775	6060.74
DA	0.8131	0.4381	42.091371	175.7525	6061.0801
WOA	0.8131	0.4381	42.099451	175.6416	6060.71429
SSA	1.126	0.626	55.9886601	84.4652124	8540.8361
HHO	0.8126	0.4381	42.098211	176.649889	6060.739
HPDO	0.8125	0.4381	42.098353	176.626642	6060.7245

that HPDO can successfully tackle the welded beam design issue.

D. RESOURCE ALLOCATION OF WIRELESS NETWORKS

This section illustrates the problem formulation and the system model of resource allocation in wireless networks by finding the optimal resource allocation for the highest number of users. This section also conducts the simulation results for data and convergence rates for several algorithms, such as WOA, HHO, SMA, and DA.

1) SYSTEM MODEL AND PROBLEM FORMULATION

In this work, we consider a narrowband interference-limited wireless network (IWN) with N users (as in [18]). We consider different communication links M. Let $\mathbf{P} = (P_1, P_2, \cdot, P_M)$, where P_j denotes the transmit power of the single-antenna transmitter of link j. And g_{ij} is the channel gain

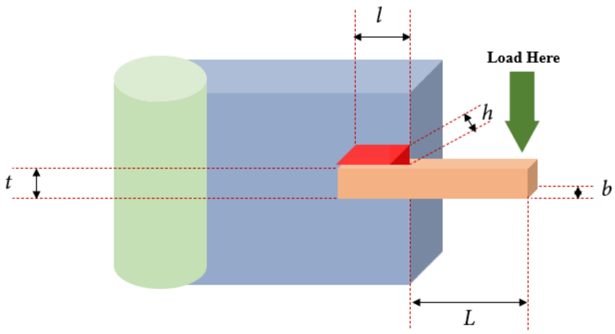

FIGURE 10. Welded beam design issue.

from the single-antenna transmitter of link j to the receiver of link i. The received signal-to-interference-plus-noise-ratio (SINR) at the receiver of link i is

$$\gamma(P) = \frac{P_i \cdot g_{ij}}{\sum_{j=1,j\neq i}^{M} P_i \cdot g_{ij} + n_i} \tag{56}$$

The power consumption P_{tot} in the wireless network can be calculated by two components: circuit power consumption p_i^c and The transmit power consumption p_i.

Thus, P_{tot} can be calculated as a following:

$$P_{tot}(p) = \sum_{i=1}^{N} (\xi_i p_i + p_i^C) \tag{57}$$

where ξ_i is a constant power-amplifier inadequacy parameter of the link i.

The EE-SE tradeoff problem is defined as maximizing global EE (GEE), subject to transmit power budgets and minimum rate specifications. Therefore, by resolving the following optimization problem, the EE-SE tradeoff can be calculated. [47]:

$$\text{max power} \quad \eta = \sum_{i=1}^{N} \frac{R_i(p)}{P_{tot}(p)} \tag{58}$$

$$C1 : R_i(\mathbf{P}) \geq r_i^{req}, \quad \forall i$$
$$C2 : 0 \leq p_i \leq p_i^{max}, \quad \forall i \tag{59}$$

where $i = 1, \ldots,$ N., And C1 represent the guarantee of minimum rate requirements r_i^{req} for each link i, C2 represents the peak power p_i^{max} and the non-negative constraints, and the η unit is bits/Joule/Hz.

The previous problem can be solved successively by successive convex (SCA) and bisection methods. The issue can be solved by using the following formula for a given value of η:

$$\text{max power} \sum_{i=1}^{N} R_i(p) - \eta P_{tot}(p) \quad \text{s.t C1 and C2.} \tag{60}$$

employing the d.c. exemplification of the objective function and ordering the constraint C1, the problem in (5) can be solved by solving regular convex optimization problem to every iteration.

TABLE 10. The HPDO results for solving the Welded beam design issue.

	Optimal results for variables				
Algorithm	h	l	t	b	Best cost
MPA	0.2491	6.18	8.1792	0.2634	2.4301
PSO	0.20683	3.470501	9.037724	0.20613	1.724902
SMA	0.245	6.2191	8.2895	0.2457	2.382
GWO	0.2441	6.2602	8.2895	0.2634	2.3839
DA	0.18113	3.856899	10.001	0.202416	1.87987
WOA	0.2512	6.2321	8.2885	0.2401	2.3797
SSA	0.230794	3.068992	8.989079	0.208805	1.723011
HHO	0.204187	3.527557	9.004333	0.206941	1.734857
HPDO	0.25306111	1.8423029	8.27022978	0.253219	1.725701

The formula for determining a user's i security rate is $\varphi_i(p) = \{maxR_i - qP_{tot}, 0\}$. The maximum secrecy rate (MMSR) can be modeled using the formulation found [48]:

$$\max \text{power} \;\; \varphi(p) = mini = 1, \ldots, M\left[R_i - qP_{(tot)}\right]$$
$$s.t \;\; 0 \leq p_i \leq p_i^{max}, \;\; \forall i = 1, \ldots, M. \tag{61}$$

At each iteration t, the total power consumption qP_{tot} and the data rate $R_i(p)$, approximated by an upper bound $q^{(t)}p_{tot}^{(t)}$ and a low bound rate $R_i^{(t)}(p)$. starting from the feasible solution $p^{(0)}$, we can solve the following convex optimization function at the t-th iteration.

$$\max \text{power} \;\; \varphi^{(t)}(p) = mini = 1, \ldots, M\varphi_i^{(t)}(p)$$
$$s.t \;\; 0 \leq p_i \leq p_i^{max}, \;\; \forall i = 1, \ldots, M. \tag{62}$$

As a result, the path-following method is used repeatedly until the stopping requirement ϵ as represented by this rule $\left[R_i^t - q^t P_{tot}^{(t)}\right] \leq \epsilon$ is met.

2) PERFORMANCE ANALYSIS

To assess the performance, we calculate the minimum secrecy throughput, which finds the optimal and minimum rate among all the users. The number of users has been varying (i.e., 20, 50, and 100), which represents the dimension for the studied algorithms.

Fig. 11 displays the convergence outcome of the proposed HPDO algorithm and the path-following process algorithm based on the number of iterations. The HPDO approach needs 25 iterations, while the path-following method only needs 15. This means that the two techniques can converge relatively quickly. However, the path-following method results in the solution of a convex problem after each iteration.

Fig. 12 compares the HPDO, WOA, and path path-following procedure algorithm performance. The result demonstrates that the HPDO provides highly competitive outcomes with minimum secrecy throughput.

According to another finding made from the convergence curves, the HPDO algorithm might exhibit nearly the same convergence pattern over the duration of iterations with every implemented set of users. The algorithm has seen extremely strategic turning points at nearly identical iteration points. After 20 iterations, it favors better optimal solutions, starting with the first iterations' average best scores.

Tables 11 through 11 show that when the dimension (number of users) is ten, the HPDO performance is slightly better than other algorithms to other algorithms, which means the HPDO can efficiently distribute the power with optimal utilization.

Moreover, the HPDO shows an outperformance when the number of users increases. For instance, when the dimension is 50 (12), HPDO performs significantly compared to other benchmark algorithms. Similarly, when we change the number of users to a higher value, as shown in Table 13, 100 users, we observe that the HPDO algorithm outperforms other algorithms with high standers deviation.

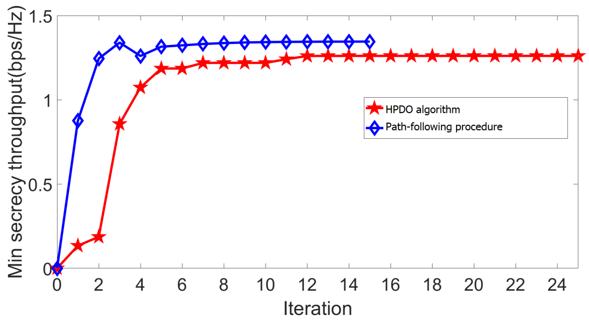

FIGURE 11. Convergence solution of the HPDO algorithm and the path-following procedure algorithm.

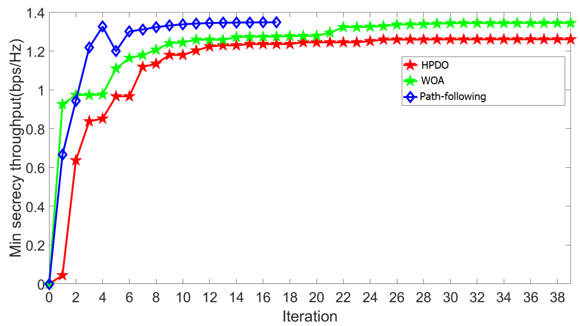

FIGURE 12. Convergence solution of the HPDO algorithm and the path-following procedure algorithm.

TABLE 11. Achieved results for 10 users.

	Comparative methods				
Measure	WOA	HHO	SMA	DA	HPDO
Worst	7.49E-01	4.49E-01	2.99E-01	1.01E+01	6.17E-05
Average	4.66E-01	6.43E-02	4.62E-01	4.12E+00	6.07E-02
Best	1.35E-01	3.00E-01	5.94E-01	6.50E+00	3.04E-01
STD	2.29E-01	2.76E-01	1.50E-01	2.59E+00	1.36E-01
Rank	4	2	3	5	1

TABLE 12. Achieved results for 50 users.

	Comparative methods				
Measure	WOA	HHO	SMA	DA	HPDO
Worst	7.41E-01	4.48E-01	2.96E-04	4.68E-01	8.29E+00
Average	5.30E-01	1.94E-02	6.98E-05	8.51E-01	7.02E+00
Best	2.99E-01	6.41E-01	6.17E-05	1.23E+00	6.59E+00
STD	2.08E-01	3.97E-01	1.37E-04	3.62E-01	2.75E+00
Rank	5	3	4	2	1

TABLE 13. Achieved results for 100 users.

	Comparative methods				
Measure	WOA	HHO	SMA	DA	HPDO
Worst	7.82E-01	6.35E-01	3.02E-01	2.99E-01	1.12E+01
Average	4.47E-01	1.05E-01	6.04E-02	6.15E-01	7.66E+00
Best	3.00E-01	3.11E-01	6.17E-05	1.25E+00	5.34E+00
STD	2.00E-01	4.42E-01	1.35E-01	3.72E-01	3.64E+00
Rank	3	4	5	2	1

Based on the results acquired by the HPDO algorithm, in statical results, mathematical benchmark functions, and the real-world example for the resource allocation in the wireless network. We can conclude that using the modified PDO algorithm by the HHO algorithm to achieve the balance between the exploration and exploitation stages can significantly enhance the performance of the basic PDO algorithm. From the accumulated results, analysis, and presented discussions in previous sections. We can conclude that the PDO and HHO algorithms could support adequate control of the stage size in converging stability and finding the optimal resource allocation using the HPDO algorithm with high number of users.

Even though the performance of the suggested HPDO is highly promising, more time overhead optimization is needed to address additional real-world application challenges that differ from all engineering difficulties. Additionally, the updating system heavily relies on the fitness value that is returned after each iteration. Because of this, a new update method for the HPDO might be considered to enhance its functionality. Because of the time overhead involved, HPDO performs poorly in parallel machine scheduling and feature extraction.

VII. CONCLUSION

Enhancing the performance of wireless networks and communication systems requires careful resource allocation. Resource allocation optimization, however, is regarded as a mixed-integer non-linear programming (MINLP) problem, which is NP-hard and non-convex. Due to the serious limitations of conventional procedures, solving such optimization problems requires specialized approaches. Heuristic algorithms, for example, cannot guarantee optimal performance, and global optimization systems, which create a standard dataset for machine learning-based techniques, suffer from exponential processing complexity and lengthy training times. As a method for global optimization, the prairie dog optimization (PDO) algorithm is enhanced in this study. By utilizing the Harris Hawks Optimization (HHO) operators, the developed technique, HPDO, can increase PDO's exploitation and search capability. The effectiveness of the proposed HPDO is investigated and analyzed using 23 benchmark functions with various dimension sizes. The experimental findings showed that the HPDO's convergence rate and exploration and exploitation search strategy had greatly improved. The power allocation issue in wireless networks is also investigated in this paper using a real-world case study. The outcomes supported the HPDO's superiority to the conventional HHO, PDO, and numerous other models using cutting-edge algorithms.

This work proposes a new optimization technique with promising outcomes in resolving different issues. For future research, the suggested algorithm might be integrated with various optimization techniques, like the Arithmetic Optimization Algorithm (AOA) or Harmony search algorithm (HS), to produce hybrid algorithms that maximize the benefits of both methodologies. For some types of engineering design issues, the performance of hybrid algorithms may even be superior. The paper proposes a potential optimization approach that can be improved and used to solve engineering issues. This work can serve as a foundation for future research to enhance the algorithm's implementation and broaden its application field.

CONFLICT OF INTERESTS

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data presented in this study are available in the article.

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