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RESEARCH ARTICLE

Hybrid Harris Hawks With Sine Cosine for Optimal Node Placement and Congestion Reduction in an Industrial Wireless Mesh Network

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ABSTRACT The optimal performance of a wireless mesh network (WMN) can be greatly improved by strategically placing wireless mesh routers. As a result, it is crucial to optimally locate the WMN routers for better coverage and connectivity. Besides the optimal placement, the network congestion due to overlaying routers has to be taken into consideration. These issues have become a motivation for researchers to identify a variety of approaches to optimize WMN performance. Multiple metaheuristic algorithms have been employed for identifying the trade-offs between coverage and connectivity in WMN. Consequently, a novel hybrid Harris Hawks optimization with the sine cosine algorithm (HHOSCA) is presented in this work to tackle the aforementioned WMN optimization problems. The proposed HHOSCA seeks optimal router placement that leads to significantly increased network coverage and achieves full connectivity between the mesh routers. In addition, the proposed HHOSCA produces a cost-effective WMN by reducing the congestion in the network to the minimum number of routers whilst ensuring maximum coverage and connectivity. The superiority of the proposed HHOSCA in comparison to the other algorithm was validated by using 33 benchmark functions. It was compared against four well-known algorithms including Sine Cosine Algorithm (SCA), Harris Hawks optimization (HHO), Gray Wolf Optimization (GWO), and Particle Swarm Optimization (PSO). These algorithms are statistically analyzed and compared to the simulated results of the proposed method. In addition, the performance of HHOSCA is compared to the state-of-the-art to highlight the efficacy of the proposed algorithm. The statistical analyses and simulation findings confirm that the HHOSCA outperforms the other algorithms in terms of network connectivity, coverage, network reduction, and convergence. The experimental results reveal that the proposed HHOSCA method achieves favourable optimization results compared with other relevant methods.

INDEX TERMS Optimal node placement, reliable wireless networks, network deployment optimization, particle swarm optimization, gray wolf optimization, Harris Hawks optimization, sine cosine optimization, industrial wireless mesh networks.

I. INTRODUCTION

In the last two decades, industrial applications have seen rapid adoption of wireless mesh networks (WMNs). From

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TABLE 1. List of abbreviations.

ANOVA	Analysis of Variance
AOA	Arithmetic Optimization Algorithm
AVOA	African vultures optimization algorithm
BA	Bat algorithm
BBO	Biogeography-based Optimization
BES	Bald eagle search
CHIO	Coronavirus herd immunity optimizer
COA	Coyote Optimization Algorithm
FA	Firefly Algorithm
GA	Genetic Algorithm
GW	Gateway
GWO	Grey Wolf Optimization
HHO	Harris Hawks Optimization
IWMN	Industrial Wireless Mesh Network
MC	Mesh Client
MFO	Moth Flame Optimizer
MR	Mesh Router
MSE	Mean Square Error
MVOA	Multi-Verse Optimizer Algorithm
NFL	No FreeLunch
ONU	Optimal Network Unit
PSO	Particle Swarm Optimization
QoS	Quality of Service
RNP	Router Node Placement
SA	Simulated Annealing
SCA	Sine Cosine Algorithm
SSA	Salp Swarm Algorithm
STDV	Standard Deviation
TS	Tabu Search
WMN	Wireless Mesh Network
WOA	Whale Optimization Algorithm

the industrial and public perspectives, IWMNs are now very important in facilitating internet access. This networking paradigm is currently in its early stages of development; nonetheless, it has some advantages over wired networks, including the ability to minimise failures through the use of a self-healing network structure and expand coverage to difficult locations [1], [2], [3]. In addition, this technology guarantees to give comparable and greater services of control than wired alternatives. First, the technology removes the restriction of expensive and burdensome wiring. Consequently, this eliminates the need to maintain cables and greatly reduces the time it takes to deploy, redeploy, install, and start up sensor nodes in the network. Second, wired network capabilities may be extended to regions that wires could not reach (i.e., dangerous environments where cables cannot be run). Another benefit of WMNs is their capacity to self-organize and sustain a vast group of battery-powered nodes [4].

In traditional networks, end-users are traditionally provided with internet access through a network of intermediate wired hotspots and nodes that are connected to the Internet. In contrast, wireless mesh networks (WMNs) are formed using a collection of wireless nodes that are able to have two-way communications with each other. Mesh routers (MRs) and Mesh clients (MCs) are the two categories of nodes that make up a wireless mesh network (WMN). These nodes collaborate to build a wireless mesh network with several hops that are connected to the internet through the usage of an internet gateway (GW). Depending on the purpose of the network, nodes may either be stationary or mobile. A middle node exists and functions as a handshake between the GW and end users. That is to forecast a path depending on the topology of a network [5], [6], [7].

In spite of the many benefits offered by WMNs, some issues are still there and require to be resolved to enhance the performance of the network. Some of these issues include coverage, connectivity, congestion, compatibility, security, etc [8]. Covering a wider outdoor area than indoor wireless networks requires the outdoor WMN to overcome the issues and difficulties that are inherent in outdoor environments, which include restricted interference source control. Since outdoor implementations might well involve fewer clients than indoor implementations in some regions [9]. Moreover, because the mesh networks could be implemented in a region that has control services than an indoor environment, identifying the most suitable position for mesh routers to be implemented for real-world applications is critical. There are many different deployment choices sufficient to fulfill the connectivity and user coverage demands in these critical environments. These environments include public transportation, natural disasters, offshore oil rigs, underground mines, combat surveillance, etc. If the Quality-of-Service (QoS) parameters are appropriately calibrated, the WMNs could be a feasible choice to support local phone calls [10].

When establishing WMNs, one must have a comprehensive understanding of a number of elements, including transmission power, network topology, and the density of wireless nodes. If wireless mesh routers were deployed without taking into account the technological limitations of the real deployment region and the topology beneath them, the consequence would be inadequate client coverage and poor network connectivity [3].

The challenge of effectively deploying WMNs might, in some respects, be understood as an issue pertaining to the location of the facilities involved [11], [12], [13], [14]. Prior research conducted over a long time period outlined and confirmed the NP-hardness of this subject [13]. Meanwhile, the theory known as ''There Is No Free Lunch'' (NFL) states that it can be difficult to deal with all different kinds of optimization challenges by using a single meta-heuristic [15]. There have been multiple works produced, each of which uses different kinds of meta-heuristic algorithms, so as to discover the mandatory network attributes within a suitable time frame and thereby facilitate the network engineer's role in the design process. The significant and original contributions of this paper are summarised below:

- A novel optimization algorithm named hybrid Harris hawks optimization with sine cosine algorithm (HHOSCA) for optimal Node placement and congestion Reduction in an industrial Wireless Mesh Network (WMN).
- Both the WMN model and thirty-three benchmark functions have been investigated to fully evaluate the performance of HHOSCA against that of other typical algorithms. Modified versions of standard optimization algorithms that use the local search improvement mechanism have been used so that all the investigated algorithms can be compared fairly.
- The optimized placement of the routers in the WMN by HHOSCA considerably enhances the connectivity and coverage, which is a significant achievement of inter-disciplinary research between wireless communication, optimization, and industrial planning.
- Furthermore, usage of HHOSCA yields less number of node placements which directly minimizes the cost reduction and also greatly improves the network congestion in WMN while comparing the other algorithms. However, the reduction in the number of nodes will not affect the performance of the HHOSCA in producing a robust WMN with full connectivity and maximum coverage.

II. LITERATURE REVIEW

In spite of the fact that meta-heuristic optimization techniques only determine the local optimum solution, they have attained broad development and success compared to other techniques. Throughout the majority of real-world scenarios, meta-heuristic techniques identify the best and most reliable network design for overcoming mesh router positioning issues.

Although a number of earlier research, such as [16] and [13] investigated the placement of wireless routers in consistent network zones, this investigation prevented the spread of mesh routers. On the other hand, some other studies took into consideration a continuous deployment region, which allows for a larger level of pliability in the positioning of mesh routers and ultimately leads to an improvement in network design. Additionally, they looked into the possibility of employing hierarchy optimization as a strategy for improving network connection and client coverage, however, this approach was shown to be inappropriate for achieving non-convex goals [17], [18], [19].

There have been a number of studies that are employing a variety of meta-heuristics to improve client coverage and network connectivity such as the studies in [13] and [20]. The work in [20] implemented a simulation system based on Hill Climbing (HC) and Simulated Annealing (SA) for solving node placement problem in WMNs. In addition, the authors in [13] employed the Tabu Search (TS) technique to find a solution for the optimal node placement problem. According to the data that was collected, the TS approach performed significantly better than the Simulated Annealing (SA) method. The Friedman test allowed authors in [21] to evaluate and contrast the performance of the simulated-annealing, hill-climbing, tabu-search, and genetic algorithm.

The PSO meta-heuristic was utilized in the process of trying to handle the problem of placing router nodes in a WMN for maximizing network connection and also the coverage of mobile client [22], [23]. Multiple aspects influencing the PSO algorithm's performance were investigated, such as the impact of various network design characteristics. According to the same authors in [22], it is anticipated that each mesh network client is assigned a digit that denotes its service priority. Lin et. al. [24] have also adopted Bat-inspired methods, with an additional variant that addresses client motion while still keeping to the same service priorities. A PSO technique for dynamic WMNs that incorporates social cognition was also proposed by [23]. Then, the wireless mesh network-router node placement (WMN-RNP) was implemented as a combined objective function in a dynamical configuration. The problem of service priority in wireless mesh networks (WMNs) was solved by the research effort presented in [17]. The researchers used a simulated annealing approach that incorporated momentum requirements. An electromagnetism-like algorithm was developed by [25] in order to maximise network connectivity and client coverage.

On the optimal placement of relay nodes in fiber-wireless networks, Singh and Prakash [26] used an approach called the Whale Optimization Algorithm (WOA) to position a large number of Optical Network Units (ONUs) in the best possible manner, following a various dispersion of ONUs and mesh routers. Both the Moth Flame Optimization (MFO) and the Greedy methods were tested in order to make a comparison with the findings of their research. In the research carried out by Gupta and Jha, a biogeography-based optimization (BBO) algorithm was used to optimise the position of sensor devices. This was done in order to guarantee that the sensor network would satisfy the requirements of both the k-coverage and the m-connectivity [27].

In addition, Nitesh and Jana presented a location technique for relay nodes in [28]. The strategy that they suggested in their work ensured that there would be k-coverage of the sensing region and s-connectivity between the relays, respectively. Their technique made use of fewer relay nodes so that the network's costs may be reduced to the maximum possible extent. It was attained by reducing the amount of coverage overlapping that existed between the relays. The authors of the work in [29] made use of an algorithm known as the moth flame optimizer (MFO) to determine the best places for situating the nodes. The main goal was to make sure that every part of the network was linked. The heuristic of a completely connected network was utilised by the suggested method so as to assess the network's connectivity. Table 2 summarizes

TABLE 2. Recent studies on router placement in WMN.

Ref. Year	Algorithm	Optimization issue	Advantages	Drawbacks
[13] 2015	TS	Client coverage and network connectivity	- Providing a solution for routers placement issues in WMNs using TS approach. - Implementing several memory forms to avoid repeating the visited solutions in the search region	- The method focused on increasing connectivity however the user coverage was poor.
[23] 2016	PSO	Client coverage and network connectivity	- Involving social community behavior as a dynamic adaptation - Enhancing network connectivity - Enlarging network coverage in social circumstances	- The mesh routers are restricted to cover a limited number of clients - The article lacks a cost function that helps to relocate free routers to support the busy routers
[30] 2020	SA	Network cost and client coverage	- Proposal of a new SA-based Centre of mass (SAC) - Faster convergence as compared to conventional SA - Enhancing the network quality and performance	- The work has not addressed the connectivity of the network. - The obstacles in harsh environments have not been considered.
[31] 2021	PSO	Client coverage and network connectivity	- Developing Accelerated PSO (APSO) - Reducing complexity while increasing efficiency as compared to LDWPSO	- The work has significantly improved the connectivity while the coverage is still unsolved. - The validation was done with one algorithm which might not be enough to demonstrate its superiority
[16] 2022	MVOA	Client coverage and network connectivity	- Identifying new criteria for network assessment by considering the active clients to routers ratio - Increasing connectivity and reducing path losses when compared to PSO, WOA, and GA	- Quality of transmission and the quality of service (QoS) have not been addressed in this work. - The coverage of the network has not been optimally resolved.
[32] 2022	COA	Client coverage and network connectivity	- Implementing COA to tackle the deployment issue of routers - Comparing the COA with various algorithms in solving the optimization issue	This work has not yet considered the connectivity to the gateway of mesh routers.
[3] 2022	HHO	Client coverage and network connectivity	- A novel implementation of HHO in a WMN - Increasing the coverage and connectivity of the network. - Performing various statistical analyses to showcase the enhancement	The work didn't include a cost function to reduce the network's congestion.

some of the recent studies that are concerned with the mesh router placement problem in WMNs.

In the same context, the work in [3] conducted a novel implementation of the HHO algorithm to optimally identify mesh routers in a wireless mesh network to enhance connectivity and coverage of three network configurations and the simulation results and statistical analyses demonstrated that the HHO algorithm outperforms the compared algorithms. Although the effective performance of the HHO algorithm has been verified in past work, the original HHO may still have problems with early convergence and getting stuck in the local best solution. Therefore, scholars from a variety of disciplines have successfully developed many new modified and hybrid algorithms to address flaws in the original algorithm.

One of the efficient optimization algorithms that are used to address the drawback of the HHO algorithm is referred to as the sine cosine algorithm (SCA) which was recently developed by Seyedali Mirjalili in 2016, [33]. This approach utilizes the arithmetic equations of sine and cosine to randomly obtain the solutions of the global optima. Specific qualities such as rapid convergence speed, great global searchability, excellent optimization precision, and minimal tuning parameters all contribute to the SCA's advantages when applied to an optimization issue. The SCA has been utilised successfully in the solving of optimization issues in a variety of fields, including image processing [34], power system engineering [35], machine learning [36], networking, and other fields [37]. SCA was also hybridized with arithmetic optimization algorithm (AOA) as presented in [38].

On this basis, a novel hybrid approach termed Harris hawk optimization and sine cosine algorithm (HHOSCA) is developed in this study. Fundamentally, the developed (HHOSCA) algorithm incorporates the SCA into HHO to take advantage of both SCA and HHO features to improve the accuracy of convergence, speed, location, and exploration. The hybrid algorithm is mainly proposed to identify the optimal locations to place mesh routers that lead to full network connectivity and signifying client coverage. In addition, a cost function is proposed to perform the congestion reduction required and hence produce a cost-effective IWMN.

III. METHODOLOGY

This section explains the method that was utilised in the process of optimising the coverage and connectivity of the wireless network and the network congestion reduction, as well as the underlying operating concept of the hybrid optimization strategy and the system model. This work is primarily focused on developing a hybrid Harris Hawks optimization-Sine Cosine Algorithm (HHOSCA) technique in order to minimize network congestion and massively maximise the coverage and connectivity of a wireless mesh network (WMN). The proposed fitness function, the system assumption, and the problem formulation are all topics that are covered in the next subsections under the system model of this study.

A. HYBRID HHO-SCA OPTIMIZATION METHOD

Although HHO and SCA possess remarkable excellence, certain shortcomings, such as premature convergence and local optimum trapping, must yet be addressed. Consequently, the developed approach called hybrid HHO-SCA (HHOSCA) is presented with the incorporation of HHO and SCA. Furthermore, it is anticipated to enhance convergence behaviour and solution quality. In addition, the implementation of a hybrid method will lead to producing a search that is more adequate, since it will jump greatly and at regular intervals within the search region in an effort to escape the local optima. Therefore, this will result in producing more varied solutions.

Fig. 1 illustrates the proposed HHOSCA hierarchical form, where the bottom layer, i.e. SCA, updates the individuals that are produced by the HHO at the top layer. There are M HHO search agents at the top layer that correspond to the bottom layer's M number of groups, and every group in the bottom layer consists of N SCA population. The execution of the SCA on the bottom layer is the initial step in the process of updating the new positions. Consequently, each agent in the top layer retains the optimal solution found by its associated group in the bottom layer. Thereafter, according to the acquired optimal solution, the HHO individuals' positions are updated in the top layer. Therefore, new equations representing the phases of exploitation and exploration are produced.

The exploration phase of the HHOSCA is performed by the following arithmetic equation.

$$Y_{t+1}^{i}=\begin{cases} y_{\text{rand}}-r_2\left|y_{\text{rand}}-2r_2\left[y_t+r_8\sin\left(r_9\right)\times\right.\right. \\ \left.\left.\left|r_{10}p_i^t-y_t\right|\right]\right|, \quad c\geq 0.5\&r_{11}<0.5 \\ y_{\text{rand}}-r_2\left|y_{\text{rand}}-2r_2\left[y_t+r_8\cos\left(r_9\right)\times\right.\right. \\ \left.\left.\left|r_{10}{p_i}^t-y_t\right|\right]\right|, \quad c\geq 0.5\&r_{11}\geq 0.5 \\ y_{\text{prey}}-y_m-r_3\left[lb_t+r_4\left[ub_t-lb_t\right]\right], \quad c<0.5 \end{cases} \tag{1}$$

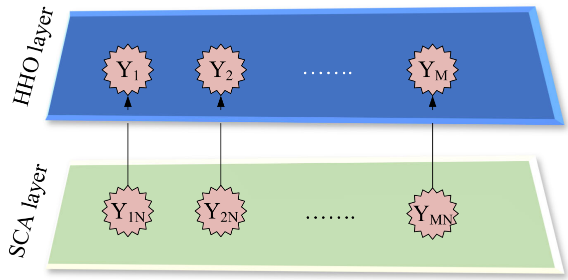


FIGURE 1. Proposed HHOSCA hierarchical form.

where Y_{t+1}^{i} denotes the location of t -th individual in the top layer that corresponds to the i -th search element in the bottom layer. y_t describes the location of t -th top layer's search agent. The current iteration number is denoted by t. $y_{prey}=p_i^t$ which represents the best position obtained up to the current iteration. r_2, r_3, r_4, r_{11} and c are random variables. y_m, lb, and ub denote the population average mean, lower bound, and upper bound, respectively.

$$\begin{aligned} r_8 &= 2-t\left(\frac{2}{T}\right) \\ r_9 &= 2\pi\cdot rand() \\ r_{10} &= 2\cdot rand() \end{aligned} \tag{2}$$

The exploitation phase is performed by the aforementioned besieging strategies and the modifications in terms of the formulas are as follows:

- **Tough besiege**: Hawks apply this strategy to prey that has low energy to escape the hunt and this is referred to by $r\geq 0.5$ and $E<0.5$. The proposed hybrid method performs this strategy as in the following formula

$$Y_{t+1}^{i}=\begin{cases} y_{\text{prey}}-E\left|y_{\text{prey}}-2r_2\left[y_t+r_8\sin\left(r_9\right)\times\right.\right. \\ \left.\left.\left|r_{10}p_i^t-y_t\right|\right]\right|, \quad r_{11}<0.5 \\ y_{\text{prey}}-E\left|y_{\text{prey}}-2r_2\left[y_t+r_8\cos\left(r_9\right)\times\right.\right. \\ \left.\left.\left|r_{10}p_i^t-y_t\right|\right]\right|, \quad r_{11}\geq 0.5 \end{cases} \tag{3}$$

$$E=2E_0\left(1-\frac{t}{T}\right),\quad t=\{1,2,3,\ldots,T\} \tag{4}$$

- **Tough besiege with progressive fast dives**: when there occurs a depletion of the prey's energy, this kind of besiege is established i.e., $r<0.5$ and $E<0.5$.

$$Y_{t+1}^{i}=\begin{cases} Z \ \text{ if } \ F(Z)<F\left(y_t\right)\& \\ y_t=\begin{cases} y_t+r_8\sin\left(r_9\right)\times\left|r_{10}p_i^t-y_t\right|, r_{11}<0.5 \\ y_t+r_8\cos\left(r_9\right)\times\left|r_{10}p_i^t-y_t\right|, \ r_{11}\geq 0.5 \end{cases} \\ X \ \textit{if} \ F(X)<F\left(y_t\right)\& \\ y_t=\begin{cases} y_t+r_8\sin\left(r_9\right)\times\left|r_{10}p_i^t-y_t\right|, r_{11}<0.5 \\ y_t+r_8\cos\left(r_9\right)\times\left|r_{10}p_i^t-y_t\right|, \ r_{11}\geq 0.5 \end{cases} \end{cases} \tag{5}$$

where

$$\begin{aligned} Z &= X+S\times LF(D) \\ X &= y_{\text{prey}}-E\left|Jy_{\text{prey}}-y_m\right| \\ S &= \text{Random vector of } 1\times D \end{aligned}$$

$$J = 2(1 - r_7)$$
$$r_7 = \text{Random variable}$$
$$D = \text{Dimension} \tag{6}$$
$$LF(D) = \frac{\beta \times u}{|v|^{\frac{1}{\sigma}}} \times 0.01 \tag{7}$$
$$\beta = \left(\frac{\sin\left(\frac{\pi\sigma}{2}\right) \times \Gamma(1+\sigma)}{\Gamma\left(\frac{1+\sigma}{2}\right) \times \sigma \times 2^{\left(\frac{\sigma-1}{2}\right)}} \right) \tag{8}$$

- **Mild beseige**: this strategy is performed by hawks when $r \geq 0.5$ and $E \geq 0.5$

$$Y_{t+1}^{i} = \begin{cases} y_{\text{prey}} - \left[y_t + r_8 \sin(r_9) \times \left|r_{10} p_i^t - y_t\right|\right] - E\left|y_{\text{prey}} - 2r_2\left[y_t + r_8 \sin(r_9) \times \left|r_{10} p_i^t - y_t\right|\right]\right|, \ r_{11} < 0.5 \\ y_{\text{prey}} - \left[y_t + r_8 \cos(r_9) \times \left|r_{10} p_i^t - y_t\right|\right] - E\left|y_{\text{prey}} - 2r_2\left[y_t + r_8 \cos(r_9) \times \left|r_{10} p_i^t - y_t\right|\right]\right|, \ r_{11} \geq 0.5 \end{cases} \tag{9}$$

- **Mild besiege with progressive fast dives**: during this phase, the prey has adequate energy $E \geq 0.5$ to flee the hunt, but the hawk creates a mild besiege $r < 0.5$.

$$Y_{t+1}^{i} = \begin{cases} Z \ \text{ if } \ F(Z) < F(y_t) \& y_t = \\ \begin{cases} y_t + r_8 \sin(r_9) \times \left|r_{10} p_i^t - y_t\right|, r_{11} < 0.5 \\ y_t + r_8 \cos(r_9) \times \left|r_{10} p_i^t - y_t\right|, \ r_{11} \geq 0.5 \end{cases} \\ X \ \textit{if} \ F(X) < F(y_t) \& y_t = \\ \begin{cases} y_t + r_8 \sin(r_9) \times \left|r_{10} p_i^t - y_t\right|, r_{11} < 0.5 \\ y_t + r_8 \cos(r_9) \times \left|r_{10} p_i^t - y_t\right|, \ r_{11} \geq 0.5 \end{cases} \end{cases} \tag{10}$$

where

$$Z = X + S \times LF(D)$$
$$X = y_{\text{prey}} - E\left|J y_{\text{prey}} - y_t\right|$$

B. PSEUDO-CODE OF HYBRID HHO-SCA METHOD

The hybrid HHO-SCA implements two top layer phases including exploration and exploitation. The bottom layer role comes at the time of updating the current location of the optimization iteration. Table 3 outlines the conditions for switching between exploration and exploitation phases. It is worth noting that the exploitation phase is implemented with four different strategies. The flowchart for implementing the proposed HHOSCA method is described in Algorithm Fig. 2

Moreover, the hybrid HHO-SCA has been translated into a pseudo-code that can be easily comprehended. The principle of the HHOSCA optimization technique with respect to the WMN optimization issue is shown in Algorithm 1

C. SYSTEM MODEL

This subsection mainly focuses on the implementation of the proposed HHOSCA approach to tackle the issue of optimal placement of WMN routers. It is worth mentioning that the

Algorithm 1 Hybrid Harris Hawk's Optimization - Sine Cosine Algorithm (HHOSCA)

Input: Randomly positioned mesh routers in a wireless mesh network with foreknown mesh clients' positions.
Output: The fully connected WMN with maximum clients' coverage

Initiate the random positions of the mesh routersy_i^0(i= 1, 2, 3, …, N)

Initiate the search iterations t= 1 and T = maximum iterations
while ($t \leq$ T) **do**
  Obtain the initial solution y_{prey} using the proposed fitness function
  for (every hawks (y_i)) **do**
    Update the position of mesh routers MR
    Use (4) to update the E
    EXPLORATION
    Top layer condition
    if $|E| \geq 1$ **then**
      Bottom layer condition
      if $r_{11} < 0.5$ **then**
        Use (1) case 1 to update the solution
      else if $r_{11} \geq 0.5$ **then**
        Use (1) case 2 to update the solution
      end if
    end if
    EXPLOITATION
    Top layer condition
    if $|E| < 1$ **then**
      if ($|E| < 0.5$ and r < 0.5) **then**
        Bottom layer condition
        if $r_{11} < 0.5$ **then**
          Use (5) case 11 or 21 to update the solution
          $r_{11} \geq 0.5$
          Use (5) case 21 or 22 to update the solution
        end if
        Top layer condition
      else if ($|E| < 0.5$ and r ≥ 0.5) **then**
        Bottom layer condition
        if $r_{11} < 0.5$ **then**
          Use (3) case 1 to update the solution
        else if $r_{11} \geq 0.5$ **then**
          Use (3) case 2 to update the solution
        end if
        Top layer condition
      else if ($|E| \geq 0.5$ & r ≥ 0.5) **then**
        Bottom layer condition
        if $r_{11} < 0.5$ **then**
          Use (9) case 1 to update the solution
        else if $r_{11} \geq 0.5$ **then**
          Use (9) case 2 to update the solution

TABLE 3. List of HHOSCA conditions and various operational phases.

Phase category	Strategy	Top layer Condition	Bottom layer condition	Related expression
Exploration		$\|E\|\geq$ & c≥0.5	r_{11}<0.5	Bottom layer exploration Case 1 of (1)
		$\|E\|\geq$ & c≥0.5 1	r_{11}≥0.5	Bottom layer exploitation Case 2 of (1)
		$\|E\|\geq$ & c<0.5		Default top layer Cases 3 of (1)
Exploitation	Tough besiege	$\|E\|$<1 & $\|E\|$<0.5 &r≥0.5	r_{11} < 0.5	Bottom layer exploration Case 1 of (3)
		$\|E\|$<1 & $\|E\|$<0.5 & r≥0.5	r_{11}≥0.5	Bottom layer exploitation Case 2 of (3)
	Mild Besiege	$\|E\|$<1 & $\|E\|$≥0.5 & r≥0.5	r_{11}<0.5	Bottom layer exploration Case 1 of (9)
		$\|E\|$<1 & $\|E\|$≥0.5 & r≥0.5	r_{11}≥0.5	Bottom layer exploitation case 2 of (9)
	Tough besiege with progressive fast dives	$\|E\|$<1 & $\|E\|$<0.5 & r <0.5	r_{11}<0.5	Bottom layer exploration Case 11 or case 21 of (5)
		$\|E\|$<1 & $\|E\|$<0.5 & r<0.5	r_{11}≥0.5	Bottom layer exploitation case 12 or case 22 of (5)
	Mild besiege with progressive fast dives	$\|E\|$<1 & $\|E\|$≥0.5 & r<0.5	r_{11}<0.5	Bottom layer exploration case 11 or case 21 of (10)
		$\|E\|$<1 & $\|E\|$≥0.5 & r<0.5	r_{11}≥0.5	Bottom layer exploitation case 12 or case 22 of (10)

Algorithm 2 Hybrid Harris Hawk's Optimization - Sine Cosine Algorithm (HHOSCA) (Cont.)

end if
Top layer condition
else if ($|E| \geq 0.5$ & r < 0.5) **then**
Bottom layer condition
if $r_{11} < 0.5$ **then**
Use (10) case 11 or 21 to update the solution
else if $r_{11} \geq 0.5$ **then**
Use (10) case 21 or 22 to update the solution
end if
end if
end if
end for
t=t+1
end while
Return Y_{prey} representing the optimum WMN topology with full routers connectivity and maximum clients coverage

proposed HHOSCA is compared against other well-known metaheuristic algorithms including HHO, SCA, GWO, and PSO. The effectiveness of the proposed method as well as the benchmark algorithms were tested using MATLAB software. Moreover, the client's original positions were generated using the Atarraya simulator [39], which are involved as the results are analyzed.

1) SYSTEM ASSUMPTIONS

In reality, the process of locating mesh routers can be very difficult with no prior planning. Therefore, it is a crucial task to determine the best location for deploying the mesh routers. In addition, telling the number of required routers to provide full coverage and connectivity is also a hard task. In Table 4, there are some notations of the network model which is investigated in this work. It is assumed that the mesh clients are stationary, and their locations are predefined. The importance of this assumption lies in the fact that the positions of the mesh routers are installed in the industrial environment depending on the mesh clients' distribution. Nevertheless, there is still a computational complexity to resolving the WMN-RNP issue by utilizing a rapid precise approach. The following assumptions are made that is to address the mesh routers' placement in a wireless mesh network:

- The mesh clients are stationary in 2D area,
- The transmission range for every router in the network is equal,
- The connectivity between the routers is determined based on the transmission range.

2) PROBLEM MODEL FORMULATION

Locating $P = \{P(x_1, y_1), P(x_2, y_2), \ldots, P(x_n, y_n)\}$ of an n set of routers in an optimal manner is the main focus of this work. This is done so to improve the coverage and connectivity within the WMN. On the other hand, the congestion reduction of mesh routers in the WMN is also another task to be optimized in this work.

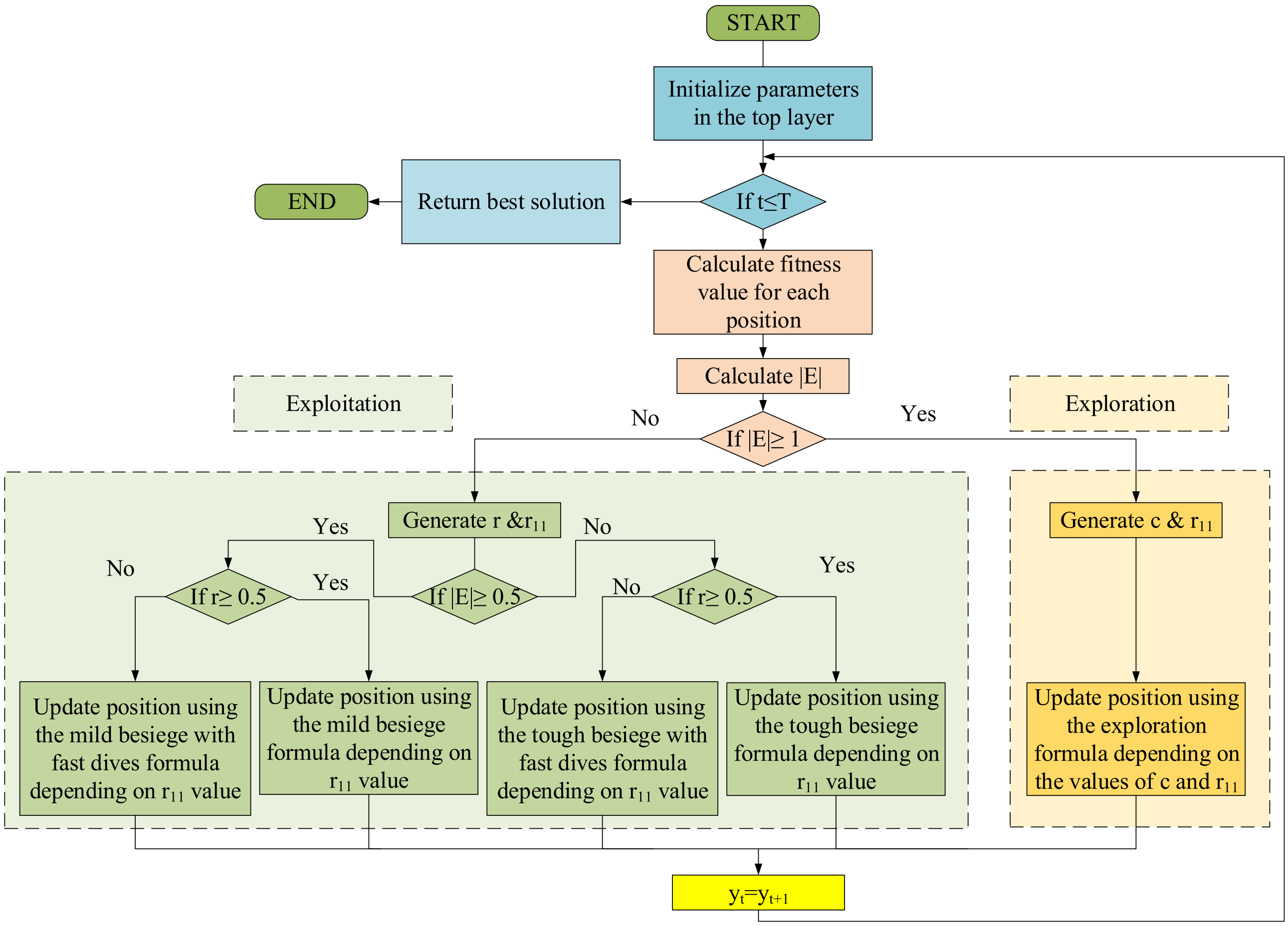


FIGURE 2. **Proposed HHOSCA optimization flowchart.**

The coverage in the WMN is measured by the size of clients that fall within the covered regions by the mesh routers. On the other hand, the connectivity is measured by summing up the number of adjacent mesh routers that form the largest subgraph through having contact in their transmission range. These two main factors indicate the quality of service (QoS) in a WMN. However, it is worth mentioning that a high rate of coverage doesn't necessarily mean that the connectivity is high, i.e, these two factors are incompatible.

Consider a network with a two dimensional W x H area in which C mesh clients and R mesh routers are distributed. Each client $c_i \in$ C is located at P$(x_i, y_i) \in \mathbb{P}^2$ of the deployment area.

The optimal placement of mesh routers is determined by the position of mesh clients and denoted by $P = \{P(x_1, y_1), P(x_2, y_2), P(x_3, y_3), \ldots, P(x_n, y_n)\}$. Nondirected graph of topology $\mathbb{G}$ = (E, R) emerges for any mesh routers' placement such that:

- When the transmission range of two mesh routers intersects,
- If a mesh client is within a router's range of transmission, the client is said to be covered.

It is important to keep in mind that a graph $\mathbb{G}$ might not be completely connected, i.e. the graph might be composed of several different subgraphs. The connectivity of the WMN could be improved by making the largest subgraph component of the network as large as it possibly can be. A network is said to be fully connected if all mesh routers have a linkage between them.

Assume there are l subgraph components G_1,G_2,..., G_q in $\mathbb{G}$ i.e., $\mathbb{G} = G_1 \bigcup G_2 \bigcup G_l$, and $G_i \cap G_q = \emptyset$; for $i, q \in$ 1,2,...,l.

The client coverage is formulated as:

$$\alpha(G) = \sum_{q=0}^{c} \delta_q \tag{11}$$

where

$$\delta_i = \begin{cases} 1 \text{ if the client q is covered by a router} \\ 0 \text{ Otherwise} \end{cases}$$

The largest subgraph that is used to measure the connectivity in a WMN is given by the following expression:

$$\theta(G) = \max_{q \in \{1,\ldots,h\}} \left|G_q\right| \tag{12}$$

TABLE 4. Model formulation variables definitions.

Symbol	Meaning
$Stdv$	Standard Deviation
Y_t	The t-th particle
δ_i	The coverage of ith client
l	No. of subgraphs component
$\theta(G)$	Network's connectivity
$\alpha(G)$	Client's coverage
MC_i	Mesh client i
$\|G_i\|$	i-th subgraph size
G_i	i-th subgraph component
E	Mesh router edge
MR_i	Mesh router i
c_i	The i-the client
C	Set of clients
r_i	The i-th router
W	Area width
H	Area height
R	Set of routers
$P(x_i, y_i)$	Node location
$\mathbb{G}$	WMN graph
n	No. of mesh routers
m	No. of mesh clients
P	Mesh router placement vector

3) THE FITNESS FUNCTION

The primary goal of this novel proposed HHOSCA is to optimize the WMN and therefore, to maximize the network coverage and connectivity with minimum utilization of mesh routers that is to reduce network congestion. The client coverage $\alpha(G)$ is given by (11). In addition, for the purpose of creating the fitness function, the connectivity factor between the routers is considered and denoted as $\theta(G)$ and given by (12). Therefore, the weighted sum method is used, which turns a multi-objective problem into a single-objective problem by adding up each goal and multiplying it by a weight set by the user. Then, the fitness function F_t is given as in the following expression (13):

$$F_t = \zeta \cdot \left(1 - \frac{\theta(G)}{n}\right) + (1-\zeta) \cdot \left(1 - \frac{\alpha(G)}{m}\right) \tag{13}$$

where m is the mesh clients count, n is the mesh routers count and $0 < \zeta < 1$ represents a weighting coefficient for each objective relative rank. For the equation to be normalised, the denominator should be used in each part of the equation. The minimum value should try to reach the global minima of the fitness function which is ideally zero.

4) THE CRITERIA OF STATISTICAL EVALUATION

The following standard metrics are utilised in the process of evaluating and testing the algorithms in line with the fitness function (13):

1) The mean value of the average fitness value is calculated after R runs of the algorithm are completed, which is given as:

$$\text{Mean} = \frac{\sum_{t=1}^{R} (f_t)}{R} \tag{14}$$

2) Standard deviation (stdv.) calculates the difference between the fitness values obtained by executing the algorithm multiple times (i.e., R times). Notably, the algorithm's capacity to converge to a similar value every time represents its ability to produce a small standard derivation value, proving that it is stable and resilient. The occurrence of big numbers suggests that the algorithm produces inconsistent results. The definition of the standard deviation is as follows:

$$Stdv = \sqrt{\frac{1}{R-1} \Sigma_{t=1}^{R} (f_t - \text{Mean})^2} \tag{15}$$

3) The minimum final fitness value among each run's fitness values is defined as the best value and given as:

$$\text{Best} = \min_{1 \le t \le R} f_t \tag{16}$$

4) The biggest value of fitness obtained during optimization in R runs is considered as the worst value and is given as:

$$\text{Worst} = \max_{1 \le t \le R} f_t \tag{17}$$

where f_t is the run's (R) best value of fitness.

5) COST FUNCTION

It is well-known all companies and factories always aspire to spend the least possible value when installing equipment and devices. This helps them reduce installation costs and makes them look forward to any possible solutions that lead to the lowest possible installation cost. The same is the case in wireless networks, where it is preferable to install wireless routers to the fullest extent and at the lowest costs. If there is a way to install as few wireless routers as possible to cover the largest possible area, it will be the best way. Sometimes the connection and coverage ratio of a network is very high, but there are a number of mesh routers that are very close and overlaying, where some of them can be removed, and this will not affect the connection or coverage ratio. From this point of view, we had to come up with a function that reduces the cost and rearranges the wireless devices in a way that maintains the level of connectivity and coverage. The cost function is represented by the formula given in (18)

$$\check{C} = \mathbb{R} - \sum_{i=1}^{\mathbb{R}} (\gamma_i + \varnothing_i), \quad \gamma_i \neq \varnothing_i \tag{18}$$

TABLE 5. Setting of parameters.

Algorithm	Parameter	Value
HHOSCA	Convergence constant a	2
	default constant β	1.5
	escaping energy r	[0 1]
	initial energy E_0	[-1 1]
GWO	Convergence constant a	[2 0]
PSO	Factor of inertia	0.3
	c_1	1
	c_2	1
SCA	Convergence constant a	2
HHO	default constant β	1.5
	escaping energy r	[0 1]
	initial energy E_0	[-1 1]

$$\gamma = \begin{cases} 1 & d \geq x \\ 0 & d < x \end{cases} \tag{19}$$

$$\varnothing = \begin{cases} 1 & \text{if the mesh router has no task} \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

$$x = \sqrt{(r_{x1} - r_{x2})^2 + \left(r_{y1} - r_{y2}\right)^2} \tag{21}$$

where $\mathbb{R}$ is the total number of mesh routers, d is the desired distance set by the user, γ overlaying router, $\varnothing$ non-task router and x is the Euclidean distance between any two routers.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL CONFIGURATION SETUP

All algorithms including PSO, GWO, SCA, HHO, and the proposed HHOSCA were implemented under MATLAB 2022a on a PC that uses Windows 11 environment, Intel(R) Core(TM) i7-8700, RAM 32GB, and clocked at 3.20 GHz. All optimizers have swarm sizes and maximum iterations set to 30 and 500, respectively. Then a comparison is performed based on the recorded results of the optimizers' average performance across 30 separate runs.

The parameters' settings of PSO, GWO, SCA, and HHO are similar to the settings that were recommended by the original works. Table 5 also shows a list of these parameters.

B. VALIDATION OF THE PROPOSED HHOSCA

The efficacy of the proposed HHOSCA algorithm is investigated by doing Multiple experiments and comparing it with four well-known algorithms. Thirty-three different benchmark functions are used to analyze the robustness and viability of the proposed hybrid method. Initially, the plots of those functions are presented and followed by the statistical analysis and convergence study. The statistical test known as Friedman is utilised to validate the rank of the proposed approach as compared to other algorithms. In addition, the proposed method is used to optimize the WMN in order to improve its performance metrics.

1) BENCHMARK FUNCTIONS

The selection of various benchmark functions for the validation depends on multiple local minimal, multiple dimensions, ranges, and limits bounding. These functions are provided in Table 6. The categories including multimodal, unimodal, and hybrid systems are used to classify the benchmark functions. The exploitation accuracy of the algorithm is evaluated based on functions (F1 through F6), which are unimodal functions. Simultaneously, the multimodal functions have several local minima that are used to evaluate the algorithm's capacity to reach the final global optima without getting local minima entrapment,i.e, to avoid getting trapped in one position (i.e., exploration). The multimodal functions (F7 through F10) have varying dimensions, whereas the multimodal functions (F11 to F18) have fixed dimensions; together, these functions will evaluate the stability of the algorithm. On the other hand, the hybrid functions (F19 through F33) are used to evaluate the algorithm's capability of identifying the space search for both global and local minima, in addition to the next position movement.

In addition, Fig. 3 presents the benchmark functions' surface plots. These plots have a variety of shapes, each of which is differentiated by the functions that it performs. The various available shapes include egg holder-shaped, valley, plate, cone, and bowel functions in multiple and single dimensions with multiple and single local minimum values. The search agents and the maximum number of iterations that are assigned during the simulation are constant at 30 and 500, respectively. Other additional parameters of the optimization are assigned as follows: $\epsilon = 2.2204 \times 10^{-16}$, $\mu = 0.499$, $\alpha = 5$, min $= 0.2$ and max $= 1.0$.

2) BENCHMARK FUNCTIONS NUMERICAL ANALYSIS

This part discusses the numerical comparison of the proposed HHOSCA approach with other algorithms including HHO, SCA, GWO, and PSO. Table 7 shows the statistical results including mean, worst, best, and standard deviation of all the competing algorithms for every different benchmark function.

The performance of all the algorithms is evaluated by measuring how close the statistical data are to the global minima for the tested benchmark function. When compared to all of the other algorithms, the proposed HHOSCA has the performance indices that are the lowest. It is important to note that the smallest mean value suggests that HHOSCA can generally discover a better optimum with a smaller fitness function, while the lowest standard deviation (Stdv) means the maximum convergence stability and reliability. Herein, HHOSCA has the capability of successfully avoiding a local optimum. The statistical results that are tabulated in Table 7 confirm the above statement that the proposed hybrid HHO-SCA algorithm outperforms the other algorithm on different unimodal functions. Among the competing algorithms, HHO and SCA are the close competitors who nearly reached the global optima in all the statistical comparisons. In contrast,

TABLE 6. List of utilized benchmark functions.

Func.	Range	Description
F1	[-100,100]	$F(\mathbf{x})=\sum_{i=1}^{n} x_i^2$
F2	[-10,10]	$F(\mathbf{x})=\sum_{i=0}^{n}\lvert x_i\rvert+\prod_{i=0}^{n}\lvert x_i\rvert$
F3	[-100,100]	$F(\mathbf{x})=\sum_{i=1}^{d}\left(\sum_{j=1}^{i} x_j\right)^2$
F4	[-30,30]	$F(\mathbf{x})=\sum_{i=1}^{n-1}\left[100\left(x_i^2-x_{i+1}\right)^2+\left(1-x_i\right)^2\right]$
F5	[-100,100]	$F(\mathbf{x})=\sum_{i=1}^{n}\left(\left[x_i+0.5\right]\right)^2$
F6	[-128,128]	$F(\mathbf{x})=\sum_{i=0}^{n} i x_i^4+\operatorname{random}(0,1)$
F7	[-500,500]	$F(\mathbf{x})=\sum_{i=1}^{n}\left(-x_i \sin\left(\sqrt{\lvert x_i\rvert}\right)\right)$
F8	[-32,32]	$F(\mathbf{x})=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos\left(2\pi x_i\right)\right)+20+e$
F9	[-50,50]	$F(\mathbf{x})=\frac{\pi}{n}\left\{10\sin\left(\pi y_1\right)\right\}+\sum_{i=1}^{n-1}\left(y_i-1\right)^2\left[1+10\sin^2\left(\pi y_{i+1}\right)+\sum_{i=1}^{n}u\left(x_i,10,100,4\right)\right],$ where, $y_i=1+\frac{x_i+1}{4}, u\left(x_i,a,k,m\right)\begin{cases}K\left(x_i-a\right)^m & \text{if } x_i>a\\ 0 & -a\leq x_i\geq a\\ K\left(-x_i-a\right)^m & -a\leq x_i\end{cases}$
F10	[-50,50]	$F(\mathbf{x})=0.1\left(\sin^2\left(3\pi x_1\right)+\sum_{i=1}^{n}\left(x_i-1\right)^2\left[1+\sin^2\left(3\pi x_i+\quad 1\right)\ \right]+\left(x_n-1\right)^2 1+\sin^2\left(2\pi x_n\right)\right)+\sum_{i=1}^{n}u\left(x_i,5,100,4\right)$
F11	[-65,65]	$F(\mathbf{x})=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}}\left(x_i-a_{ij}\right)\right)^{-1}$
F12	[-5,5]	$F(\mathbf{x})=\sum_{i=1}^{11}\left[a_i-\frac{x_1\left(b_i^2+b_i x_2\right)}{b_i^2+b_i x_3+x_4}\right]^2$
F13	[-5,5]	$F(\mathbf{x})=4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$
F14	[-5,5]	$F(\mathbf{x})=\left(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6\right)^2+10\left(1-\frac{1}{8\pi}\right)\cos x_1+10$
F15	[-4,5]	$f(\mathbf{x})=\sum_{i=1}^{d/4}\left(x_{4i-3}+10x_{4i-2}\right)^2+5\left(x_{4i-1}-x_{4i}\right)^2+\quad\left(x_{4i-2}-2x_{4i-1}\right)^4+10\left(x_{4i-3}-x_{4i}\right)^4$
F16	[-1,2]	$F(\mathbf{x})=-\sum_{i=1}^{4}c_i\exp\left(-\sum_{i=1}^{3}a_{ij}\left(x_j-p_{ij}\right)^2\right)$
F17	[0,1]	$F(\mathbf{x})=-\sum_{i=1}^{4}c_i\exp\left(-\sum_{i=1}^{6}a_{ij}\left(x_j-p_{ij}\right)^2\right)$
F18	[0,1]	$F(\mathbf{x})=-\sum_{i=1}^{5}\left[\left(X-a_i\right)\left(X-a_i\right)^T+c_i\right]^{-1}$
F19	[-512,512]	$F(\mathbf{x})=-\left(x_2+47\right)\sin(\sqrt{\lvert x_2+\frac{x_1}{2}+47\rvert})-\quad x_1\sin(\sqrt{\lvert x_1-\left(x_2+47\right)\rvert})$
F20	[-10,10]	$F(\mathbf{x})=-\left\lvert\sin\left(x_1\right)\cos\left(x_2\right)\exp\left(\left\lvert 1-\frac{\sqrt{x_1^2+x_2^2}}{\pi}\right\rvert\right)\right\rvert$
F21	[-5.12,5.12]	$F(\mathbf{x})=\left(\sum_{i=1}^{5}i\cos\left(\left(i+1\right)x_1+i\right)\right)\left(\sum_{i=1}^{5}i\cos\left(\left(i+1\right)x_2+i\right)\right)$
F22	[1.5,4]	$F(\mathbf{x})=\sin\left(x_1+x_2\right)+\left(x_1-x_2\right)^2-1.5x_1+2.5x_2+1$
F23	[3,3]	$F(\mathbf{x})=\left(4-2.1x_1^2+\frac{x_1^4}{3}\right)x_1^2+x_1x_2+\left(-4+4x_2^2\right)x_2^2$
F24	[-100,100]	$F(\mathbf{x})=-\cos\left(x_1\right)\cos\left(x_2\right)\exp\left(-\left(x_1-\pi\right)^2-\left(x_2-\pi\right)^2\right)$
F25	[-5,10]	$F(\mathbf{x})=a\left(x_2-bx_1^2+cx_1-r\right)^2+s(1-t)\cos\left(x_1\right)+s$
F26	[-2,2]	$F(\mathbf{x})=[1+\left(x_1+x_2+1\right)^2(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)]\times[30+\left(2x_1-3x_2\right)^2 (18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$

TABLE 6. ***(Continued.)*** **List of utilized benchmark functions.**

F27	[-5,5]	$F(\mathbf{x})=\frac{1}{2}\sum_{i=1}^{d}\left(x_i^4-16x_i^2+5x_i\right)$
F28	[-10,10]	$F(\mathbf{x})=\sin^2(\pi w_1)+\sum_{i=1}^{d-1}(w_i-1)^2[1+10\sin^2(\pi w_i+1)]+\quad(w_d-1)^2[1+\sin^2(2\pi w_d)]$, where , $w_i=1+\frac{x_i-1}{4}$, for all $i=1,\ldots,d$
F29	[-10,10]	$F(\mathbf{x})=100\left(x_1^2-x_2\right)^2+(x_1-1)^2+(x_3-1)^2+90\left(x_3^2-x_4\right)^2+10.1\left((x_2-1)^2+(x_4-1)^2\right)+19.8\left(x_2-1\right)\left(x_4-1\right)$
F30	[0,1]	$F(\mathbf{x})=-\sum_{i=1}^{4}\alpha_i\exp\left(-\sum_{j=1}^{3}A_{ij}\left(x_j-P_{ij}\right)^2\right)$, where, $\alpha=(1.0,1.2,3.0,3.2)^T$ $\mathbf{A}=\begin{pmatrix}3.0&10&30\\0.1&10&35\\3.0&10&30\\0.1&10&35\end{pmatrix}\mathbf{P}=10^{-4}\begin{pmatrix}3689&1170&2673\\4699&4387&7470\\1091&8732&5547\\381&5743&8828\end{pmatrix}$
F31	[0,10]	$F(\mathbf{x})=-\sum_{i=1}^{m}\left(\sum_{j=1}^{4}(x_j-C_{ji})^2+\beta_i\right)^{-1}$, where, $m=10;\beta=\frac{1}{10}(1,2,2,4,4,6,3,7,5,5)^T$ $\mathbf{C}=\begin{pmatrix}4.0&1.0&8.0&6.0&3.0&2.0&5.0&8.0&6.0&7.0\\4.0&1.0&8.0&6.0&7.0&9.0&3.0&1.0&2.0&3.6\\4.0&1.0&8.0&6.0&3.0&2.0&5.0&8.0&6.0&7.0\\4.0&1.0&8.0&6.0&7.0&9.0&3.0&1.0&2.0&3.6\end{pmatrix}$
F32		$F(\mathbf{x})=-\sum_{i=1}^{4}\alpha_i\exp\left(-\sum_{j=1}^{6}A_{ij}\left(x_j-P_{ij}\right)^2\right)$, where, $\alpha=(1.0,1.2,3.0,3.2)^T$ $\mathbf{A}=\begin{pmatrix}10&3&17&3.50&1.7&8\\0.05&10&17&0.1&8&14\\3&3.5&1.7&10&17&8\\17&8&0.05&10&0.1&14\end{pmatrix},\mathbf{P}=10^{-4}\begin{pmatrix}1312&1696&5569&124&8283&5886\\2329&4135&8307&3736&1004&9991\\2348&1451&3522&2883&3047&6650\\4047&8828&8732&5743&1091&381\end{pmatrix}$
F33	[0,π]	$F(\mathbf{x})=-\sum_{i=1}^{d}\sin\left(x_i\right)\sin^{2m}\left(\frac{ix_i^2}{\pi}\right)$

the PSO has shown poor response by evaluating the statistical parameters obtained. On the other hand, the GWO algorithm showed an unstable response where it performed better in some functions and showed a performance degradation in other unimodal functions. These results show the improvement in the accuracy of the exploration phase of the proposed hybrid HHO-SCA algorithm. In analysing different multimodal functions, the developed HHOSCA exhibited extraordinary exploratory ability by moving between local minimum values without becoming entrapped. Similarly, the proposed HHOSCA is at the forefront of most hybrid benchmark functions due to its superior ability to find the optimal value. Most functions with non-zero or numerous local minima have the optimal solution discovered in the early stage of HHO or HHOSCA's search.

An exception is made here where by observing Table 7, the HHOSCA has the lowest mean value when tackling the Goldstein-Price function (F26), however, the best value obtained has reached the global minima. This is due to the fact that the Goldstein-Price function has several global minima solutions that the proposed hybrid method tries to acquire every run. Furthermore, Table 8 presents the test of Friedman ranking for the metaheuristic approaches used for comparison in this simulation. The order of the algorithms is determined by which one has come up with the best mean value for the respective functions. For example, rank 1 indicates the value that is closest to the global minimum, and rank 5 indicates the value that is farthest from the global minima. The proposed HHOSCA achieved the minimum mean value of 1.247 which indicates its superiority in achieving the ranking's top, followed by HHO, SCA, GWO, and PSO. This confirms that the proposed hybrid method has significantly improved the search capability and consistency of the existing techniques.

3) THE BENCHMARK FUNCTIONS ANALYSIS OF CONVERGENCE

The benchmark functions are independently tested with 300 iterations each for the analysis of convergence. In this context, "convergence" refers to the first instance in which an algorithm locates a minimal fitness value in the maximal iterations that have been scheduled. In the presence of several distinct kinds of algorithms, the convergence plottings of the benchmark functions are depicted in Fig. 4. In benchmark functions under the unimodal category, the proposed

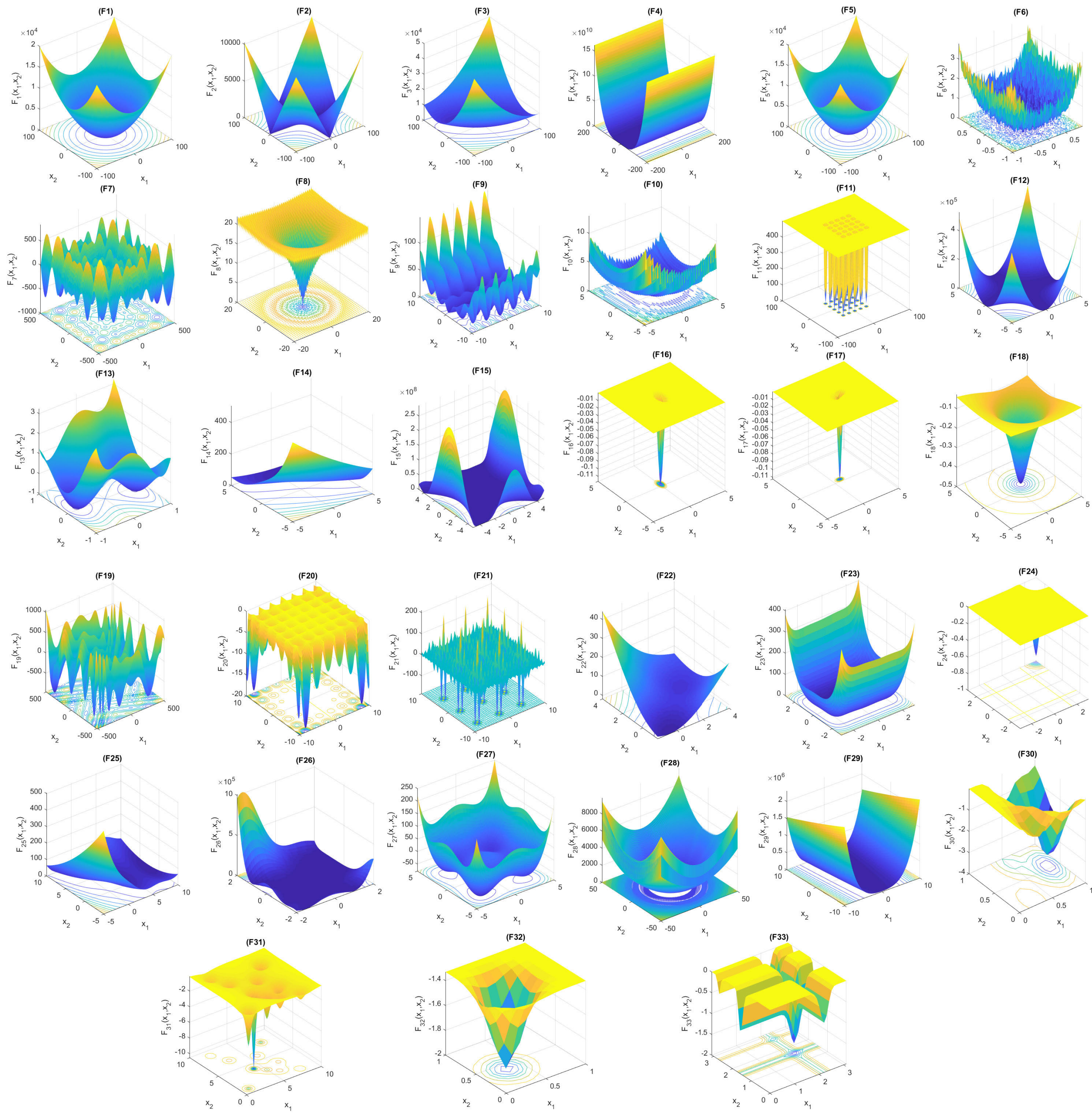


FIGURE 3. **Plots of the search space for benchmark functions.**

HHOSCA undertook a broad search, which spread out the solutions it found and led to further iterations. However, it shows a significant improvement in obtaining the global minima as compared to the other algorithms. Evaluating this tremendous performance from the Friedman ranking method, the proposed hybrid algorithm achieved the first rank by having the best mean speculating the global minima. It is worth mentioning that the second competitors of the proposed HHOSCA (i.e. HHO and SCA) were the closest in the Friedman ranking. In contrast, the GWO showed a less effective performance in the unimodal functions. In the same context, PSO has recorded the worst performance by having a huge difference between the obtained value and the target global minima.

In the multi-dimension multimodal functions (F7 to F10), the proposed HHOSCA approach has the most stable convergence of the five algorithms because it finds a good balance between exploiting and exploring. GWO, PSO, and

TABLE 7. Statistical comparison of the proposed HHOSCA with other algorithms.

Function	Global Minima	Statistical Parameter	GWO	HHO	SCA	PSO	HHOSCA
F1	0	Mean	4.657E-69	1.880E-97	5.381E-71	4.357E+04	5.042E-149
		Best	1.611E-74	9.477E-112	6.231E-83	2.867E+04	5.177E-163
		Worst	2.276E-68	1.879E-96	3.622E-70	5.375E+04	4.127E-148
		Stdv	8.393E-69	5.943E-97	1.215E-70	7.196E+03	1.289E-148
F2	0	Mean	1.361E-42	1.349E-48	4.136E-36	2.767E+08	8.858E-78
		Best	1.575E-44	9.895E-56	4.102E-46	1.202E+03	6.924E-85
		Worst	6.289E-42	1.301E-47	2.637E-35	2.753E+09	6.494E-77
		Stdv	2.145E-42	4.100E-48	9.123E-36	8.702E+08	1.996E-77
F3	0	Mean	6.605E-07	1.173E-64	6.646E-34	5.682E+04	1.631E-77
		Best	9.866E-15	7.048E-92	3.188E-59	4.071E+04	2.209E-110
		Worst	3.050E-06	1.173E-63	4.274E-33	1.163E+05	1.631E-76
		Stdv	1.264E-06	3.709E-64	1.470E-33	2.210E+04	5.158E-77
F4	0	Mean	2.879E+01	1.240E-02	2.390E-01	1.075E+08	1.318E-03
		Best	2.876E+01	1.644E-04	7.199E-03	8.365E+07	7.026E-11
		Worst	2.881E+01	5.497E-02	1.832E+00	1.733E+08	6.318E-03
		Stdv	2.092E-02	2.095E-02	5.615E-01	3.305E+07	2.596E-03
F5	0	Mean	1.976E+00	9.990E-05	1.711E-02	4.444E+04	2.639E-05
		Best	1.413E+00	9.130E-06	2.148E-04	3.268E+04	2.689E-09
		Worst	2.591E+00	4.023E-04	1.004E-01	5.475E+04	1.308E-04
		Stdv	4.398E-01	1.236E-04	3.167E-02	6.578E+03	4.929E-05
F6	0	Mean	3.135E-04	1.441E-04	1.543E-04	5.146E+01	1.511E-04
		Best	6.901E-05	1.501E-05	3.508E-06	2.345E+01	1.478E-06
		Worst	9.032E-04	2.537E-04	6.111E-04	6.378E+01	5.662E-04
		Stdv	2.856E-04	7.478E-05	1.930E-04	1.133E+01	1.586E-04
F7	-418.9829	Mean	1.434E-01	-1.257E+04	-3.882E+02	-2.216E+03	-1.257E+04
		Best	5.528E-04	-1.257E+04	-1.914E+03	-3.500E+03	-1.257E+04
		Worst	9.171E-01	-1.256E+04	6.770E-01	-1.196E+03	-1.257E+04
		Stdv	2.823E-01	2.067E+00	6.194E+02	7.031E+02	8.119E-03
F8	0	Mean	5.507E-15	8.882E-16	8.882E-16	1.978E+01	8.882E-16
		Best	4.441E-15	8.882E-16	8.882E-16	1.920E+01	8.882E-16
		Worst	7.994E-15	8.882E-16	8.882E-16	2.023E+01	8.882E-16
		Stdv	1.716E-15	0.000E+00	0.000E+00	3.427E-01	0.000E+00
F9	0	Mean	1.378E-01	6.533E-06	2.248E-04	2.301E+08	4.151E-06
		Best	4.730E-02	2.340E-07	1.120E-05	8.552E+07	1.080E-10
		Worst	2.225E-01	1.671E-05	7.573E-04	3.940E+08	1.958E-05
		Stdv	4.653E-02	5.980E-06	2.811E-04	1.038E+08	7.661E-06
F10	0	Mean	9.061E-01	1.509E-04	7.421E-03	4.464E+08	1.134E-05
		Best	4.036E-01	6.090E-06	1.111E-05	3.209E+08	1.676E-09
		Worst	1.378E+00	6.247E-04	4.846E-02	6.799E+08	5.213E-05
		Stdv	3.080E-01	1.906E-04	1.473E-02	1.076E+08	1.880E-05
F11	0	Mean	5.224E+00	1.197E+00	1.196E+00	3.370E+00	9.980E-01
		Best	1.000E+00	9.980E-01	9.980E-01	1.003E+00	9.980E-01
		Worst	1.082E+01	1.992E+00	2.982E+00	6.254E+00	9.980E-01
		Stdv	4.091E+00	4.191E-01	6.274E-01	2.040E+00	1.585E-07
F12	0.0003	Mean	1.424E-03	3.693E-04	7.144E-04	2.005E-02	3.463E-04
		Best	4.527E-04	3.182E-04	3.393E-04	7.997E-03	3.081E-04
		Worst	3.793E-03	4.457E-04	2.252E-03	4.189E-02	3.998E-04
		Stdv	1.090E-03	3.976E-05	6.879E-04	1.148E-02	3.435E-05
F13	-1.0316	Mean	9.235E-06	-1.032E+00	7.213E-44	-2.753E-01	-1.032E+00
		Best	7.646E-64	-1.032E+00	7.780E-102	-9.865E-01	-1.032E+00
		Worst	4.681E-05	-1.032E+00	7.213E-43	1.955E-02	-1.032E+00
		Stdv	1.590E-05	1.101E-09	2.281E-43	3.641E-01	6.531E-08

TABLE 7. *(Continued.)* Statistical comparison of the proposed HHOSCA with other algorithms.

F14	0.398	Mean	4.005E-01	3.979E-01	3.991E-01	4.396E-01	3.979E-01
		Best	3.979E-01	3.979E-01	3.979E-01	3.985E-01	3.979E-01
		Worst	4.091E-01	3.979E-01	4.085E-01	5.146E-01	3.979E-01
		Stdv	4.507E-03	7.750E-08	3.303E-03	4.054E-02	4.897E-06
F15	3	Mean	6.421E+00	3.000E+00	3.002E+00	3.437E+01	8.400E+00
		Best	3.000E+00	3.000E+00	3.000E+00	3.058E+00	3.000E+00
		Worst	3.155E+01	3.000E+00	3.007E+00	1.109E+02	3.000E+01
		Stdv	8.905E+00	8.866E-08	2.438E-03	3.681E+01	1.138E+01
F16	-3.86	Mean	-3.861E+00	-3.861E+00	-1.552E+00	-3.310E+00	-3.859E+00
		Best	-3.863E+00	-3.863E+00	-2.884E+00	-3.825E+00	-3.863E+00
		Worst	-3.855E+00	-3.856E+00	-3.836E-03	-2.211E+00	-3.852E+00
		Stdv	3.194E-03	2.095E-03	1.151E+00	4.631E-01	4.091E-03
F17	-3.26	Mean	-3.231E+00	-3.117E+00	-1.354E-01	-1.450E+00	-3.142E+00
		Best	-3.322E+00	-3.318E+00	-6.785E-01	-2.453E+00	-3.286E+00
		Worst	-3.087E+00	-2.828E+00	-1.225E-03	-8.219E-01	-3.000E+00
		Stdv	1.001E-01	1.224E-01	2.097E-01	5.180E-01	8.069E-02
F18	-10.1532	Mean	-9.646E+00	-5.513E+00	-1.554E-01	-4.013E-01	-1.015E+01
		Best	-1.015E+01	-9.686E+00	-3.660E-01	-5.497E-01	-1.015E+01
		Worst	-5.100E+00	-5.038E+00	-1.019E-01	-3.122E-01	-1.015E+01
		Stdv	1.597E+00	1.466E+00	8.174E-02	7.504E-02	2.352E-03
F19	-959.6407	Mean	4.220E-03	-9.052E+02	-1.900E+02	-6.254E+02	-9.472E+02
		Best	1.476E-05	-9.596E+02	-5.776E+02	-9.078E+02	-9.596E+02
		Worst	2.606E-02	-7.531E+02	2.164E-02	-2.487E+02	-9.353E+02
		Stdv	8.339E-03	7.422E+01	2.090E+02	2.193E+02	1.255E+01
F20	-19.2085	Mean	-1.92E+01	-1.921E+01	-2.424E+00	-1.283E+01	-1.921E+01
		Best	-1.92E+01	-1.921E+01	-5.221E+00	-1.810E+01	-1.921E+01
		Worst	-1.92E+01	-1.921E+01	-4.563E-02	-7.402E+00	-1.921E+01
		Stdv	3.27E-05	1.555E-13	1.943E+00	3.709E+00	6.372E-06
F21	-186.7309	Mean	2.478E-04	-1.867E+02	-1.206E+01	-8.636E+01	-1.867E+02
		Best	4.006E-06	-1.867E+02	-4.780E+01	-1.803E+02	-1.867E+02
		Worst	6.505E-04	-1.867E+02	1.361E-04	-3.101E+01	-1.866E+02
		Stdv	1.973E-04	6.539E-05	1.622E+01	5.247E+01	2.988E-02
F22	-1.9133	Mean	1.024E-05	-1.913E+00	1.802E-04	-1.088E+00	-1.913E+00
		Best	4.058E-09	-1.913E+00	1.956E-05	-1.858E+00	-1.913E+00
		Worst	4.269E-05	-1.913E+00	7.055E-04	4.274E-01	-1.913E+00
		Stdv	1.294E-05	4.681E-16	2.209E-04	8.264E-01	3.656E-08
F23	-1.0316	Mean	1.505E-06	-1.032E+00	2.820E-22	-5.441E-01	-1.032E+00
		Best	9.629E-79	-1.032E+00	1.299E-104	-1.017E+00	-1.032E+00
		Worst	8.547E-06	-1.032E+00	2.820E-21	1.980E-03	-1.032E+00
		Stdv	2.856E-06	3.894E-10	8.918E-22	3.717E-01	1.802E-08
F24	-1	Mean	0.000E+00	-1.000E+00	0.000E+00	-3.164E-21	-1.000E+00
		Best	0.000E+00	-1.000E+00	0.000E+00	-3.156E-20	-1.000E+00
		Worst	0.000E+00	-9.999E-01	0.000E+00	0.000E+00	-9.999E-01
		Stdv	0.000E+00	1.954E-05	0.000E+00	9.977E-21	2.215E-05
F25	0.3978	Mean	3.997E-01	3.979E-01	3.983E-01	4.876E-01	3.979E-01
		Best	3.979E-01	3.979E-01	3.979E-01	4.248E-01	3.979E-01
		Worst	4.139E-01	3.979E-01	4.002E-01	6.443E-01	3.979E-01
		Stdv	5.003E-03	2.469E-06	6.811E-04	6.607E-02	1.301E-05
F26	3	Mean	3.075E+00	3.000E+00	3.001E+00	4.248E+00	1.110E+01
		Best	3.000E+00	3.000E+00	3.000E+00	3.065E+00	3.000E+00
		Worst	3.457E+00	3.000E+00	3.004E+00	1.094E+01	3.002E+01
		Stdv	1.466E-01	4.128E-06	1.270E-03	2.365E+00	1.305E+01

TABLE 7. *(Continued.)* **Statistical comparison of the proposed HHOSCA with other algorithms.**

F27	-39.1659	Mean	4.454E-04	-7.833E+01	-2.670E+01	-6.531E+01	-7.833E+01
		Best	1.850E-07	-7.833E+01	-5.714E+01	-7.751E+01	-7.833E+01
		Worst	4.015E-03	-7.833E+01	1.033E-05	-5.452E+01	-7.833E+01
		Stdv	1.258E-03	2.887E-05	2.393E+01	6.979E+00	2.231E-04
F28	0	Mean	6.518E-02	1.021E-05	1.343E-03	2.979E-01	4.499E-06
		Best	3.407E-04	1.182E-09	1.599E-05	1.192E-01	9.692E-10
		Worst	2.083E-01	4.277E-05	5.961E-03	9.142E-01	2.874E-05
		Stdv	6.540E-02	1.738E-05	1.903E-03	2.391E-01	8.944E-06
F29	0	Mean	3.353E+00	4.578E-04	1.947E-03	4.836E+02	2.126E-05
		Best	1.703E-01	2.774E-06	2.260E-05	3.024E+00	4.725E-08
		Worst	9.430E+00	2.194E-03	1.208E-02	1.476E+03	8.266E-05
		Stdv	3.124E+00	7.057E-04	3.667E-03	5.583E+02	3.055E-05
F30	-3.8627	Mean	-3.861E+00	-3.859E+00	-1.033E+00	-3.415E+00	-3.858E+00
		Best	-3.863E+00	-3.863E+00	-3.466E+00	-3.774E+00	-3.863E+00
		Worst	-3.855E+00	-3.854E+00	-6.459E-04	-3.033E+00	-3.846E+00
		Stdv	2.729E-03	3.549E-03	1.246E+00	3.181E-01	5.916E-03
F31	-10.536	Mean	-1.032E+00	-9.994E+00	-5.635E+00	-2.950E-01	-1.053E+01
		Best	-1.868E+00	-1.054E+01	-1.022E+01	-6.576E-01	-1.054E+01
		Worst	-5.934E-01	-5.128E+00	-5.119E+00	-1.647E-01	-1.051E+01
		Stdv	4.553E-01	1.710E+00	1.612E+00	1.476E-01	8.783E-03
F32	-3.3223	Mean	-2.02E+00	-2.91E+00	-2.86E+00	-1.49E+00	-2.999E+00
		Best	-2.35E+00	-3.01E+00	-2.96E+00	-2.07E+00	-3.042E+00
		Worst	-1.77E+00	-2.82E+00	-2.73E+00	-1.33E+00	-2.927E+00
		Stdv	1.88E-01	5.75E-02	6.00E-02	2.24E-01	4.040E-02
F33	-9.6601	Mean	-7.376E+00	-5.807E+00	-1.373E+00	-2.961E+00	-5.905E+00
		Best	-9.292E+00	-6.762E+00	-3.080E+00	-3.835E+00	-7.046E+00
		Worst	-6.701E+00	-4.831E+00	-6.319E-01	-2.128E+00	-4.882E+00
		Stdv	7.810E-01	6.064E-01	8.567E-01	5.560E-01	6.983E-01

TABLE 8. **Friedman ranking of the proposed HHOSCA with the other algorithms.**

Function	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**	**F12**
GWO	4	3	4	5	4	4	5	2	4	4	5	4
HHO	2	2	2	2	2	1	2	1	2	2	2	2
PSO	5	5	5	4	5	5	3	3	5	5	4	5
SCA	3	4	3	3	3	3	4	1	3	3	3	3
HHOSCA	1	1	1	1	1	2	1	1	1	1	1	1
Function	**F13**	**F14**	**F15**	**F16**	**F17**	**F18**	**F19**	**F20**	**F21**	**F22**	**F23**	**F24**
GWO	4	3	3	2	3	2	5	1	5	3	4	4
HHO	1	1	1	1	2	3	2	1	1	1	1	1
PSO	2	4	5	4	5	4	3	2	3	2	2	3
SCA	3	2	2	5	4	5	4	3	4	4	3	4
HHOSCA	1	1	4	3	1	1	1	1	2	1	1	1
Function	**F25**	**F26**	**F27**	**F28**	**F29**	**F30**	**F31**	**F32**	**F33**	**Final Mean**	**Final Rank**	
GWO	3	4	5	4	4	1	4	4	1	3.272	4	
HHO	1	1	2	2	2	2	2	2	3	1.560	2	
PSO	4	3	3	5	5	5	5	5	4	3.829	5	
SCA	2	2	4	3	3	4	3	3	5	3.130	3	
HHOSCA	1	5	1	1	1	3	1	1	2	1.247	**1**	

SCA algorithms have difficulty obtaining the global minimal when they switch from local minima in the function of egg-holder-shaped (F7). The SCA and GWO managed to improve the convergence in functions (F8-F10) while PSO struggled to escape the entrapment from the local optima and continued to record the weakest performance. On the other hand, the fixed dimension multimodal functions (F11 to F18) convergence rate demonstrates that the developed HHOSCA continued to show a high degree of competence by achieving the best global minimal except for flat valley-shaped function (F15) where HHO and SCA recorded higher rank. The outstanding convergence behavior produced by HHOSCA is due to the enhancement added to the exploration and exploitation search space of the original HHO and SCA algorithms.

The performance of hybrid functions (F19 through F33) exhibited a similar pattern as multidimensional multimodal functions where the proposed HHOSCA acquired the best convergence and was the closest to replicating the global minima. Due to the single local minimum, almost all of the algorithms for plate-shaped functions (F22) and valley-shaped functions (F23 and F29) converged at the same number of iterative steps. In the plate-shaped function (F24), the HHO needed more iterations to converge as compared to the other algorithms which converged at the same time. Comparatively, the functions with many local minima (F19, F21, F30, F31, and F33) are slower because it takes more steps to move between the local minima and convergence, as can be seen in Fig. 4.

Lastly, the convergence analyses verify the Friedman rank of the proposed HHOSCA along with the competing algorithm which is as follows: HHOSCA obtained the first rank, and the HHO and SCA obtain the second and third ranks, respectively. GWO and PSO, on the other hand, acquired the fourth and fifth ranks in the overall performance of the 33 benchmark functions.

C. SIMULATION ANALYSIS OF THE PROPOSED HHOSCA ON WMN OPTIMIZATION

Based on the established WMN, the simulation test is conducted on a PC (Intel (R) Core(TM) i7-8700 CPU @ 3.20GHz with 32 GB RAM). The simulations were run in an area with dimensions of 1000 metres by 1000 metres, and the distribution of the clients was carried out in an even manner across the entirety of the deployment area. Table 9 summarizes the network setup parameters. It is worth noting that the version of Matlab used in this simulation is R2022a. In order to analyze the proposed HHOSCA performance in optimizing the WMN, it is compared with the four well-known algorithms in terms of the fitness value, convergence, and network size reduction rate. In this evaluation, 30 runs of each optimization algorithm are performed. To achieve thorough comparison findings, the summarised results of the entire simulation tests are provided and assessed first. Then, analysis and discussion of the findings that are representative of a typical run are carried out.

1) SUMMARY OF RESULTS AND ANALYSIS FOR THE 30 RUNS

Three sets of iterations were performed and each set is associated with 30 runs. Calculated and reported in Table 10 are the fitness values average and variance that represent a different set of iterations during the entire 30 runs 10. Considering the 100 iterations set, the HHOSCA population has the lowest average fitness value at 0.043652, making it the least fit. On the other hand, the fitness value variance of HHOSCA has a mean of 0.00037, less than that of HHO, PSO, GWO, and SCA. This indicates that HHOSCA possesses better searchability and robustness in tackling the targeted optimization issue. One can observe that PSO has the highest mean variance of fitness value and highest mean average fitness value, with respective values of 0.0009 and 0.1294. In addition, the HHO has the second best average fitness and variance fitness values of 0.059059 and 0.0005, respectively. However, the searchability of HHOSCA is better than HHO obviously due to the huge difference in the fitness mean-variance.

TABLE 9. Simulation parameters of the WMN.

Parameter	Initial value	Value
Coverage range	40 meter	[20,120]
Number of clients	30	[30,100]
Number of routers	30	[40,100]
Region width	1000 meter	1000 meter
Region height	1000 meter	1000 meter

Moreover, the average and variance fitness values of the 500 iterations are also tabulated in Table 10. The proposed HHOSCA has acquired an average fitness mean of 0.04112, which is the smallest. Similarly, the mean variance of the fitness value of HHOSCA is 0.00025, smaller than that of HHO, GWO, PSO and SCA. This indicates that HHOSCA continues to show good searchability and robustness in tackling the optimization issue. Notably, the PSO again recorded the largest mean average fitness and mean variance of fitness values, with respective values of 0.0973 and 0.0009. HHO, on the other hand, has obtained the values of 0.05192 and 0.00058 which represent mean average fitness and the mean-variance of fitness values, respectively. Despite the average fitness value close-up of HHO as compared to the proposed algorithm, the searchability of HHOSCA surpasses HHO because of the notable difference in the fitness mean variance. Other algorithms including GWO and SCA outperforms the HHO in terms of achieving smaller mean-variance, however, the HHO outperforms these algorithms in term of the average fitness mean value. PSO, on the other hand, has recorded the worst performance in comparison with all algorithms used for this optimization problem. The analysis results of fitness value confirm that HHOSCA has the best search accuracy.

Similarly, the proposed HHOSCA has obtained the best average and variance fitness values with 1000 iterations as can be observed from Table 10. The average and variance fitness that has been achieved by the proposed HHOSCA are 0.033257 and 0.000377, respectively. They make the smallest as compared to HHO, GWO, PSO, and SCA. This record strongly confirms the robustness and the better searchability

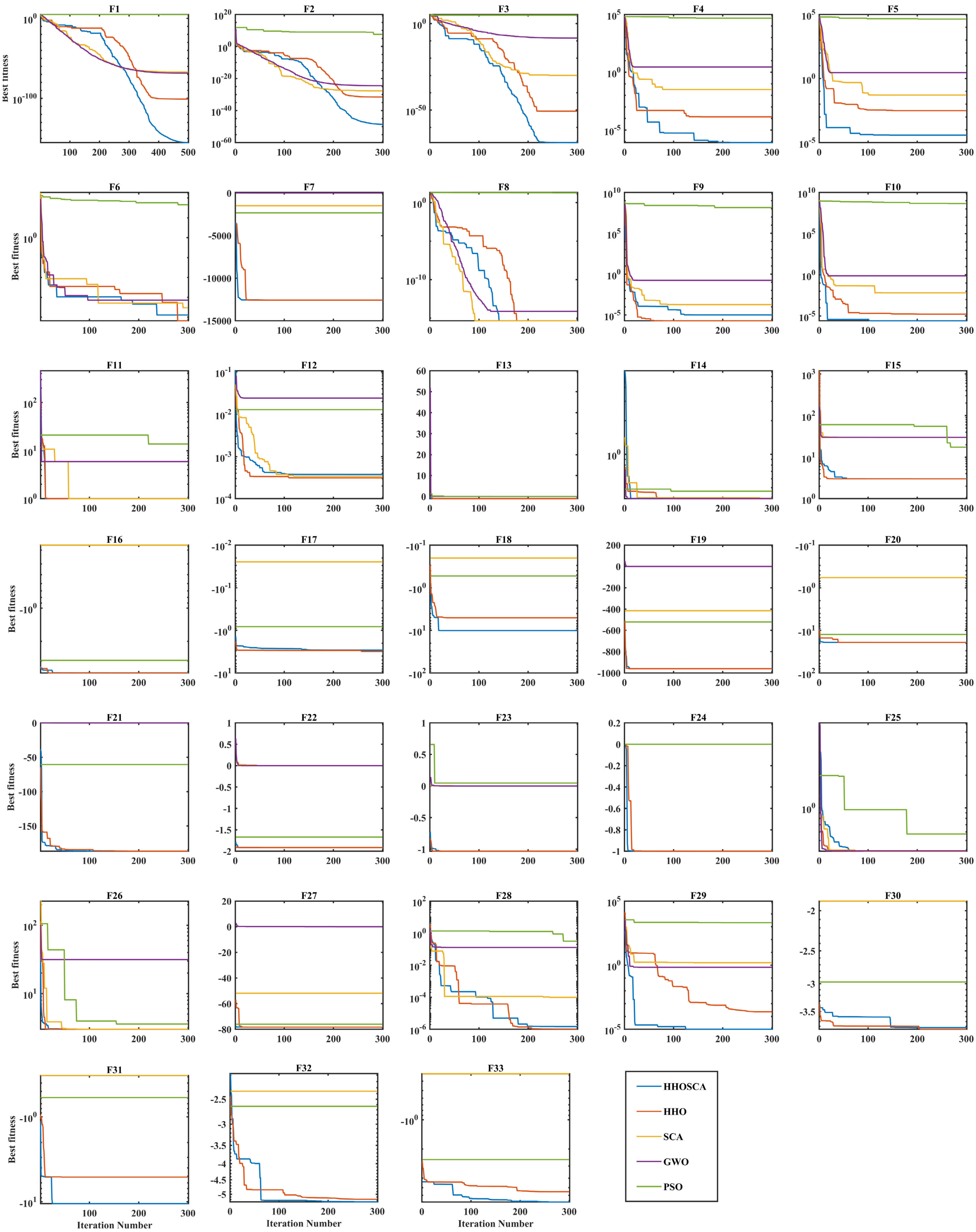
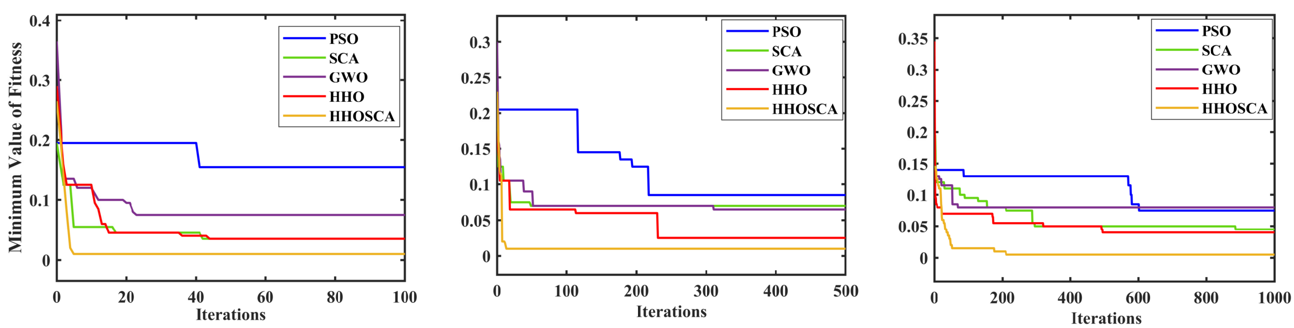


FIGURE 4. Convergence curves of HHOSCA(blue), HHO(red), SCA (yellow), GWO (purple), and PSO (green).

for solving the WMN optimization issue. In contrast, the PSO algorithm has again shown a poor performance by having the largest mean average fitness value and the largest mean variance of fitness value, which are 0.091451 and 0.000959,

TABLE 10. Fitness value of the proposed HHOSCA with the other algorithms in 30 runs.

100 iterations								
Algorithm	Average fitness values				Variance fitness values			
	Mean	Best	Worst	Stdv	Mean	Best	Worst	Stdv
HHOSCA	**0.043652**	0.01	0.08	0.01965	**0.00037**	0.00042	0.000404	0.0004
HHO	0.059059	0.02	0.115	0.02281	0.0005	0.00056	0.000586	0.00056
PSO	0.129402	0.08	0.2	0.02747	0.00073	0.00082	0.00088	0.00107
SCA	0.078704	0.025	0.12	0.02471	0.00059	0.0007	0.00063	0.0007
GWO	0.074664	0.045	0.12	0.02136	0.00044	0.00047	0.0005	0.00054
500 iterations								
Algorithm	Average fitness values				Variance fitness values			
	Mean	Best	Worst	Stdv	Mean	Best	Worst	Stdv
HHOSCA	**0.04112**	0.01	0.085	0.0159	**0.00025**	0.00028	0.0003	0.00027
HHO	0.05192	0.025	0.125	0.0245	0.00058	0.00061	0.00073	0.00062
PSO	0.0973	0.055	0.165	0.0305	0.0009	0.00097	0.00102	0.00106
SCA	0.06067	0.03	0.11	0.0206	0.00041	0.00045	0.00048	0.00047
GWO	0.06564	0.035	0.11	0.0161	0.00025	0.00028	0.00031	0.00033
1000 iterations								
Algorithm	Average fitness values				Variance fitness values			
	Mean	Best	Worst	Stdv	Mean	Best	Worst	Stdv
HHOSCA	**0.033257**	0.005	0.085	0.019695	**0.000377**	0.000412	0.00044	0.000387
HHO	0.043208	0.01	0.11	0.020318	0.0004	0.000444	0.00052	0.000423
PSO	0.091451	0.045	0.19	0.031462	0.000959	0.00104	0.001232	0.001089
SCA	0.04812	0.025	0.1	0.020478	0.000406	0.000429	0.000478	0.000437
GWO	0.067725	0.03	0.11	0.020318	0.0004	0.000452	0.000447	0.00048



(a) 100 iterations (b) 500 iterations (c) 1000 iterations

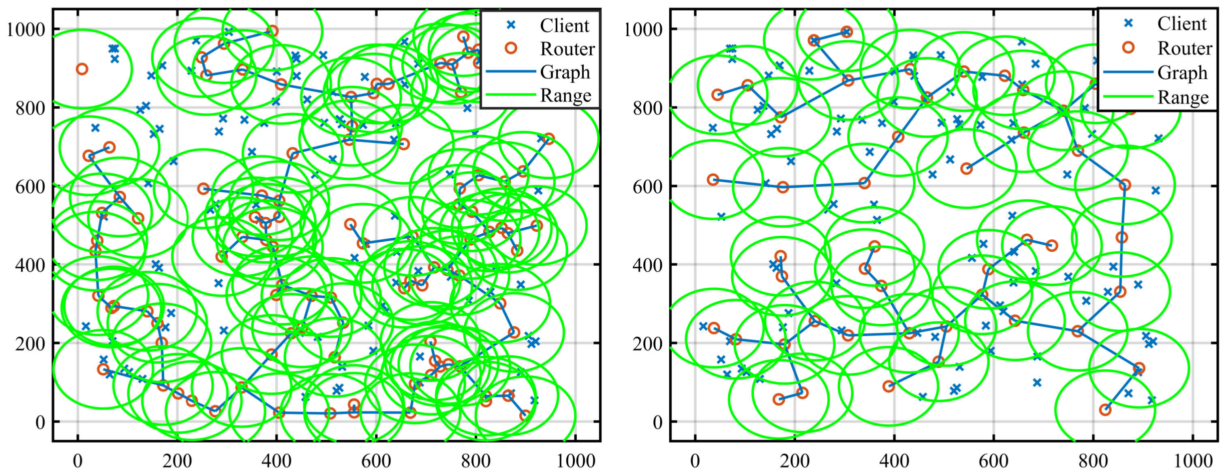
FIGURE 5. Convergence curve of HHOSCA vs other algorithms.

respectively. Therefore, one can conclude that the proposed hybrid HHOSCA algorithm has shown higher stability and search accuracy during the process of optimizing the WMN problem.

2) CONVERGENCE STUDY

Convergence curves are the most important visual assessments to understand when it comes to producing an optimal solution by use of optimization algorithms. One typical run of the total 30 runs is picked to analyse the convergence behavior of the proposed HHOSCA against the other algorithm for three different iterations sets. This is done so to analyze and observe the convergence ability of these algorithms. By the use of the proposed objective function, each algorithm will try to obtain minimum fitness value which in turn indicates better connectivity and coverage. Fig. 5 shows the convergence curves of the proposed HHOSCA algorithm and other algorithms based on different iterations size.

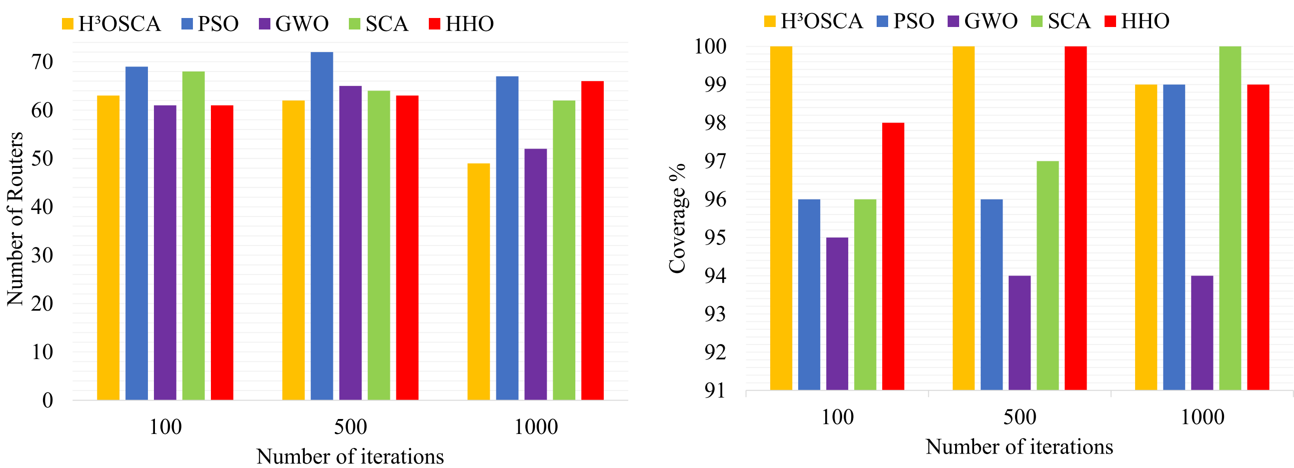
In the early phases of iterations, both the proposed HHOSCA and the competing algorithms exhibit rapid changes, but these changes lessen drastically as the iteration advances. However, the PSO algorithm often gets stuck in



(a) Topology of the initial network

(b) HHOSCA-based optimal topology

FIGURE 6. Coverage and connectivity of the WMN after 1000 iterations.



(a) Network Size

(b) Network Coverage

FIGURE 7. Reduced Network size and coverage of mesh network after 100, 500, and 1000 iterations.

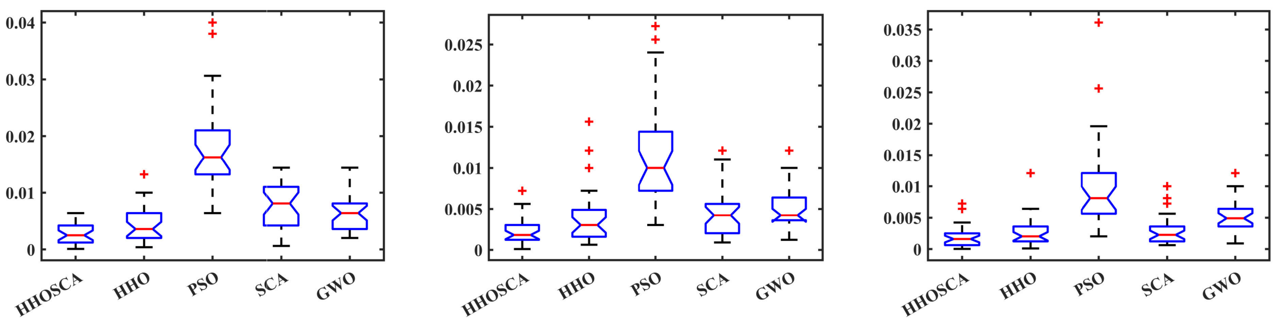
the local optimum rather than a global optimum due to its tendency toward premature convergence. The rate at which an algorithm evolves is a crucial factor in determining its overall effectiveness. Figs. 5a, 5b, and 6 demonstrate that after a number of iterations, HHOSCA has achieved superior performance and faster convergence than other algorithms, while also locating the minimum value of fitness. The HHOSCA algorithm has proven to be a suitable solution for the optimization problem of the WMN routers' placements. This can be observed from the consistency of the proposed HHOSCA in achieving the minimum fitness values of 0.01, 0.01, and 0.005 for 100, 500, and 1000 iterations, respectively.

3) COVERAGE, CONNECTIVITY AND CONGESTION REDUCTION IN WMN USING THE PROPOSED HHOSCA

Fig. 6 depicts an example of the topology that is produced by the proposed HHOSCA when compared to the topology that was present during the first iteration of the optimization process. As depicted in Fig. 6a, the initial iteration yields a mesh client coverage that is significantly low. Furthermore, the network is very congested with multiple mesh routers overlaying which in turn increases the deployment cost. Despite the redundancy of mesh routers, the connectivity is still not reaching 100% between the routers. The proposed HHOSCA, as can be seen from Fig. 6b, has tremendously improved coverage of clients, and the mesh routers have been optimally deployed to obtain full network connectivity with the least number of routers. The connectivity has been notably maximized where the largest subgraph is θ=100. This in turn confirms significant connectivity enhancement by the proposed HHOSCA. Furthermore, the reduction of the network congestion was significant as the proposed HHOSCA has reduced the number of mesh routers by 51% while maintaining the coverage and connectivity at a very high range.

TABLE 11. Assessments and comparison with the-state-oFthe-art.

Reference	Approach	Region size (meters)	Topology size	Connectivity Rate	Coverage Rate	Remarks
[13]	TS	132 × 132	64 routers and 192 clients	89%	87%	Moderate coverage and connectivity
[31]	PSO	1000 × 1000	40 routers and 120 clients	99%	87%	High connectivity and moderate coverage
[23]	PSO	128 × 128	64 routers and 192 clients	-	-	-
[16]	MVO	2000 × 2000	45 routers and 100 clients	-	90%	High connectivity
[3]	HHO	1000 × 1000	100 routers and 100 clients	98%	98%	High connectivity and coverage
[32]	COA	2000 × 2000	40 routers and 100 clients	93%	80%	Moderate coverage and High connectivity
Current Work	HHOSCA	1000 × 1000	49 routers and 100 clients	**100%**	**99 %**	**Very high connectivity and coverage**



(a) 100 iterations (b) 500 iterations (c) 1000 iterations

FIGURE 8. Boxplot on MSE of HHOSCA vs other algorithms.

In contrast, the competing algorithms cause several mesh routers to overlap, resulting in higher interference, whereas the network topology formed by the HHOSCA approach is more dispersed, enabling it to provide better client coverage.

The performance of HHOSCA in comparison to other algorithms is shown in Fig. 7, including the reduction in network size and coverage of three different iteration sets. The proposed HHOSCA outperforms the other algorithm in obtaining a higher coverage as well as higher congestion reduction of the WMN routers for optimal deployment. Fig. 7a shows that the proposed algorithm has reduced the network size with a rate of 37%, 38%, and 51% after 100, 500, and 1000 iterations, respectively. The GWO, on the other hand, has achieved the second-best in terms of obtaining a higher network size reduction. However, it has shown a coverage degradation as compared to the other algorithm. The proposed HHOSCA approach is the only algorithm that recorded a high performance on all the aspects of WMN evaluation metrics. One can see in Fig. 7b that the proposed approach has kept consistency in acquiring tremendous coverage rates. With only 49 routers, it managed to produce a 99% coverage rate whilst other algorithms such as PSO, HHO and GWO have shown lower coverage rates despite having bigger network sizes.

D. PERFORMANCE ASSESSMENTS AND COMPARISON

1) STATE-oFthe-ART COMPARISON

In Table 11, the performance comparison and assessments against the state-of-the-art are displayed. It shows a comparison between the proposed HHOSCA algorithm utilised in this study and the relevant literature in terms of their coverage rate, connectivity rate, network size, grid size, and proposed algorithm. Although this work employs a large grid, it still surpasses the state-of-the-art. One can observe that the HHOSCA algorithm has obtained 100% and 99% in terms of both connectivity and coverage metrics, respectively. This high percentage is performed with a fewer number of routers in the network as compared to [13], [32], and [31]. In addition, the statistical analyses and simulation findings confirm that the HHOSCA outperforms the other algorithms

TABLE 12. Mean square error results using ANOVA.

100 iterations					
Source	**SS**	**df**	**MS**	**F**	**P-Value**
Groups	0.00439	4	0.00110	52.71	2.37E-27
Error	0.00302	145	0.00002		
Total	0.0074	149			
500 iterations					
Source	**SS**	**df**	**MS**	**F**	**P-Value**
Groups	0.00145	4	0.00036	24.34	2.02E-15
Error	0.00217	145	0.00001		
Total	0.00362	149			
1000 iterations					
Source	**SS**	**df**	**MS**	**F**	**P-Value**
Groups	0.00137	4	0.00034	22.95	1.05E-14
Error	0.00217	145	0.00001		
Total	0.00354	149			

in terms of network connectivity, coverage, and network reduction. The higher performance of the proposed HHOSCA is due to the understanding of the designer during the design phase.

2) SIGNIFICANT ANALYSIS OF THE DEVELOPED APPROACH

In order to validate the results of the proposed HHOSCA algorithm further, the analysis of variance (ANOVA) test was considered. The purpose of this test was to determine whether or not there was a statistically significant difference in the results pertaining mean square error (MSE) obtained by the proposed HHOSCA algorithm and those obtained by other algorithms. The null hypothesis states that the MSE between the proposed method and other methods is not significantly different. Acceptance of the null hypothesis happens at a significance level larger than 0.05, and rejection occurs at a significance level less than 0.05. The P-value obtained by the ANOVA test is the parameter that identifies the significance level of any proposed approach. Due to the comparison of more than three algorithms that are considered in this work, the ANOVA test was used to determine the significance of the differences. The parameters that are used to perform the ANOVA test are the square sum (SS), degree of freedom (df), mean square (MS), test static (F), and p-value [40]. The P-values that were obtained and are displayed in Table 12 provide evidence that the null hypothesis is rejected. These P-values also provide evidence that there is a significant difference between the benchmarking methods and the proposed HHOSCA algorithm. The p-values produced by the ANOVA test are 2.37E-27, 2.02E-15, and 1.05E-14 for 100, 500, and 1000 iterations of the 30 runs, respectively. The obtained p-values are extremely smaller than 0.05 which confirms the high reliability of the proposed HHOSCA method compared to other algorithms. The boxplot in Figure 8 shows that the proposed algorithm has achieved the lowest mean and median for 100, 500, and 1000 iterations. This simply confirms that the proposed algorithm has acquired the least mean square error as compared to the benchmark algorithms.

V. CONCLUSION AND FUTURE WORK

The placement of the mesh routers within the WMN is an important factor that makes a major contribution to the network's increased mobility in terms of network connectivity and coverage. Once this concern was framed as an optimization problem, a number of different metaheuristics were proposed. These algorithms, in turn, demonstrated excellent results on networks ranging in size from small to medium. This work was motivated by the need to address the issue of router placement in large-scale networks. Subsequently, the novel proposed optimization approach named hybrid HHOSCA, in which HHO was hybridised with SCA, outperforms standard HHO and SCA in terms of convergence speed and avoidance of local optima entrapment which was validated using the benchmark functions. Yet, the primary objective is to enhance network coverage and connectivity by optimally locating the wireless mesh routers. In addition, the network congestion reduction was also considered to produce a cost-effective WMN. Considering these optimization problems, HHOSCA results were compared with PSO, HHO, GWO, and SCA metaheuristic algorithms. The fitness function for optimizing this problem was used to confirm the superiority of the proposed HHOSCA in achieving the best solutions with maximum coverage and connectivity, as measured by a variety of assessment metrics. Moreover, the proposed HHOSCA resulted in a less congested network with a reduction rate of the mesh routers of 37%, 38%, and 51% for 100, 500, and 1000 iterations, respectively. The findings of the simulation clearly showed that the HHOSCA method had a significant improvement in topology construction in comparison to the benchmarking algorithms. These findings provide conclusive evidence that the novel hybrid approach that was proposed might be applied effectively to the problem of optimising wireless mesh network performance.

This work has addressed the network optimization problem of the WMN including connectivity, coverage, and congestion, however, it was a fully simulation-based experiment. On the other hand, energy consumption is a key factor to be considered when optimizing the WMN, therefore, the future direction of this research can tackle solving this issue. In addition, an industrial environment usually contains obstacles and disturbances. Hence, an obstacle avoidance model should introduce a significant contribution to further enhance the WMN performance. Moreover, the implementation of real working scenarios of WMN optimal deployment should add a huge knowledge to this area of research.

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