Optimal Coverage and Connectivity in Industrial Wireless Mesh Networks Based on Harris’ Hawk Optimization Algorithm

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ABSTRACT The placement of wireless mesh routers is a significant matter in enhancing the performance of a wireless mesh network. Therefore, it is essential that the mesh routers are optimally placed to guarantee strong connectivity and coverage for ensuring the best network accessibility. The importance of this issue has motivated the researchers to pursue more investigation on optimizing the networks’ performance. Various optimization algorithms have been developed in the literature to identify the trade-offs between network connectivity and client coverage. This work is aimed at implementing a novel application of Harris Hawk’s Optimization (HHO) algorithm to optimally place mesh routers in a wireless mesh network so as to improve connectivity and coverage. The HHO seeks optimal routers placement that leads to maximizing the connection between routers and increasing the number of covered clients. In this study, three network configurations are used with sizes of 40, 60, and 100 mesh routers. The simulation results are statistically analyzed and compared to other population-based algorithms such as Sine Cosine Algorithm (SCA), Gray Wolf’s Optimization (GWO), and Particle Swarm Optimization (PSO). Moreover, the performance of HHO is compared with the state-of-the-art to validate the effectiveness of the proposed approach. The simulation findings and statistical analysis confirm that the HHO outperforms the other algorithms in terms of network coverage and connectivity. The outcomes demonstrate that HHO can be considered an efficacious means to enhance the performance of wireless mesh networks (WMNs).

INDEX TERMS Wireless mesh networks, optimization, sine cosine optimization, Harris Hawk optimization, gray wolf optimization, particle swarm optimization, network deployment optimization, reliable wireless networks, reliable routing, optimal node placement.

I. INTRODUCTION Wireless Mesh Networks (WMNs) have been rapidly deployed in industrial environments during the last two decades. The WMNs have become very essential in providing internet access to the public. Although this networking paradigm is still emerging, it has an advantage over wired networks in minimizing failures through self-healing topology and expanding the coverage to difficult areas [1]–[3]. Conventional networks are made up of multiple hotspots and intermediate wired nodes to provide the end users with an internet connection. Internet access is traditionally provided to end users via a series of intermediate wired hotspots and nodes. In contrast, in WMNs, the network is built by a number of wireless nodes that communicate with one another. There are two types of nodes that make up a WMN: Mesh Routers (MRs) and Mesh Clients (MCs), which work together...
to create a wireless mesh network with multiple hops that uses an internet gateway (GW) to connect to the internet. Nodes can be either static or mobile, depending on the application. There exists a cooperative forwarding node that acts as an intermediate node between an internet GW and clients in order to predict a route based on network topology [1], [4].

Despite the numerous advantages of WMNs, there are still a number of challenges that need to be solved in order to improve the overall network performance metrics such as compatibility, security, coverage, connectivity, etc [5].

In order to cover a broader area than wireless indoor networks, outdoor WMN deployments must contend with the challenges of limited interference sources control that are inherent in outdoor networks. For real-world applications, determining the best location for mesh network devices to be installed is critical because outdoor installations may have lower user densities than indoor installations in some areas [5], [6] and also, mesh network devices can be installed in an environment that is far less regulated than an indoor environment. There are numerous deployment options available to meet the user coverage and connectivity requirements in a variety of crucial conditions including combat surveillance, underground mines, offshore oil rigs, natural disasters, or public transportation, amongst other applications. The WMNs may also be a viable option for supporting domestic phone calls if the Quality-of-Service settings are properly tuned [1], [7].

Wireless node density, network topology, and transmission power are all elements that must be thoroughly understood when deploying WMNs. Poor network connectivity and low client coverage would result from deploying wireless mesh routers while neglecting the technological limits of the actual deployment area and the underlying topology [5].

The problem of deploying WMNs efficiently can be characterised as a facility-based location issue in some ways [8]–[11]. NP-hardness of this issue has been established and proven in previous studies over a lengthy period of time [10]. The No Free Lunch (NFL) theorem, on the other hand, asserts that coping with all types of optimizations issues by having a single metaheuristic can be difficult [12]. Multiple works have been presented, each employing a different type of metaheuristic algorithm, in order to determine the needed network features in an acceptable amount of time and thereby ease the planning process for the network engineer.

The contributions of this paper are mainly focused on:

- Proposing a fitness function that maximises both mesh router connectivity and meshes client coverage at the same time.
- Applying a recent proposed Harris Hawks Optimization (HHO) algorithm to optimally locate mesh routers in a WMN.
- Comparing HHO and other algorithms convergence for examining network performance based on a set of parameters and the WMN-RNP issue.

To the best of the authors knowledge, the research on HHO for WMNs on optimal mesh routers placement has not been reported in the literature related to WMNs. The remainder of this article is organized as follows. Section II covers a detailed literature review of related studies. In section III, the methodology of optimizing the wireless mesh networks is detailed out. Section IV shows the simulation results of the proposed methodology and compared with the other algorithms. Finally, a conclusion is given in Section V.

II. LITERATURE REVIEW

Despite the fact that metaheuristic approaches identify only locally optimal solutions, they have achieved widespread development and success in comparison to other approaches. Meta-heuristic approaches determine the most and best robust network topology for solving mesh router placement issues in the majority of practical situations.

There are numerous metaheuristic approaches that have been used to optimize the routers localization as it is considered as a non-deterministic polynomial-time (NP)-hard problem [13]. According to the latest researches, it can be stated that population-based metaheuristics have demonstrated significant effectiveness in this area. When compared to deterministic optimization approaches, these metaheuristics rely on collective intelligence to solve optimization problems in the shortest amount of time and with the least computations. Authors in [14] proposed a method based on the cat swarm optimization (CSO) algorithm to tackle the problem of determining the single router localization i.e., sink node localization [15]. When compared to PSO, the authors confirmed that the new technique has demonstrated efficiency in increasing the lifetime of the network. The efficient creation of least transmission pathways between routers in a wireless mesh network using the greedy algorithm contributed significantly to the reduction of energy consumption during transmitting and receiving data. There is yet another PSO implementation in this domain in [16]. The authors in [16] suggested a mechanism for selecting the most energy-efficient position for the sink node by employing energy-aware control topology protocol in the entire network in order to extend its lifetime. The suggested approach was compared to other methods in order to verify its ability to reduce the power consumption of the sensor nodes. According to the simulation results, they argue that the proposed approach outperforms other methods in terms of active nodes count, number of possible formed topologies, and operational network longevity.

A number of previous studies, including [10], [17], looked at the deployment of wireless routers in a uniform grid region, however, this theory restricted the mesh router spread. Some other studies, on the other hand, considered a continuous deployment region, which provides greater flexibility in the placement of mesh routers, resulting to improved network structure. Aside from that, they explored the approach of hierarchical optimization for client coverage and network connection, which was shown to be unsuitable for non-convex objectives [18]–[20]. Multiple related studies have been conducted using various metaheuristics to increase network connectivity and client
coverage. These studies have taken into consideration two parameters: network connectivity and client coverage [10], [21], [22]. A genetic algorithm was proposed by [23] for the placement of router nodes, and [24] looked into the influence of mutation in genetic algorithms. Additional research has been done by [25], [26], in which they constructed a hierarchical simulated annealing approach in two stages to determine the positions of mesh routers and a hill-climbing strategy to hierarchically optimize the same parameters has been developed by [21]. Additionally, the same issue was addressed by the same researchers in [22] thru employment of the Tabu Search (TS) technique. The collected findings revealed that the TS method outperformed the Simulated Annealing (SA) approach. Through the use of Friedman test, [27] were able to compare the simulated annealing, hill climbing, tabu search and genetic algorithm.

When attempting to solve the router nodes placement in a WMN, a PSO metaheuristic has been employed in order to maximise mobile client coverage as well as network connectivity [28], [29]. Several factors affecting the performance of the PSO algorithm have been investigated, including the influence of different factors on the network design. It has been assumed that every client in a mesh network is given a digit that represents its priority of service as addressed in [28], by the same authors. A Bat-inspired method has also been employed by [30], with the authors introducing an extra variant that considers client mobility while still adhering to the same service priority requirements. Likewise, [29] presented a PSO method in dynamic WMNs that included social awareness as a component. This was followed by the implementation of wireless mesh network-router node placement (WMN-RNP) as a merged fitness function in a dynamical setup. The research work in [18] resolved the service priority issue in WMNs by using simulated annealing algorithm incorporating momentum conditions. To optimize network connectivity and client coverage, [31] developed a mechanism called an electromagnetism-like algorithm.

There have been similar studies on the placement of wireless sensor nodes. Wang et al. [32] have developed an improved grey wolf optimizer (IGWO) for enhancing the metrics including limited search accuracy, sluggish convergence and rapid local optima entrapment of the grey wolf optimizer (GWO) algorithm. Additionally, a Virtual Force-Levy-embedded Grey Wolf Optimization (VFLGWO) algorithm was proposed to tackle the aforementioned issues, (i.e., limited search accuracy, sluggish convergence and rapid local optima entrapment) by the same authors in [33].

Singh and Prakash [34] employed Whale Optimization Algorithm (WOA) to optimally place numerous Optical Network Units (ONUs) following diverse diffusion of ONUs and mesh routers in their work on relay node placement in Fiber-Wireless networks. Moth Flame Optimization (MFO) and Greedy algorithms were used to compare with the results obtained from their study.

A biogeography-based optimization (BBO) algorithm was utilised in Gupta and Jha’s work to optimize the placement of sensor nodes in order to ensure that they meet both the m-connectivity and k-coverage requirements [35]. The proposed BBO-based approach provides an adequate habitat representation and encoding technique while also determining an objective function along with the BBO’s mutation and migration operators. It was recommended to use a GA-based technique to locate the router nodes to ensure the greatest possible coverage [36]. Monte Carlo-based simulation and mathematical modelling were used to resolve this issue. They considered two objectives: (1) minimal sensors selection and (2) maximizing the coverage area. Nevertheless, they didn’t consider the connectivity parameter.

In order to improve the network’s connectivity, a number of studies have been investigating the placement of relay nodes [37], [38]. Authors in [39] proposed a novel approach to optimize connectivity of relay nodes in multiple hops wireless network. Specifically, PSO and leave-one-out (LOO) methods were created for the use at the optimal placement stages and solution selection, respectively, in their methodology. There has also been a proposal for a relay node placement method that makes use of multi-objective metaheuristics methods [40]. There were three sub-objectives in [40]: reliability, area coverage and residual energy. However, full coverage and connectivity requirements were not considered. The ACO-Greedy deployment method was also presented to address the grid-based coverage issue. The approach combined greedy migration mechanism with ant colony optimization. Objectives of the proposed approach were: (1) ensuring the connectivity, (2) ensuring the full coverage (3), and reducing the deployment cost [41]. Likewise, Gupta [42] proposed a GA-based method to optimize the placement of relay nodes. They have made some assumptions that the nodes were manually or randomly positioned in bigger sensing area, and some prespecified locations were provided for the placement of the relay nodes. It was mainly proposed to deploy fewer relay nodes necessary to establish k-connectivity between every node. Their technique, on the other hand, did not take into account the relay nodes full connectivity [42].

Furthermore, Nitesh and Jana proposed relay nodes positioning algorithm [43]. The approach proposed in their work ensured an s-connectivity and k-coverage of the relay nodes and sensing area, respectively. In order to keep the network’s cost as low as possible, their algorithm employed less relay nodes. This was accomplished by minimizing coverage overlapping between the relay nodes. Sensor nodes spiral sequence was constructed utilising the technique developed by Jarvis March [44] that they used in their approach.

Authors in [45] used moth flame optimizer (MFO) algorithm for determining the most ideal locations for the nodes’ placement. The primary goal was to guarantee that the network was completely connected. To assess network connectivity, the proposed approach used the heuristic fully connected network.

In the same context, this work investigates the optimal routers placement problem using Harris Hawks
III. METHODOLOGY
This section outlines the method used in optimizing the wireless network connectivity and coverage, the working principle of the optimization technique, and the system model. This work mainly focuses on implementing the Harris Hawks optimization technique in maximizing the coverage and connectivity of a WMN. The system model of this study is thoroughly discussed in the following subsections which cover the problem formulation, system assumption, and the proposed fitness function.

A. HARRIS HAWK’S OPTIMIZATION (HHO)
The inspiration of nature has led to the development of a new algorithm known as Harris hawks optimization (HHO) [46]. Harris hawk, also known as a dusky hawk, is the primary source of inspiration for HHO because of its hunting habits. The Harris birds perch in the air, scan for prey from a distance, and spend the effort to pounce on the prey. Modelling of the hawks’ perching behavior is performed during the exploration phase of HHO, and a simulation of their pouncing technique is performed during the exploitation phase. Subsections III-A1 and III-A2 provide an explanation of the mathematical modelling of HHO algorithm. Notably, in HHO, a candidate solution is denoted by the symbol \((y)\), whereas the best solution is denoted by the symbol \( (y_{prey})\).

1) HHO EXPLORATION PHASE
The problem landscape is rigorously searched in optimization methods to identify the best among the many solutions that are widely available. Exploration phase is the early phase of the metaheuristic to determine the best position among hills and valleys. During this phase, a comprehensive search is conducted in the most remote areas. For example, search agents are distributed broadly throughout search space in population-based metaheuristic algorithms such as HHO. This phase is performed in HHO algorithm by mimicking hawks’ perching behaviour, which begins with a high-altitude exploration of the region for potential prey localization which could either be a big insect, a small animal, or a rabbit. Bearing in mind the aforementioned scenario, HHO begins by deploying \(N\) hawks (search agents) in a randomized manner \(y_i^0, i = 1, 2, \ldots, N\) throughout the search region according to:

\[
y_i^0 = lb_i + r_1 \times (ub_i - lb_i), \quad r_1 = \text{rand}()
\]

where \(ub\) and \(lb\) are the bounds of the problem, and the generator \(\text{rand}()\) which randomly generates a value limited to the range \([0,1]\) each time being used. The exploration phase continues after the population has been initially established until reaching the prey escaping energy \(|E|\geq1\), calculation of \(E\) follows:

\[
E = 2E_0 \left(1 - \frac{ite}{T}\right), \quad ite = \{1, 2, 3, \ldots, T\}
\]

where \(T\) and \(E_0\) represent the iterations maximum number and prey initial energy, respectively. During initial iterations, HHO performs exploration while \(|E|\geq1\). This stage involves a searching agent that searches in a random manner among other searching agents or among probable ideal searching zones that have been recognised as \(y_{prey}\) in the environment. This phenomenon is controlled by the random generated variable \(c\) using:

\[
\begin{align*}
& y_{new} = \begin{cases} y_{\text{rand}} - r_2 |y_{\text{rand}} - 2r_2y|, & c \geq 0.5 \\
& (y_{\text{prey}} - y_m) - r_3 [lb_1 + r_4 (ub_1 - lb_1)], & c < 0.5,
\end{cases} \\
& r_2 = \text{rand}(), \quad r_3 = \text{rand}(), \quad r_4 = \text{rand}(), \quad r_5 = \text{rand}(), \\
& y_m = \frac{1}{N} \sum_{i=1}^{N} y_i,
\end{align*}
\]

where \(y_{\text{rand}}, y_m, \) and \(y_{new}\) are a randomly selected position, populations dimension-wise average, and new position, respectively.

2) HHO EXPLOITATION PHASE
When the convergence of potential population solutions is around a favourable area in the search region that has previously been identified, this is known as exploitation. This phase is activated following the completion of multiple iterations for the purpose of exploring the problem landscape. Once a prospective neighbourhood has been identified based on the search agents’ collective experience, an exploitation approach is implemented to gradually force potential solutions to adopt data from a single global best solution that has been previously identified. Based on these data, the potential solution gets improved. It is crucial to note, however, that reaching the local area early may result in premature convergence, that leads to an unsatisfactory solution. Consequently, HHO employs several distinct exploitation tactics for hawks in various hunting settings in order to overcome this issue. For instance, when closing on prey, the hawks might choose to either wait for an abrupt pounce when the prey is attempting to flee or make a fast dive for an instant strike.

HHO algorithm implements four exploitation strategies: soft besiege, soft besiege with gradual quick dives, hard besiege, and hard besiege with gradual quick dives. In HHO, soft besiege occurs when hawks spot preys from a certain range, and the preys have the power to flee the hunt, therefore the hawks perform encircling behaviour to exhaust the prey. The soft besiege with gradual quick dives refers to a circumstance in which the hawks are attempting to catch a victim by doing gradual dives, while the preys are putting up a tremendous effort to avoid the catch by making random zigzag movements. On the other hand, the term “hard besiege” refers to a prey that is either fatigued or particularly well positioned for a successful catch by a hawk. When the hawk considers the condition as unsuitable for trying the...
catch, it strives to approach as close as possible to the preys, thus executing hard besiege with gradual quick dives.

HHO employs the Levy flight, \( LF(D) \), function to implement progressive movement towards the currently defined potential local area. The \( LF(D) \) is utilised in both hard and soft besiege scenarios with progressive quick dives. On the other hand, HHO employs the prey’s jump strength, \( J \), which indicates the prey’s escape attempt, to inject some randomness into the local search results in order to improve the search results in the area. Table 1 outlines the prerequisites for conducting the four exploitation processes, along with related mathematical equations.

- Gradual quick hard besiege dives:

\[
\begin{align*}
\text{if } & F(Y) < F(y_i) \quad \text{then } \quad X = y_{\text{prey}} - E |Jy_{\text{prey}} - y_i|, \\
& J = 2(1 - r_6), \quad r_6 = \text{rand}(), \\
& Z = X + S \times LF(D), \quad \text{where} \\
& S = \text{Size of a random vector} \quad 1 \times D, D = \text{Dimension} \\
& LF(D) = 0.01 \times \frac{\beta}{|v|^\frac{\beta}{2}}, \\
& \beta = \left( \frac{\Gamma(1+\sigma) \times \sin \left( \frac{\pi \sigma}{2} \right)}{\Gamma \left( \frac{1+\sigma}{2} \right) \times \sigma \times 2^{\frac{\sigma-1}{2}} \right), \\
& \sigma = 1.5, \quad u = \text{rand}(), \quad v = \text{rand}() \\
\end{align*}
\]

(4)

- Hard besiege:

\[
y_{\text{new}} = y_{\text{prey}} - E |\Delta y_i|, \quad \text{where } \Delta y_i = y_{\text{prey}} - y_i
\]

(5)

- Soft besiege:

\[
y_{\text{new}} = \begin{cases} 
X, & \text{if } (Y) < F(y_i) \\
Z, & \text{if } (Z) < F(y_i) 
\end{cases}, \quad \text{where} \\
X = y_{\text{prey}} - E |Jy_{\text{prey}} - y_i|
\]

(6)

- Gradual quick soft besiege dives:

\[
y_{\text{new}} = \begin{cases} 
X, & \text{if } (Y) < F(y_i) \\
Z, & \text{if } (Z) < F(y_i) 
\end{cases}, \quad \text{where} \\
X = y_{\text{prey}} - E |Jy_{\text{prey}} - y_i|
\]

Therefore, the HHO optimisation can be summarised as follows:

**Algorithm 1 Harris Hawk’s Optimization (HHO)**

**Input:** A wireless mesh network topology with the coordinates of the mesh clients and randomly positioned mesh routers

**Output:** The optimized WMN that maximizes coverage and connectivity

1. Generate the mesh routers’ positions randomly \( y_i^0 \) \((i = 1, 2, \ldots, N)\)
2. Initialize the starting of iterations \( \text{ite}= 1 \) and \( T= \) maximum iteration

**LOOP Process**

3. while (\( \text{ite} \leq T \)) do
4. Perform hawk set \( y_{\text{prey}} \) fitness values calculation as the network array of preys (finest layout)
5. Update the position of mesh routers MR
6. Use Eq. (2) to update the E
7. if \( |E| < 1 \) then
8. Update \( |E| < 0.5 \) and \( r < 0.5 \) then
9. Use Eq. (4) to update the solution
10. else if \( r < 0.5 \) and \( |E| \geq 0.5 \) then
11. Use Eq. (6) to update the solution
12. else if \( r \geq 0.5 \) and \( |E| < 0.5 \) then
13. Use Eq. (5) to update the solution
14. else if \( r \geq 0.5 \) and \( |E| \geq 0.5 \) then
15. Use Eq. (7) to update the solution
16. end if
17. end if
18. if \( |E| \geq 1 \) then
19. Use Eq. (2) to update the solution
20. end if
21. end for
22. \( \text{ite} = \text{ite} + 1 \)
23. end while
24. end while
25. Return \( Y_{\text{prey}} \) Optimal Mesh Routers Deployment Topology featuring maximum connectivity and coverage

**B. SYSTEM MODEL**

On the optimal router placement problem in WMNs, this subsection covers the HHO implementation with respect to other meta-heuristic algorithms. HHO algorithm is evaluated in comparison to other well-known algorithms in order to determine its overall performance level. MATLAB software was utilised for the implementation of these algorithms.
TABLE 2. Model formulation variables definitions.

| Symbol | Meaning |
|--------|---------|
| $Stdv$ | Standard Deviation |
| $X_i$  | The $i$-th particle |
| $\delta_i$ | Boolean determines if client $i$ is covered |
| $MC_i$ | Mesh client $i$ |
| $\alpha(G)$ | Client coverage |
| $\theta(G)$ | Network connectivity |
| $h$ | Number of subgraph components |
| $|G_i|$ | Size of the $i$-th subgraph component |
| $G_i$ | $i$-th subgraph component |
| $E$ | Edges set between mesh routers |
| $MR_i$ | Mesh router $i$ |
| $c_i$ | The $i$-the client |
| $C$ | Set of clients |
| $r_i$ | The $i$-th router |
| $R$ | Set of routers |
| $H$ | Deployment area height |
| $W$ | Deployment area width |
| $P(x_i,y_i)$ | Node location |
| $P$ | Placement vector of mesh routers |
| $m$ | Number of mesh clients |
| $n$ | Number of mesh routers |
| $G$ | WMN graph |

In addition, the Atarraya simulator [47] was utilised to generate network graphs (datasets) for different network sizes, as well as client and router coordinates, which were included in the analysis. The technique is evaluated by comparing it to three well-known algorithms: PSO, GWO, and SCA, in order to demonstrate its effectiveness.

1) SYSTEM ASSUMPTIONS

In the actual world, it’s impossible to tell at a first look where to locate mesh clients. As a result, determining the best location for mesh routers is incredibly difficult to accomplish. The optimum connectivity and coverage wireless network (OCCWN) network model is presented using the notation listed in Table 2.

Mesh clients are assumed to be stationary, and their geographic distribution is known. This assumption is important because the routers positions are depending on the distribution of mesh clients in the installation region. However, the WMN-RNP issue is still complex and hard to resolve using a fast precise method because obtaining optimality is still computationally complex.

For the purpose of addressing the problem of mesh router placement, the following assumptions were made:

- The positions of mesh clients are fixed in 2D region.
- Every router in the mesh network has the same range of transmission.
- Transmission range determines whether or not two mesh routers can communicate with one another.

2) PROBLEM MODEL FORMULATION

The main focus of this work is the connectivity and coverage in WMN such that locating $P = \{P(x_1,y_1), P(x_2,y_2), P(x_3,y_3), \ldots, P(x_n,y_n)\}$ of the n routers as close to optimally as possible in order to maximise the coverage of the mesh clients and network connectivity.

Client coverage in the proposed approach is measured by the number of clients that are within the mesh routers’ transmission range, whereas network connectivity is measured by the size of the largest subgraph of mesh routers that are connected, which indicates the quality of service (QoS) in WMNs. It is worth noting that the aforementioned two goals are incompatible: big size of the largest subgraph component does not necessarily indicate widespread mesh client coverage.

Suppose there is a network of two-dimensional $H \times W$ area where n mesh routers and m mesh clients are spread out in the network. Assume that $C$ denotes the set of clients and $R$ represents the set of routers. Every clients $c_i \in C$ are positioned at $P(x_i, y_i) \in \mathbb{R}^2$ of the installation region.

Optimal placements of mesh router are dependent on the location of mesh clients, which are represented by $P = \{P(x_1,y_1), P(x_2,y_2), P(x_3,y_3), \ldots, P(x_n,y_n)\}$. Undirected topology graph $\mathbb{G} = (R, E)$ exists for any given placement of mesh routers such that:

- If and only if two mesh routers are inside each other’s transmission range, there exists an edge $E$ between them
- A mesh router covers a mesh client only if the client is inside the router’s transmission range.

Note that the graph $\mathbb{G}$ may not be fully connected, i.e. the graph may be made up of a number of subgraphs. Making the largest subgraph component of the WMN as large as possible would help in improving the connectivity of the network.

Suppose there are $h$ sub-graph components $G_1, \ldots, G_h$ in $\mathbb{G}$ i.e., $\mathbb{G} = G_1 \cup G_2 \cup G_h$, and $G_j \cap G_i = \emptyset$; for $j, i \in 1,2,\ldots,h$.

The coverage of clients is expressed as:

$$\alpha(G) = \sum_{i=0}^{m} \delta_i$$  \hspace{1cm} (8)

where

$$\delta_i = \begin{cases} 1 & \text{if there at least one router covering client } i \\ 0 & \text{Otherwise} \end{cases}$$

The following expression represents the connectivity of the network depending on the largest subgraph size in the $G$ graph:

$$\theta(G) = \max_{i \in [1, \ldots, h]} |G_i|$$  \hspace{1cm} (9)

A network with thirty clients ($m = 30$) and thirty routers ($n = 30$) is depicted in Fig. 1a as an example of WMN.
Each mesh router is having a 20-meters of transmission range. If two routers are within the transmission range of one another, a blue link will represent the connection (e.g., observe the blue line between node 7 and node 28). A client is linked to the nearest router as long as it falls within router’s transmission range. Moreover, the graph topology contains six subgraph components in which the biggest subgraph includes 8 routers (i.e., $\theta(G) = 8$), and 25 clients have coverage (i.e., $\alpha(G) = 25$). The number of subgraphs can be reduced to one big subgraph containing 29 mesh routers (i.e., $\theta(G) = 29$) if mesh routers are shifted toward the most densely populated mesh clients region, as depicted in Fig. 1b, and the coverage will reach out all 30 mesh clients (i.e., $\alpha(G) = 30$). As a result, moving some mesh routers will increase network connectivity as well as client coverage.

3) THE FITNESS FUNCTION
Main objective of the proposed HHO is to maximize two parameters: client coverage $\alpha(G)$ and network connectivity $\theta(G)$, which are given by Eqs. (8) and (9), respectively. As a result, the weighted sum approach is employed, which reduces a multi-objective issue to a scalar issue which sums each objective multiplied by a user-defined weight before summing the results.

The definition of the proposed merged fitness function $f(x)$ is in Eq. 10:

$$f(x) = \zeta \cdot \frac{\theta(G)}{n} + (1 - \zeta) \cdot \frac{\alpha(G)}{m}$$

(10)

where $0 < \zeta < 1$ denotes a characterization weighting coefficient of each objective relative rank, $n$ is the number of mesh routers and $m$ is the number of mesh clients. In order to normalise the equation, the denominator should be utilized in every term of the formula.

4) STATISTICAL EVALUATION CRITERIA
When evaluating and validating the algorithms in accordance with the fitness function provided by Eq.(10), the following standard metrics are employed:

1) Upon the completion of $R$ runs of the algorithm, the mean value is calculated as the average of the fitness values and can be defined as:

$$\text{Mean} = \frac{\sum_{x=1}^{R} f(x)}{R}$$

(11)

2) Standard deviation (stdv.) computes the difference between the objective function values acquired by running the algorithm for a certain number of times (i.e., $R$ times). It is important to note that the algorithm’s capability of convergent to the same value most of the time is measured by producing small standard derivation values, hence demonstrating its stability and robustness. The presence of large values indicates that the algorithm provides results that are inconsistent. The standard deviation is defined as:

$$\text{Stdv} = \sqrt{\frac{1}{R-1} \sum_{x=1}^{R} (f(x) - \text{Mean})^2}$$

(12)

3) Best value is the lowest value of fitness function attained in $R$ runs which is given by:

$$\text{Best} = \min_{1 \leq x \leq R} f(x)$$

(13)

4) Worst value is the largest value of fitness function attained in $R$ runs and can be expressed as:

$$\text{Worst} = \max_{1 \leq x \leq R} f(x)$$

(14)

where $f(x)$ is the iteration best value of fitness.

IV. RESULTS AND DISCUSSION
Many experiments were carried out and three well-known algorithms, namely PSO, GWO, and SCA, were compared to verify HHO algorithm performance. The simulations were conducted in Windows 10 environment, Intel core i5-3210M, memory 8GB, and clocked at 2.5 GHz. The simulations were implemented in MATLAB 2020a.
A. SIMULATION SETUP

The simulations were carried out in a square region of 1000 m × 1000 m, and the distribution of the clients was performed uniformly throughout the deployment region. Table 3 summarizes the network.

B. RESULTS

Fig. 2 illustrates an example of the topology generated by HHO as compared to the topology at the initial iteration when the 100 routers set is utilized. As illustrated in Fig. 2a, a significantly low mesh clients’ coverage is obtained in the initial iteration. Furthermore, poor connectivity of the network can also be observed in which the biggest subgraph is $\theta = 24$. The proposed HHO, as shown in Fig. 2b, has significantly enhanced client coverage, and the mesh router placements have been carefully selected to achieve maximum network connectivity. The connectivity has increased where the biggest subgraph is $\theta = 98$. Meaning that 98 out of 100 mesh routers are forming one big subgraph which confirms the great connectivity achieved by the proposed HHO. The competing algorithms, on the other hand, cause numerous mesh routers to overlap, leading to increased interference, whereas the network topology created by the HHO algorithm is more scattered out, allowing it to produce greater clients’ coverage.

The performance of HHO against the competing algorithms is presented in Fig. 3, which includes the connectivity and coverage of three different network sizes. A low mesh clients’ coverage is obtained in the initial iteration when the network is constructed with 40 routers which is as low as 70%. This percentage has slightly increased when the network size is increased without applying any optimization technique. However, it is not optimum as compared to the plot in Fig. 3b that HHO has significantly increased the coverage of all network sizes. In addition, the proposed HHO outperforms the competing algorithms in providing wider coverage of 79%, 98%, and 98% for network sizes of 40, 60 and, 100 routers, respectively. On the other hand, very low network connectivity is obtained in the initial iteration which can be as low as $\theta = 6$ of a network composed of 40 mesh routers. This can be seen in Fig. 3a, where the network connectivity was very low for all network sizes. The reason is that multiple subgraphs were created as supposed to a greater subgraph, which then reduces the network connectivity. Therefore, HHO and other algorithms, as shown in Fig. 3a, have significantly enhanced client coverage, and the mesh router placements have increased the network connectivity. The proposed HHO has shown greater connectivity compared to other algorithms where the size of the biggest subgraph $\theta$ has increased to produce values of 94, 96, and 98 connected routers for network sizes of 40, 60 and 100 mesh routers, respectively.

C. CONVERGENCE STUDY

When it comes to developing an optimal solution through optimization algorithms, the convergence curves are the most crucial visual analyses to comprehend. The convergence curves are obtained from every used algorithm, in this work, after 100 iterations in order to observe and analyse the ability of convergence for all algorithms in terms of applying and minimising the fitness function to achieve maximum coverage and connectivity. Figs. 4, 5 and 6 show the convergence curves of HHO and other algorithms with respect to different network sizes. The fitness function described in Eq. (10) is

![Figure 2. Connectivity and Coverage of Mesh Network with 100 routers and 100 clients.](image-url)
used to generate the convergence curve. Six experiments are carried out to demonstrate the effectiveness of HHO algorithm by evaluating the convergence curve. Figs. 4, 5 and 6 show six convergence curves for different values of $\zeta$ against the value of fitness. The generated results were tested against a variety of network setup parameters to see which ones were the most accurate.

All algorithms exhibit rapid changes in the early stages of iterations, but these changes diminish dramatically as the iteration progresses. The PSO algorithm, on the other hand,
struggles from premature convergence, which means that it is more likely to become trapped in a local optima rather than a global optima.

The evolution speed of an algorithm is a key component that determines its overall performance. After a number of iterations, as shown in Figs. 4, 5 and 6, HHO has achieved better performance and faster convergence compared to other algorithms while also finding a minimum fitness function value. HHO algorithm outperforms other algorithms in solving mesh router placement problem for different $\zeta$ aggregation values, as demonstrated by the results. It can be observed that the convergence of the algorithms degrades as the aggregation value of $\zeta$ increases due to the direct proportion in the fitness function.

D. STATISTICAL ANALYSIS

In this work, different network sizes (N) from 40 through 100 routers are used to form the mesh network datasets. A total of 100 runs of the algorithms are performed in order to determine whether or not the results are statistically significant. The goal of this work is to analyse the HHO algorithm’s performance using the fitness function that was described previously. Three well-known algorithms, PSO, GWO, and SCA, are utilised to verify and compare the findings. This subsection contains a collection of statistical findings that are presented both qualitatively and quantitatively. In this work, it is worth noting that 100 iterations and 100 runs were used, as well as 40 through 100 search agents based on the network size were used in the experiments. It should be mentioned that a wide range of performance indicators have been used to quantify the performance of the algorithms to obtain the quantitative findings. It can be seen in Fig. 7, that the HHO algorithm has achieved the minimum mean value for all the network sizes and different values of $\zeta$. As the value of $\zeta$ decreases, the fitness function produces minimum values and hence better performance of the network. This indicates that HHO outperforms the other algorithms in obtaining the minimum fitness value, and hence the optimum mesh network topology.

Table 4 outlines the statistical findings of the objective function obtained by HHO, PSO, GWO, and SCA algorithms for 40, 60, and 100 mesh routers with two $\zeta$ values of
0.5 and 0.7. The findings affirmed that the HHO algorithm has the smallest performance values compared to benchmarking algorithms that have been investigated. In this context, the smallest mean values show that HHO finds the best value with the smallest fitness function, however, the smallest standard deviation signifies that convergence identically, reliability, and stability are at the top level.

### E. SIGNIFICANCE ANALYSIS

For further validation, the one-way analysis of variance (ANOVA) test was considered to verify if the differences between the results obtained by the proposed HHO algorithm and other algorithms were statistically significant. The null hypothesis implies non-significant difference in the objective function values between the proposed algorithm and other algorithms. The null hypothesis acceptance is occurred at states level greater than 0.05, while the rejection occurs at states level lower than 0.05 (i.e., if P-value is less than 0.05, the differences between the proposed and benchmarking algorithms are statistically significant). This work utilised the ANOVA test to find the significance difference because there are more than three algorithms to be compared. The obtained P-values presented in Table 5 verify the rejection of the null hypothesis and also confirm that there is a significance difference between the proposed HHO algorithm and the benchmarking algorithms.

### F. PERFORMANCE ASSESSMENTS AND COMPARISON

The performance assessment and comparison with the state-of-the-art are presented in Table 6. It presents the comparison of the HHO algorithm used in this work with the literature regarding their proposed algorithm, grid size, network size, connectivity rate, and coverage rate. Despite the large grid used in this work, it still outperforms the state-of-the-art. It can be observed that the HHO algorithm has obtained 98% in term of both coverage and connectivity metrics. The

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**TABLE 4.** HHO vs other algorithms statistical metrics with network size 40, 60 and 100.

| No. Routers | Statistical Parameter | PSO | GWO | SCA | HHO | PSO | GWO | SCA | HHO |
|-------------|-----------------------|-----|-----|-----|------|-----|-----|-----|------|
| 40          | Mean                  | 0.34581 | 0.310086 | 0.33621 | **0.254925** | 0.371515 | 0.33332 | 0.3514 | **0.30816** |
|             | STDV                  | 0.066393 | 0.022357 | 0.024227 | **0.021097** | 0.025568 | 0.015771 | 0.016984 | **0.010506** |
|             | Worst                 | 0.51 | 0.4875 | 0.435 | 0.49 | 0.395 | 0.3895 | 0.387 | 0.382 |
|             | Best                  | 0.3535 | 0.3011 | 0.3201 | **0.2475** | 0.367 | 0.324 | 0.3355 | **0.301** |
| 60          | Mean                  | 0.329877 | 0.232924 | 0.240096 | **0.200883** | 0.344665 | 0.256173 | 0.264853 | **0.22891** |
|             | STDV                  | 0.028606 | 0.018453 | 0.020456 | **0.015624** | 0.026089 | 0.015999 | 0.014963 | **0.012478** |
|             | Worst                 | 0.377 | 0.4033 | 0.375 | 0.405 | 0.3818 | 0.3933 | 0.375 | 0.385 |
|             | Best                  | 0.23 | 0.2283 | 0.2317 | **0.195** | 0.3221 | 0.25 | 0.257 | **0.22** |
| 100         | Mean                  | 0.14644 | 0.0874 | 0.10525 | **0.0753** | 0.13445 | 0.10861 | 0.11735 | **0.09191** |
|             | STDV                  | 0.022304 | 0.020269 | 0.013584 | **0.010984** | 0.023375 | 0.021212 | 0.021578 | **0.005772** |
|             | Worst                 | 0.18 | 0.215 | 0.17 | 0.235 | 0.192 | 0.143 | 0.181 | 0.14 |
|             | Best                  | 0.12 | 0.08 | 0.101 | **0.07** | 0.123 | 0.098 | 0.106 | **0.091** |

**TABLE 5.** ANOVA table results on the network performance.

| No Routers | 40 Routers | 60 Routers | 100 Routers |
|------------|------------|------------|-------------|
| ζ = 0.5    | P-value = 0.002 | P-value = 0.0017 | P-value = 0.0012 |
| ζ = 0.7    | P-value = 0.0088 | P-value = 0.0058 | P-value = 0.0036 |

**TABLE 6.** Performance comparison with the-state-of-the-art.

| Reference | Optimization Algorithm | Grid size (meters) | Network size | Connectivity Rate | Coverage Rate | Remarks |
|-----------|------------------------|-------------------|--------------|------------------|--------------|---------|
| [22]      | Tabu search (TS)        | 132 × 132         | 64 routers and 192 clients | 89% | 87% | Moderate connectivity and coverage |
| [23]      | Genetic Algorithm (GA)  | 128 × 128         | 64 routers and 192 clients | 96.9% | 39.6% | High connectivity and low coverage |
| [25]      | Simulated Annealing (SA) | 64 × 64           | 32 routers and 96 clients | 91.7% | 91.7% | Moderate connectivity and high coverage |
| Current Work | Harris Hawks Optimization (HHO) | 1000 × 1000 | 100 routers and 100 clients | 98% | 98% | Very high connectivity and coverage |
superior performance of the proposed HHO is a result of the designer’s knowledge during the designing process.

V. CONCLUSION AND FUTURE WORK

The mesh routers positioning in WMN plays an essential role in enhancing its mobility in terms of network connectivity and coverage. When this issue was formulated as an optimization problem, numerous metaheuristic algorithms were proposed, which in turn showed outstanding outcomes on networks with small to medium size. Addressing the routers placement problem in networks of a large size was the motivation of this work. Hence, mesh routers placement with networks size of 40, 60 and 100 routers were optimized by applying a new effective optimization technique known as Harris’ hawk optimization (HHO). The main goal is to increase the network connectivity and coverage by optimizing the mesh routers’ locations in the targeted wireless mesh network. Considering both the connectivity and coverage problems in a wireless mesh network, HHO results were compared with PSO, GWO and SCA metaheuristic algorithms. Using the proposed objective function, the HHO algorithm achieved the best solutions with the maximum coverage and connectivity, as measured by a variety of assessment metrics. The simulation findings of three various network sizes also revealed that the HHO algorithm demonstrated a considerable improvement in topology formation when compared to benchmarking algorithms.

Efforts are underway to develop a hybrid optimization approach by combining two algorithms (e.g., HHO with one of the recent algorithms) to produce optimum coverage and connectivity while reducing the number of mesh routers to ensure less computational complexity. It is recommended that future research should consider obstacle avoidance while maximizing the coverage and connectivity when implementing a wireless mesh network.

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