

Mesh router node placement using somersault based giant armadillo optimization

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ABSTRACT

Wireless mesh networks (WMNs) have rapidly advanced in the last decade because of their ease of experimentation at minimum cost, simple network maintenance, and consistent provision coverage. However, the placement of router nodes remains a critical research challenge for network operators, as it directly impacts the overall performance and effectiveness of the WMN. Thus, this research proposes a novel approach of the somersault fraction strategy (SFS)-based giant armadillo optimization (GAO) for addressing an issue of mesh router (MR) node placement in WMN. A significance of the proposed SFS-GAO approach was estimated in terms of different scenarios under diverse settings, considering network connectivity as well as client coverage metrics. The simulation outcomes demonstrate that the proposed SFS-GAO method achieves better results in each performance metric like coverage, connectivity, and fitness, based on a varied count of mesh clients (MC), MR, and coverage radius. The findings show that the proposed function offers higher client coverage and optimal network connectivity with minimum computation power.

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1. INTRODUCTION

Wireless mesh networks (WMNs) have arisen as the most popular because of their capability to enhance network usage owing to their dynamic individual organization, configuration, and adaptive nature [1], [2]. They can be integrated with different types of wireless networks that are utilized for community and neighborhood networks. Through the advancement of 5G, WMN play an important role in various applications that require dynamic, autonomous networks, and self-organization [3], [4]. The term “mesh networks” comprises of different network standards like wireless sensor networks (WSN), mobile ad-hoc networks (MANET), vehicular ad-hoc networks (VANET), home networks, and underwater networks [5]. The mesh networks are characterized by multi-hop communication as well as mostly wireless node connectivity, and dynamic connections as well as routers were modified for network development [6]. WMN have been utilized to enlarge individual-hop infrastructure-assisted wireless networks. This minimizes the network size by impacting poor spatial recovery in multiple-hop networks because of their greater spatial reuse, and smart antennas are important for improving transmission size [7]. On the other hand, mesh networks are comprised of the integration of fixed nodes, wireless, and mobile, where the key traffic flow is from the user to the gateway. In contrast, the routes and connections in a WMN are less dynamic [8]. WMNs

have greater expandability, minimum deployment cost, greater reliability, reliable Internet connectivity, and relatively stable topology [9], [10].

WMN is comprised of diverse forms of nodes like mesh clients (MC) and mesh routers (MR). The MR is installed through various radio interfaces associated with different wireless channels, whereas the MCs contain individual radio interfaces [11], [12]. The basic channel medium was accomplished between the MC and MR to establish effective communication. The WMN was developed to distribute the prevalent network coverage through the lack of utilization of any centralized infrastructure. Thus, the WMN is used as a support network for metropolitan area networks [13], [14]. These networks can automatically reroute the information with substitute paths and ensure continuity and reliability, even in the challenges of node failures [15]. The new nodes were extended to the network without the requirement for reconfiguration or infrastructure changes. This reliability is appropriately designed for different constraints [16]. Identifying a suitable position for installing WMN routers in real-time applications is important. Thus, optimization is important to ensure reliable and effective WMN significance [17], [18]. The optimization is utilized for fine-tuning different parameters, such as the placement of the router, transmission power, topology of the network, and routing protocols, to attain optimal network effectiveness [19]. Optimizing these parameters enables the model to ensure that the WMN offers unified coverage, minimum latency, and consistent connectivity even in challenging industrial environments. Moreover, optimizing the parameters in a WMN enhances scalability and minimizes maintenance costs [20].

The existing literature on MR node placement in WMNs suffers from critical limitations: coyote optimization algorithm (COA) and moth flame optimization (MFO) approaches struggle with local optima; enhanced chaotic Levy opposition-based MFO (ECLO-MFO) and combination of the improved Fick's law approach through inclusive learning (CFL) and particle swarm optimizer (PSO) are complex and sensitive to parameters; and accelerated particle swarm optimizer (APSO) and hounds search-based genetic algorithm (Hnds-GA) converge quickly but often at the cost of solution diversity. However, this research is enthusiastic about solving the issue of MR node placement in WMN. In particular, this research focuses on the deliberate choice of optimal router positions to enhance the connectivity and coverage of the network. Thus, this research proposes the metaheuristic approach of the somersault fraction strategy (SFS)-based giant armadillo optimization (GAO) is taken out in combination through a well-described fitness function. Unlike prior methods, SFS-GAO combines strong exploration and exploitation via mound-attacking and digging phases with a novel somersault strategy to escape local optima. This ensures higher client coverage, better connectivity, and optimized placement efficiency, even under varied MR/MC counts and coverage radii. The important aim of this study was to identify the optimal positions for MR by enhancing the conventional GA through comprehensive learning. The important contributions of this research are as pursuing.

This study proposes the novel metaheuristic approach of SFS-GAO to optimize router node placement in a WMN. To broadly estimate the effectiveness of the proposed SFS-GAO method, this study analyzed the WMN model and diverse standard functions and estimated its outcomes using various optimization approaches. SFS-GAO's optimized router placement significantly improves the connectivity as well as coverage in the WMN, demonstrating the importance of interpenalizing optimization. Moreover, the utilization of SFS-GAO results in fewer node placements, leading to cost minimization and enhanced network congestion in the WMN.

This research paper is given as trails. Section 2 specifies related work. Section 3 the proposed methodology. Section 4 illustrates the MR node placement using GAO algorithm. Section 5 specifies the results and discussion. The conclusion is given in section 6.

2. RELATED WORK

Though optimization approaches are converged to a local optimum, they demonstrated significant advancements and achievements compared to many other optimization methods approaches. Through real-time environments, meta-heuristic approaches determine the optimal and consistent network framework for solving the problems of placement of MR. Some of the approaches based on this application are analyzed. Taleb *et al.* [21] implemented the COA to tackle a problem MR placement in WMS. The implementations were employed under diverse conditions with multiple backgrounds, taking into account binary significant indices like network connectivity as well as user coverage. The findings illustrate that an efficiency and advantages of the COA in determining better MRs were compared with those of the other optimization approaches. However, the COA approach focuses on connectivity and user coverage, but lacks mechanisms to avoid premature convergence, leading to suboptimal solutions in dense scenarios.

Taleb *et al.* [22] introduced an improved version of ECLO-MFO for the placement of MR nodes in WMN. The introduced approach combines multiple mechanisms, such as the idea of a chaotic concept, levy flight, and opposition-based learning (OBL) methods, to enhance optimization effectiveness. Initially,

chaotic maps were used to improve the chaotic stochastic attitude of the MFO approach. Next, Levy flight distribution was acquired to improve the population diversity of the MFO. Eventually, the OBL was developed to improve convergence speed of MFO and identify a solution space significantly. However, the combination of multiple strategies results in high complexity and parameter sensitivity, making it less scalable. Nouri *et al.* [23] presented the MFO approach to ignore uneven networks produced through the previous formulation. Moreover, the presented MFO approach enhanced client coverage while optimizing and maximizing network connectivity for the best effectiveness through a lack of requirements for integration coefficient understanding. However, the MFO approach attempted to avoid uneven networks, but did not provide adaptive mechanisms for diverse network densities.

Nouri *et al.* [24] developed an APSO for the placement of MR in a WMN. This method was chosen due to its rapid and minimum computational complexity, as estimated with various population-assisted approaches. The multi-objective aggregation function was estimated to instantaneously enhance the MC coverage and connectivity of MR. The router placement demonstrated an occurrence of multi-objective optimization issues through a broad solution space. However, the model offered rapid convergence but failed to maintain solution diversity, risking local optimum entrapment. Angelo and Palmieri [25] implemented a Hnds-GA approach for router placement in a WMN. The implemented approach allowed the advantages provided through GA prehybridized through a local search method motivated by the hound dog's activities. The key concept is to compete with the behavior of hound dogs moving through an optimal search space, positioning themselves in the most favorable areas to efficiently locate and achieve the best possible solution. However, an integrated GA with local search suffers from slow convergence and computational overhead because of hybridization.

Abdulrab *et al.* [26] developed a hybrid Harris hawk optimization with the sine cosine algorithm (HHOSCA) approach for better node placement and bottleneck minimization in a WMN. The HHOSCA approach pursued better router placement, which effectively resulted in enhanced network coverage and comprehensive connectivity among the MR. Moreover, the developed HHOSCA approach generates a cost-efficient WMN through the minimization of congestion in the network to a lower number of routers, while ensuring enhanced coverage and connectivity. However, the HHOSCA approach lacks the dynamic adaptability to changing environments. Amer *et al.* [27] introduced a CFL-PSO for optimal router nodes placement in WSN. The CFL-PSO approach leverages the strengths of both methods to achieve a balance between network connectivity and coverage, thereby significantly enhancing the overall effectiveness of the WSN. However, the CFL-PSO approach enhanced the balance between coverage and connectivity but did not consider local optima escape mechanisms. Ussipov *et al.* [28] developed a maximum entropy genetic algorithm (MEGA) to solve a problem of MR node placement in a WMN. In the developed approach, an objective function is estimated through Shannon's entropy and targeted to attain greatest entropy value. Based on this concept, entropy is enhanced at probability distributions of the nodes are similar. However, the MEGA is computationally intensive and sensitive to parameter tuning.

3. METHOD

This section demonstrates the approach used in the procedure for optimizing coverage and connectivity in the WMN. The mathematical definition of system model and the placement of MR node in the WMN are provided here. Initially, the system model is provided, and the problem formulation is described in detail in the subsection. Figure 1 shows the architecture of MR node placement.

3.1. System model

In reality, it is impossible to identify the dispersal of an actual MC at an initial glimpse. Therefore, it is most complex to identify a better position of the MR. As compared to traditional static deployment assumptions, the proposed approach considers dynamic MC whose positions may change during network operation. The MR locations are therefore optimized based on different distribution of MCs to attain effective coverage and connectivity under dynamic conditions. Through this consideration, the placement of MR nodes in WMN issues remains challenging and cannot be addressed by an accurate rapid approach because attaining optimality is still computationally complex. Consider that MC access the internet or communicate through various probable clients by MR because MC can connect to only individual MR as well as lack the bridge or gateway function. With respect to addressing the issue of placement of the MR, the following considerations were made.

- i) The positions of the MC are familiar and survey the uniform or usual dispersals in different dimensional areas.
- ii) Every MR contains diverse broadcast series.
- iii) Binary mesh nodes communicate if and only if they are in a broadcast series.

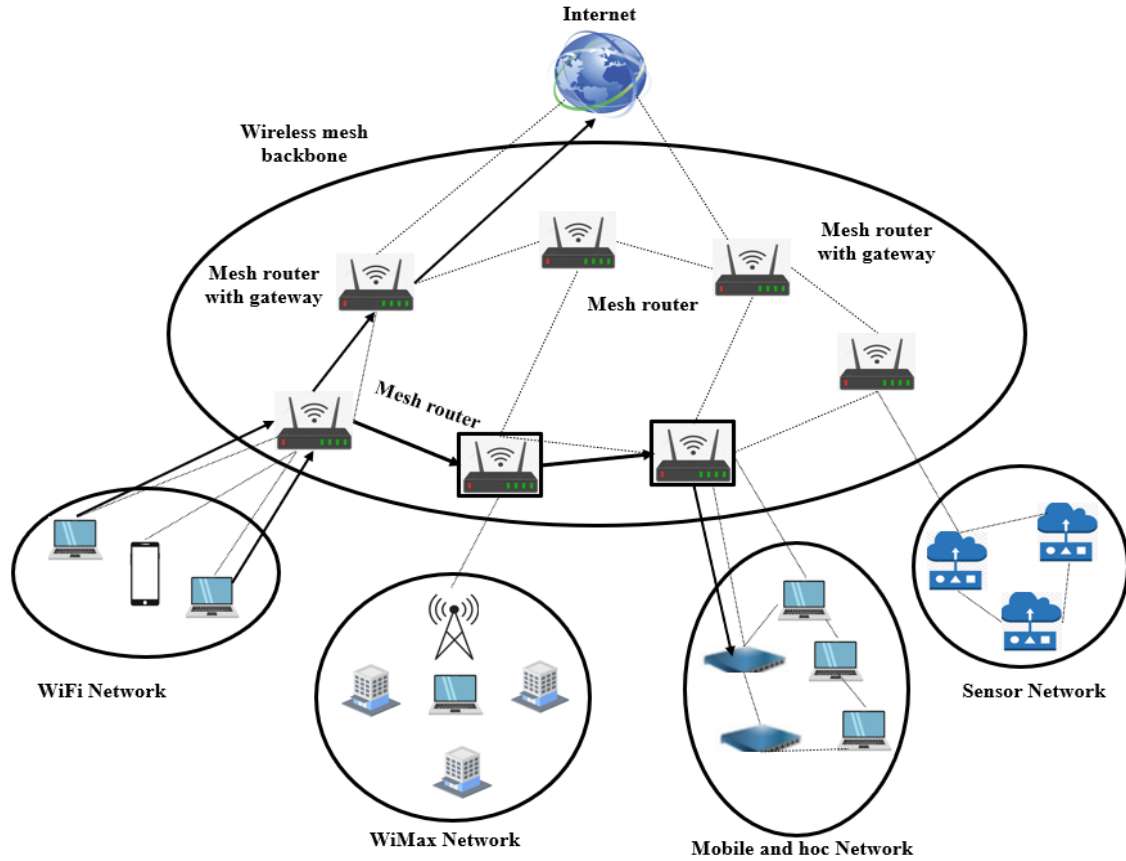


Figure 1. Architecture of the MR node placement

3.2. Problem formulation

Precisely, a WMN is denoted as an undirected graph $G = (V, E)$, where V specifies a group of network nodes, and E denotes a group of wireless networks between the nodes. In this research, the nodes are binary types, such as clients ($C \subset V$) and routers ($R \subset V$). Moreover, G comprises various disjointed sub-graphs. Assuming that m and n denotes count of MR and MC, individually, it is formulated in (1) to (3).

$$V = R \cup C \quad (1)$$

$$G = G_1 \cup G_2 \cup \dots \cup G_k \quad (2)$$

$$\bigcap_{i=1}^k G_i = \emptyset \quad (3)$$

Where R is a group of MR nodes; C is a group of MC nodes; G is a set of node groups in a network; G_k means total number of groups; G_i means i th group of nodes; $\emptyset$ denotes the empty set and $\bigcap_{i=1}^k G_i$ is a constraint indicating that the groups are mutually exclusive. $C = \{c_1, \dots, c_n\}$, $R = \{r_1, \dots, r_m\}$, $k \in [1, \dots, m]$, and $G_i \subseteq G$. Every node is prepared through the edge considered with effective coverage radius (CR). Assuming e_i becomes a CR of i th node, binary routers r_i and r_j are associated only with a distance d is lesser than or equal to a sum of their CR is formulated in (4). The overlap among the radio coverage areas of the routers is determined by their receive sensitivity and transmission effectiveness, which work in conjunction. A client c_i is assumed to associated to router r_j , which is formulated in (5).

$$d(r_i, r_j) \leq e_i + e_j \quad (4)$$

$$d(c_i, r_j) \leq e_j \quad (5)$$

Here d denotes Euclidean distance as well as e_i and e_j specifies the transmission range of router r_i and r_j respectively. This research considers the WMN arranged in 2D area (N) of dimensions $w \times h$, after that, a router's placement issue is described as determining a better group of positions (v) for routers, which enhances coverage and connectivity of clients, for the provided MC's misplacement. This refers to the number of clients associated to minimum individual router, whereas the latter is measured through evaluating a volume of greater network component. Therefore, a client coverage $\Psi(G)$ is formulated using (6). The connectivity of the network is formulated in (7).

$$\Psi(G) = |c_j: d(r_i, c_j) \leq e_i| \forall r_i \in R, \forall c_j \in C \quad (6)$$

$$\phi(G) = \max_{i \in [1, \dots, k]} \{|G_i|\} \quad (7)$$

Where $\Psi(G)$ is a coverage function of network graph G ; $d(r_i, c_j)$ denotes the Euclidean distance among router r_i and client c_j ; $\phi(G)$ is a connectivity function of network graph G ; k denotes the total count of connected components; and $|G_i|$ denotes count of reachable nodes (clients or routers) in subnetwork G_i . Both purposes cause the effectiveness of the WMN, and thus both require improvement. It is important to note that the objectives involved may be conflicting, where improving one can potentially degrade another. Due to this inconsistency, the aim often shifts to identifying an illustrative set of pareto-optimal explanations for selecting a trade-off based on particular user preferences. This research adopted the latter approach, utilizing the widely used weighted-sum method for experimentation. Consequently, the objectives are formulated in (6) and (7), which are minimized to an own objective function, as formulated in (8) and (9).

$$J = \lambda_1 \Psi(G) + \lambda_2 \phi(G) \quad (8)$$

$$\lambda_1 + \lambda_2 = 1 \quad (9)$$

Here J is an overall objective function; λ_1 and λ_2 demonstrate user preference factors assigned to coverage $\Psi(G)$ and connectivity $\phi(G)$. A user preference demonstrated through weights λ_1 and λ_2 which are most suggestive if aim functions are standardized in terms of their greatest value. Consequently, through assuming (9), (8) is modified into (10). Eventually, an issue of router placement is represented as an optimization issue, which is formulated in (11).

$$J = \lambda \frac{\Psi(G)}{n} + (1 - \lambda) \frac{\phi(G)}{n+m} \quad (10)$$

$$\max_{\forall i \in N} J \quad (11)$$

Here $\lambda \in [0,1]$ denotes user partiality; n and m specifies the total count of MC and MR respectively; N illustrates the solution search space representing all feasible router placement configurations and $\max_{\forall i \in N} J$ denotes the maximization of the fitness function over all feasible solutions. Based on the formulation, the router placement problem is clearly defined as a multi-objective optimization task, where the goal is to maximize client coverage and network connectivity while minimizing redundant deployments. To address this NP-hard problem effectively, a robust optimization technique is required. Therefore, the GAO algorithm, enhanced with the SFS is introduced in the following section to provide an efficient solution framework.

3.3. Integer linear programming formulation

To provide an exact benchmark for evaluating the solution quality of the proposed SFS-GAO algorithm, the MR placement problem is formulated as an integer linear programming (ILP) model for small-scale network instances. In this formulation, binary decision variables are defined to represent router deployment and client assignment, where $x_i = 1$ indicates that a MR is placed at candidate location i , and $x_i = 0$ otherwise. Similarly, $y_{ij} = 1$ denotes that MC j is assigned to router i , while $y_{ij} = 0$ indicates no assignment. The objective function maximizes the overall network performance by jointly considering client coverage and router connectivity under identical optimization constraints. The model is subject to deployment constraints that limit the number of routers, assignment constraints ensuring that each client is associated with at most one router, communication range constraints that permit assignments only when the client lies within the transmission range of the selected router, and binary constraints on all decision variables. The ILP formulation provides globally optimal solutions for small network instances and serves as a reference benchmark to quantify the optimality gap of the proposed SFS-GAO approach. However, due to

the combinatorial nature of the router placement problem, the computational complexity of the ILP model increases exponentially with network size, making it impractical for large-scale WMNs. Therefore, the proposed SFS-GAO algorithm is adopted as an efficient alternative that achieves near-optimal solutions with significantly lower computational cost.

4. MESH ROUTER NODE PLACEMENT USING GAO ALGORITHM

The GAO approach is appropriate for MR node placement in WMN because of its strong balance between exploration and exploitation, which is important for optimizing node positions to enhance coverage and connectivity while minimizing interference. Unlike traditional algorithms such as PSO, GA, and grey wolf optimization (GWO), the proposed GAO effectively escapes local optima using adaptive movement and mound-digging-inspired local refinement. For instance, in a WMN scenario with varying node densities, the GAO dynamically adjusts router positions to ensure a uniform signal distribution and minimal packet loss. Thus, GAO delivers more accurate and stable placement outcomes than the traditional methods.

The proposed GAO method is a biomimetic metaheuristic approach that replicates a normal action of a giant armadillo (GiA) in a barren. Among the natural behaviors of GiA, the process in which animals attack termite mounds and excavate them for nourishment is modeled in the development of GAO. In this model, the GiA, respective to a solution space and the location of every one in a wild, resembles the location of their member in a solution space as a candidate solution.

4.1. Population initialization

GAO algorithm is a populace-assisted meta-heuristic approach which considers GiA in its population [29]. GAO is capable of offering appropriate problem-solving for optimization issues in a continuous procedure according to the solution power of its candidates in a solution space. A GiA combinedly produces a population that is modelled from a mathematical perspective through a matrix based on (12). The initial position of GiAs in a solution space is arbitrarily initialized early in the approach implementation using (13).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} X_{1,1} & \dots & X_{1,d} & \dots & X_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{i,1} & \dots & X_{i,d} & \dots & X_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{N,1} & \dots & X_{N,d} & \dots & X_{N,m} \end{bmatrix}_{N \times m} \quad (12)$$

$$X_{i,d} = lb_d + r.(ub_d - lb_d) \quad (13)$$

Where X specifies a population matrix of the GAO; X_i denotes a member (candidate solution) of the GAO. $X_{i,d}$ specifies the d th dimension in a solution space; N specifies a count of GiAs; m denotes the count of decision variables; r denotes the arbitrary number in a range between 0 and 1; and ub_d and lb_d means upper and lower bounds of the d the dimension individually.

4.2. Exploration stage – attack on termite mounds

In an initial GAO stage, a location of population candidates in a solution space is updated according to the reproduction of an attack of GiA on termite mounds. Modelling this attack behavior led to crucial modifications in GiA's positions, thereby enhancing the approach's exploration capability in large search supervision. In a GAO development, for every population member which describes the GiA, a position of various population members that involves the optimal fitness function value is assumed to be a termite mound. A group of individual mounds for every candidate in a population is represented in (14).

$$TM_i = \{X_k: F_k < F_i \text{ and } k \neq i\}, \text{ where } i = 1, 2, \dots, N \text{ and } k \in \{1, 2, \dots, N\} \quad (14)$$

Where TM_i denotes group of positions of individual termite mounds for i th GiA, X_k specifies a population candidate through the value of the optimal fitness function than i th GiA, and F_k demonstrates its fitness function value. In the GAO process, an agent arbitrarily chooses termite mounds from the group and initiates an attack, simulating the natural predatory behaviour observed in the wild. According to the modelling of the program of GiA over termite mounds, an unknown location was estimated for every member of a population using (15). Subsequently, this unknown location changes a prior location of respective individual if it enhances an objective function value as defined by (16).

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j} \cdot (STM_{i,j} - I_{i,j} \cdot x_{i,j}) \quad (15)$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} \leq F_i \\ X_i, & \text{else} \end{cases} \quad (16)$$

Where $STM_{i,j}$ specifies the chosen termite mound for i th GiA in j th dimension; $x_{i,j}$ is a current position of i th agent in j th dimension; X_i is a position vector of i th agent; $x_{i,j}^{P1}$ defines an unknown position estimated for i th GiA according to the attacking stage of the introduced GAO in j th dimension; F_i^{P1} defines the value of an objective function; $r_{i,j}$ demonstrates the arbitrary numbers in the range between 0 and 1; and $I_{i,j}$ specifies the numbers that are arbitrarily chosen as 1 or 2.

4.3. Exploitation stage – digging in termite mounds

In next stage, a location of population candidates in a solution space was updated according to a simulation of GiA excavating in termite mounds to nourish them. Modelling the digging behavior of GiA for attacking and consuming termites resulted in slight adjustments to their position. Consequently, it enhances the exploitation influence of an approach in limited search supervision. In GAO modelling, according to design of the GiA's knowledge of digging into termite mounds, an unknown location is estimated for each population candidate through (17). Subsequently, if an objective value is enhanced, this unknown position modifies a preceding location of respective member based on (18).

$$x_{i,j}^{P2} = x_{i,j} + (1 - 2r_{i,j}) \cdot \frac{ub_j - lb_j}{t} \quad (17)$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} \leq F_i \\ X_i, & \text{else} \end{cases} \quad (18)$$

Where $X_{i,j}^{P2}$ denotes a new position estimated for i th GiA according to the digging stage of GAO in j th dimension and t denotes the counter of the iterations. After discussing the conventional GOA approach, the working of SFS in such algorithm is discussed in the following section.

4.4. Somersault foraging strategy

As the population iterates further, the concentration of a solution changes slightly from exploring a local problem-solving space to refining the local solution. At this stage, the iteration of a candidate is guided by the current better location. If it establishes only a local optimum, it will direct the population over performing local exploration at this local optimal position, designing it complex to pause free from restrictions of local optima. To solve this issue, this research proposes the SFS to disturb the location of the present better GiA, improving the approach's capability to exceed local optima. The SFS is formulated in (19).

$$x^{GAO} = x^b + S \times (r_1 \times x^b - r_2 \times x^*) \quad (19)$$

Where x^b denotes the global best individual GiA; x^{GAO} is an updated position vector of the current agent after applying GAO; x^* specifies the present optimal individual GiA; S is the somersault factor through a value of 2; and r_1 and r_2 specify arbitrary values in the range of zero to one, respectively.

This strategy introduces controlled perturbations that help the algorithm escape stagnation around local optima. By dynamically adjusting the search direction using the global and current best solutions, the somersault movement enhances both exploration and exploitation. Consequently, the incorporation of SFS strengthens GAO's ability to maintain diversity in the population and achieve more reliable convergence. The computational complexity of the GAO algorithm is $O(P \times I \times D)$, where P denotes the population size, I is the maximum number of iterations, and D represents the dimensionality of the solution space. The proposed SFS-GAO incorporates an additional somersault fraction update; however, this operation does not change the asymptotic complexity and retains the same order of $O(P \times I \times D)$. Due to accelerated convergence and reduced fitness evaluations, SFS-GAO exhibits lower effective computational cost in practice. Algorithm 1 shows the pseudocode of proposed SFS-GAO approach for better reproducibility.

Algorithm 1. The SFS-GAO approach

Input: network graph $G(V, E)$, number of routers (m), population size (N), maximum iterations (T), weight parameter (λ), and GAO control parameters

Output: optimal router placement X_{best}

1: Initialize population X_i ($i = 1, 2, \dots, N$) randomly

```

2: Evaluate fitness  $F_i$  for each  $X_i$  using objective function  $J$ 
3: Identify global best solution  $X_{best}$ 
4: for  $t = 1$  to  $t$  do
5:   // Stage 1: SFS-based candidate screening
6:   Compute fitness distribution of population
7:   Select elite subset  $S$  using SFS
8:   // Stage 2: GAO-based position update
9:   for each candidate  $X_i \in S$  do
10:    Generate random values  $r_1, r_2 \in [0,1]$ 
11:    Update position using GAO:
12:     $X_{i_{new}} = X_{best} + S \times (r_1 \times X_{best} - r_1 \times X_i)$ 
13:    Apply boundary constraints
14:    Evaluate fitness  $F_{i_{new}}$ 
15:    if  $F_{i_{new}} \geq F_i$  then
16:       $X_i = X_{i_{new}}$ 
17:       $F_i = F_{i_{new}}$ 
18:    end if
19:  end for
20:  Update global best solution  $X_{best}$ 
21: end for
22: return  $X_{best}$ 

```

4.5. Addressing mesh router nodes placement problem through SFS-GAO

An issue of MR node placement is familiar to be NP-hard issue, and various meta-heuristic approaches have established their achievements in this area. The integration of SFS with GAO further enhances its capacity to overcome local optima, which is crucial for handling the complexity of MR placement. Table 1 demonstrates the similarities between GAO and MR node placement issues.

Table 1. Similarities among the GAO and MR node placement issues

GAO system	MR placement issue
Search space	Deployment area
Social condition of GiA	Router's position
Solution	Group of optimal MR positions
Adaptation of GiA	Objective function value
Generating new solutions	Cultural interaction inside the packs

4.5.1. Fitness or objective function

The proposed method is to determine the best placement of the provided MR count, which enhances the user coverage as well as the network connectivity indices. The user coverage demonstrates the count of MC covered through a minimum of one router, while the network connectivity is described through a volume of greater sub-network between k-produced sub-networks in terms of count of mesh nodes. These indices are included to describe a fitness function f utilized to access the solution quality. The objective function is formulated in (20).

$$f(SC_c^p) = \lambda \frac{\Psi(G)}{n} + (1 - \lambda) \frac{\Phi(G)}{n+m} \quad (20)$$

Here G is a graph respective to a solution SC_c^p ; λ denotes the floating parameter in a range between 0 and 1, which is utilized to maintain the significance of the indices. Thus, based on this aim function formulation, a solved issue is assumed to be the maximization of $f(SC_c^p)$. Hence, it is important to convert the objective function into a minimization function. Subsequently, another function g is formulated in (21).

$$g = 1 - f(SC_c^p) \quad (21)$$

Since coverage and connectivity objectives are measured on different scales, min-max normalization is applied to map both objectives into the range $[0,1]$. The normalized coverage F_{cov} and normalized connectivity F_{con} are integrated through the weighted sum, which is formulated in (22).

$$F = \alpha F_{cov} + (1 - \alpha) F_{con} \quad (22)$$

Where $\alpha \in [0,1]$ controls the relative significance of coverage and connectivity.

4.5.2. Representation of the solution

The resolution of the MRs placement issue involves identifying the placement of every MR. This representation enables each candidate solution to encode the spatial configuration of MR in the deployment area. In this research, a problem-solving of every GiA is a placement solution of the MR, which is described through an array as formulated in (23).

$$SC_c^p = \{x_{c1}^p, y_{c1}^p, x_{c2}^p, y_{c2}^p, \dots, x_{cm}^p, y_{cm}^p\} \quad (23)$$

Where (x_{ck}^p, y_{ck}^p) denotes the (x, y) coordinates of MR ck . By mapping router positions into coordinate pairs, the algorithm can effectively evaluate coverage and connectivity through the defined fitness function. Such a structured solution encoding also facilitates efficient updates during the optimization process, ensuring consistent improvements across iterations.

5. RESULTS AND DISCUSSION

To confirm a significance of the proposed SFS-GAO approach, different simulations were employed and compared to the results of the proposed method, which were acquired using the methods. The experiments were conducted with 16 GB RAM, an Intel i5 processor, and Windows 10 with the MATLAB 2020R implementation tool. The experiments a performed in a quadrilateral area of $2,000 \text{ m} \times 2,000 \text{ m}$ and MC are dispersed in a deployment area in terms of the normal distribution density. The network parameter settings for proposed SFS-GAO method are listed in Table 2. The population size is fixed to 30, and the maximum number of iterations was fixed at 500 for all experiments. The GAO scaling factor S was initialized to 0.8 and linearly decreased to 0.2 to balance exploration and exploitation. The weighting parameter λ in the fitness function is fixed for 0.5, applying similar significance to coverage and connectivity objectives. The SFS retained the top 50% of candidate solutions at every iteration for refinement through GAO. All pseudo-random processes are controlled with fixed random seed (seed = 42) to make sure the reproducibility of the results. To ensure a fair and unbiased comparison, all evaluated algorithms were executed under identical simulation conditions. The similar WMN topology, client distribution, router constraints, and fitness evaluation criteria were applied across all methods. Additionally, common stopping conditions, population sizes, and iteration limits are maintained. Every experiment is repeated 20 independent runs, and average performance was reported.

Table 2. Network parameter settings

Parameters	Value	Default value
Number of MR or m	[5, 40]	100
Number of MC or n	[50, 400]	20
CR	[50, 500]	200 m
Height	[1,000, 3,000]	2,000 m
Width	[1,000, 3,000]	2,000 m
mn	50	50
λ	[0, 1]	0.5
Population size	50	50
Number of runs	30	30
Maximum number of iterations (it_{max})	2,000	2,000

5.1. Performance estimation

To estimate an effectiveness of the proposed SFS-GAO method, this research conducted an important experiment and compared the model performance against several conventional approaches. This study utilized diverse dissimilar standard functions to estimate the robustness and feasibility of the proposed SFS-GAO method. Finally, the proposed SFS-GAO method was used to optimize the WMN to improve its performance indices. Existing approaches, such as PSO, HHO, GWO, and traditional GAO, were estimated and compared with the proposed SFS-GAO method. The parameter settings of the existing methods were similar to those suggested by the proposed SFS-GAO method. To compare the existing approaches, different performance metrics are utilized, such as the network connectivity (ϕ), client coverage (Ψ), and objective function or fitness value f . This research estimated these performance metrics with variable numbers of MC, number of MR, CR values, and transmission range of MR.

Table 3 presents the performance estimation results of the proposed method in terms of the number of MC. In this situation, the number of M is varied from 50 to 300 through a fixed count of MR. From the result analysis, the user coverage, connectivity, and fitness are enhanced when the MC count of MC.

Different numbers of MC, such as 50, 100, 200, 300, and 400, are considered to validate the effectiveness of the proposed SFS-GAO approach with coverage connectivity and fitness. The proposed SFS-GAO approach achieves better coverage of 60.38, 90.38, 167.02, 239.28, and 310.02 on the varied counts of 50, 100, 200, 300, and 400, respectively.

Table 3. Performance estimation of proposed method in terms of different number of MC

Performance indices	Methods	Different number of MC (n)				
		50	100	200	300	400
Coverage	PSO	50.81	79.35	152.83	211.57	217.82
	HHO	53.21	83.21	158.38	215.39	219.38
	GWO	55.29	85.28	162.29	219.48	304.28
	GAO	57.38	87.56	163.28	234.29	307.39
	SFS-GAO	60.38	90.38	167.02	239.28	310.02
Connectivity	PSO	43.37	70.20	170.42	250.37	319.31
	HHO	45.59	73.12	173.81	254.29	321.39
	GWO	47.82	75.39	179.28	257.47	325.48
	GAO	49.38	79.93	180.82	263.32	326.32
	SFS-GAO	51.39	81.38	185	259.3	329
Fitness	PSO	0.81	0.80	0.71	0.64	0.79
	HHO	0.83	0.82	0.74	0.65	0.70
	GWO	0.86	0.85	0.78	0.67	0.73
	GAO	0.89	0.87	0.82	0.79	0.76
	SFS-GAO	0.93	0.91	0.84	0.82	0.79

Table 4 presents the performance estimation results of the proposed approach in terms of the number of MR. This analysis involved different numbers of MR, such as 4, 5, 10, 20, and 40. From the result analysis, the user's coverage, connectivity, and fitness are enhanced when improving the MR. The proposed SFS-GAO approach attains better connectivity of 63.28, 67.28, 70, 110.3, and 100 for different numbers of MR, respectively.

Table 4. Performance estimation of proposed method in terms of different number of MR

Performance indices	Methods	Different number of MR (m)				
		4	5	10	20	40
Coverage	PSO	40.47	45.39	50.87	80.46	90.12
	HHO	43.10	48.74	52.39	82.38	93.91
	GWO	45.61	51.38	57.29	83.31	95.28
	GAO	49.27	54.28	58.19	86.38	97.31
	SFS-GAO	51.38	56.21	60	89.13	100
Connectivity	PSO	49.38	58.39	59.28	95.29	92.49
	HHO	53.22	60.13	62.29	98.38	94.41
	GWO	59.38	62.32	63.29	101.38	95.29
	GAO	61.38	65.27	69.29	104.33	98.27
	SFS-GAO	63.28	67.28	70	110.3	100
Fitness	PSO	0.21	0.31	48	0.80	0.84
	HHO	0.23	0.33	0.50	0.82	0.88
	GWO	0.24	0.39	0.54	0.85	0.92
	GAO	0.26	0.41	0.59	0.87	0.94
	SFS-GAO	0.28	0.43	0.63	0.92	1

Table 5 presents the performance estimation of the proposed method for diverse CR values. Different numbers of CR, such as 100, 200, 300, 400, and 500, are considered to estimate the effectiveness of the proposed SFS-GAO method. From the result analysis, a user coverage, connectivity, and fitness are enhanced when the CR count of CR. The proposed SFS-GAO approach attains better fitness values of 0.42, 0.94, 1, 1, and 1 for different numbers of CR, such as 100, 200, 300, 400, and 500, respectively. Figure 2 illustrates the convergence analysis of proposed method with existing methods. The convergence curves demonstrate that the proposed SFS-GAO achieves faster stabilization and reaches higher fitness values in fewer iterations.

Table 6 illustrates the overall computational complexity and statistical analysis of the proposed method compared with the existing methods. The computational complexity metrics include average runtime, memory utilization, fitness evaluations, and computational cost. The proposed SFS-GAO approach illustrates the minimum runtime and memory utilization as compared to other existing approaches. The minimized

count of fitness evaluations significantly minimizes the complete computational cost. This enhancement is attributed to the SFS, which improves convergence and reduces redundant solution updates. On the other hand, SFS-GAO attains greater optimization effectiveness without enhancing the algorithmic complexity. Statistical significance was evaluated using paired t-tests between the proposed SFS-GAO. To validate the statistical reliability of the experimental results, a non-parametric Wilcoxon rank-sum test was employed to compare the proposed SFS-GAO with each baseline method. This test was selected due to its robustness against non-normal data distributions. The resulting p-values denotes statistically significant enhancements attained through the proposed approach at a 95% confidence level ($p < 0.05$), confirming that the observed performance gains are not because of random variation.

Table 5. Performance estimation of proposed method in terms of different number of CR values

Performance indices	Methods	Different number of CR				
		100	200	300	400	500
Coverage	PSO	47.38	79.38	87.47	90.39	93.38
	HHO	49.38	81.49	91.38	95.29	96.20
	GWO	50.48	83.38	95.23	96.20	97.38
	GAO	52.32	86.38	96.38	97.38	98.69
	SFS-GAO	54.28	89.39	100	100	100
Connectivity	PSO	35.39	92.20	109.4	118.73	119.46
	HHO	37.39	95.19	113.47	121.46	123.47
	GWO	39.38	96.13	115.38	126.37	125.38
	GAO	41.38	97.38	119.32	127.37	128.56
	SFS-GAO	43.97	99.45	125	130	130
Fitness	PSO	0.30	0.85	87.39	89.39	91.33
	HHO	0.32	0.86	90.32	92.38	95.28
	GWO	0.39	0.88	93.32	94.22	96.29
	GAO	0.40	0.91	97.37	98.38	99.82
	SFS-GAO	0.42	0.94	1	1	1

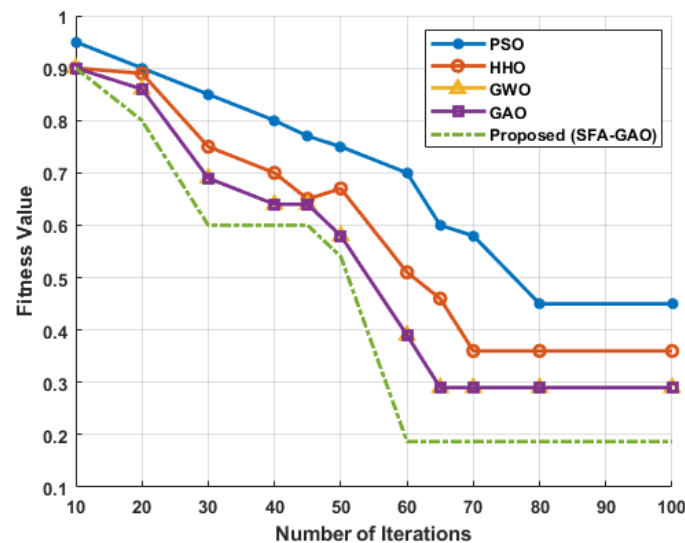


Figure 2. Convergence analysis of proposed method with existing methods

Table 6. Overall computational complexity and statistical analysis of the proposed method compared with the existing methods

Methods	Computational analysis			Statistical analysis	
	Average runtime (s)	Memory utilization (MB)	Fitness evaluations	Computational cost	P-test T-test
PSO	41.6	186	2550	High	0.009 5.31
GA	48.2	201	2760	High	0.008 4.57
COA	44.9	193	2640	Medium	0.006 3.48
GAO	37.4	172	2280	Medium	0.004 2.78
Proposed SFS-GAO	29.1	148	1830	Low	0.002 2.41

Table 7 illustrates the optimality comparison of the proposed method with ILP and mixed-integer programming (MIP) benchmarks. ILP and MIP provide globally optimal or near-optimal solutions under identical constraints, serving as reference baselines. The findings illustrate that SFS-GAO reliably attains fitness values into a small optimality gap of less than 4% relative to both ILP and MIP solutions. Whereas accurate solvers guarantee optimality, their runtime enhances fast through network size. On the other hand, SFS-GAO achieves near-optimal performance through crucially minimized computational time, designing it most consistent for large-scale and dynamic WMN deployments.

Table 7. Optimality comparison of the proposed method with ILP and MIP benchmarks

Network size	Clients	ILP optimal fitness	MIP optimal fitness	SFS-GAO optimal fitness	Gap vs ILP (%)	Gap vs MIP (%)	ILP runtimes (s)	MIP runtime (s)	SFS-GAO runtime (s)
Small	20	0.923	0.921	0.902	2.28	2.06	186.4	142.8	12.6
Medium	40	0.891	0.888	0.862	3.26	2.93	742.9	611.3	19.3
Large	60	0.854	0.851	0.824	3.51	3.17	2146.7	1789.4	27.9

Table 8 illustrates the sensitivity analysis of the key parameters. This analysis is performed for analyzing the cause of key algorithm parameters such as population size, somersault factor, and maximum iteration count. Every parameter is varied independently while keeping all other settings fixed. The results demonstrates that population size directly causes a trade-off among solution quality and computational cost. Likely, the somersault factor significantly influences convergence behavior, where greater values offer rapid exploration. Enhancing an iteration count enhances fitness up to a certain limit, beyond which marginal gains are observed. These discoveries illustrate the robustness of the proposed SFS-GAO over a broad variety of parameter settings.

Table 8. Sensitivity analysis of the key parameters

Parameters varied	Setting	Fitness (J)	Runtime (s)
Population size	20	0.912	38.6
	30	0.932	47.3
	40	0.935	59.1
Somersault factor (S)	0.4	0.918	54.2
	0.6	0.925	49.8
	0.8	0.932	47.3
Iterations	300	0.921	31.4
	500	0.932	47.3
	700	0.934	66.8

Table 9 shows the ablation study of the fitness values of the proposed method with respect to number of iterations in 30 runs. The average and variance fitness values of the proposed method with existing methods were estimated using the mean, best, worst, and standard variation. The ablation study considered fitness values with different iterations, such as 100, 500, and 1,000. The results indicate that incorporating SFS leads to faster convergence and improved fitness by prioritizing high-quality candidate solutions, thereby enhancing overall optimization efficiency.

Table 9. Ablation study of the fitness values of the proposed method with respect to number of iterations in 30 runs

Iterations	Methods	Average fitness values				Variance fitness values			
		Mean	Best	Worst	St.dv.	Mean	Best	Worst	St.dv.
100	PSO	0.06982	0.05	0.09	0.04082	0.00039	0.00052	0.00059	0.0008
	HHO	0.06103	0.04	0.08	0.03873	0.00033	0.00048	0.00055	0.0007
	GWO	0.05849	0.06	0.07	0.03522	0.00032	0.00040	0.00051	0.0006
	GAO without SFS	0.04732	0.02	0.06	0.02948	0.00028	0.00037	0.00048	0.0005
	SFS-GAO	0.03641	0.01	0.07	0.01781	0.00024	0.00034	0.00043	0.0004
500	PSO	0.06937	0.05	0.079	0.00503	0.00042	0.00032	0.00050	0.00031
	HHO	0.05622	0.04	0.075	0.00498	0.00032	0.00029	0.00039	0.00028
	GWO	0.04857	0.03	0.073	0.00463	0.00023	0.00023	0.00033	0.00022
	GAO without SFS	0.04482	0.02	0.070	0.00394	0.00019	0.00019	0.00028	0.00019
	SFS-GAO	0.03265	0.01	0.067	0.00233	0.00013	0.00016	0.00024	0.00017
1,000	PSO	0.06793	0.008	0.098	0.33952	0.00041	0.00049	0.00048	0.00046
	HHO	0.05748	0.007	0.095	0.32457	0.00039	0.00045	0.00043	0.00042
	GWO	0.04623	0.007	0.093	0.22134	0.00035	0.00041	0.00041	0.00038
	GAO without SFS	0.03332	0.006	0.089	0.19742	0.00029	0.00038	0.00039	0.00035
	SFS-GAO	0.02879	0.004	0.081	0.16737	0.00027	0.00036	0.00037	0.00031

5.2. Comparative analysis

Table 10 presents the simulation parameters for scenarios 1 and 2. Scenario 1 corresponds to [23], [24], [26], while scenario 2 corresponds to [21], [22], [25], [27], [28]. The various scenarios were compared using the proposed approach to validate the significance of the model. In the simulation analysis, m and n denote the numbers of routers and clients individually. In [22], [27], the m and n represent the number of clients and routers, respectively, but we consider m as the number of routers and n as the number of clients to avoid confusion and make this uniform in this research. Table 11 presents a comparative analysis of the proposed SFS-GAO method with the existing methods based on scenario 1. Table 12 presents a comparative analysis of the proposed SFS-GAO method with the existing methods based on scenario 2.

5.3. Discussion

The proposed SFS-GAO method significantly outperformed existing methods across all core metrics. The hybrid nature of the proposed method enables it to adaptively balance global exploration and local exploitation, solving one of the key challenges in WMN optimization. The somersault strategy becomes an important part of disturbing the best solution when stuck in local optima, allowing an approach to continue exploring the solution space. Compared with APSO and ECLO-MFO, which tend to converge prematurely or affected by parameter sensitivity, SFS-GAO demonstrates superior stability and robustness across various scenarios. The experimental evaluations under various MR, MC, and CR configurations showed consistently superior performances. For example, SFS-GAO reached a fitness of 1.0, at higher CR values, whereas the other methods plateaued. Furthermore, this approach maintains minimal variance in the results, indicating a high level of reliability. This robustness and adaptability design of SFS-GAO is a practical and efficient solution for real-time WMN deployment, with future potential in joint optimization tasks such as gateway placement and routing. To evaluate real-world applicability, dynamic client scenarios are simulated through periodically updating client positions and traffic demands at optimization. The findings demonstrates that SFS-GAO keeps consistent coverage and connectivity despite client mobility, outperforming baseline approach which suffer from continuous connectivity degradation. This confirms the robustness of proposed method in time-varying wireless mesh environments.

Table 10. Simulation parameters of different scenarios

Scenarios	Methods	Parameters			
		m	n	CR / transmission range	Area
1	[23]	[10, 100]	[50, 275]	[60, 240]	1,000 m × 1,000 m
	[24]	[10, 100]	[50, 275]	[60, 240]	1,000 m × 1,000 m
	[26]	[40, 100]	[30, 100]	[20, 120]	1,000 m × 1,000 m
2	[21]	[5, 40]	[50, 300]	[50, 400]	2,000 m × 2,000 m
	[22]	[5, 40]	[20, 250]	[50, 500]	2,000 m × 2,000 m
	[25]	[5, 40]	[50, 300]	[50, 400]	2,000 m × 2,000 m
	[27]	[5, 40]	[50, 400]	[50, 400]	2,000 m × 2,000 m
	[28]	[5, 40]	[50, 300]	[50, 40]	2,000 m × 2,000 m

Table 11. Comparative analysis of proposed SFS-GAO method with existing methods based on scenario 1

Methods	Parameters	Range	Performance metrics		
			Coverage (%)	Connectivity (%)	Fitness
APSO [24]	n	100	66.00	90.00	0.78
		200	54.00	96.66	0.75
		275	54.18	93.33	0.73
	m	20	45.00	95.00	0.70
		50	74.00	100	0.87
		100	97.00	98.00	0.97
	CR	100	66.00	90.00	0.78
		140	87.00	100.00	0.93
		240	100.00	100.00	1.00
Proposed SFS-GAO method	n	100	69.90	92.00	0.83
		200	58.03	95.49	0.78
		275	59.30	96.39	0.76
	m	20	48.00	97.00	0.73
		50	79.80	100	0.92
		100	99.00	99.00	0.98
	CR	100	70.00	92.00	0.81
		140	90.00	100.00	0.94
		240	100.00	100.00	1.00

Table 12. Comparative analysis of proposed SFS-GAO method with existing methods based on scenario 2

Methods	Parameters	Range	Performance metrics		
			Coverage	Connectivity	Fitness
COA [21]	n	100	87.12	107.12	0.88
		200	157.88	177.5	0.79
		300	226	246	0.76
	m	10	57.7	67.43	0.59
		20	87	107	0.88
		40	100	140	1
	CR	100	44.6	42.88	0.38
		200	87.12	107.12	0.88
		400	100	120	1
ECLO-MFO [22]	n	60	55.6	72.5	0.91
		100	87.4	106.9	0.88
		200	162.4	180.5	0.81
	m	4	29	33	0.30
		20	87.4	106.9	0.88
		40	100	140	1
	CR	100	47.8	32.83	0.37
		300	100	120	1
		500	100	120	1
CFL-PSO [27]	n	100	79.75	99.29	0.93
		200	160	180	0.81
		400	303	323	0.76
	m	10	57	67	0.59
		20	79.75	99.29	0.93
		40	100	140	1
	CR	100	44.3	40	0.39
		200	79.75	99.29	0.93
		400	100	120	1
MEGA [28]	n	100	87	107	0.88
		200	161.4	181.4	0.82
		300	234.6	254.6	0.79
	m	10	55.9	61.2	0.56
		20	86.2	106.2	0.88
		40	100	140	1
	CR	100	52.1	29	0.38
		200	86.8	105.5	0.87
		400	100	120	1
Proposed SFS-GAO method	n	60	59.38	75.22	0.94
		100	90.38	81.38	0.91
		200	167.02	185	0.84
		300	239.28	259.3	0.82
		400	310	329	0.79
	m	10	60	70	0.63
		20	89.13	110.3	0.92
		40	100	100	1
	CR	100	54.28	43.97	0.42
		200	89.39	99.45	0.94
		300	100	125	1
		400	100	130	1
		500	100	130	1

6. CONCLUSION

This study proposes the SFS-GAO approach for solving a problem of MR node placement in WMN. Effective MR placement is important in this application and significantly affects the network's effectiveness, coverage, connectivity, and fitness. An approach of estimating the fitness function by entropy make sures a consistently distributed placement of MR nodes while assuming the locations of the MC. By concentrating on user coverage and network connectivity, the SFS-GAO approach offers a vigorous solution for NP-hard issues. This study estimated the proposed method over diverse scenarios by changing key parameters, such as the MC, MR, and CR. The experimental results demonstrate that the proposed SFS-GAO approach achieves superior results for all performance metrics. The proposed SFS-GAO approach attains better fitness values of 0.42, 0.94, 1, 1, and 1 for different numbers of CR, such as 100, 200, 300, 400, and 500, respectively, compared to existing methods such as COA and CFL-PSO. Future work will extend the GAO approach to address joint design tasks, including gateway deployment, antenna placement, routing optimization, and channel allocation, to further enhance overall network performance and system efficiency.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

No datasets were generated or analyzed during the current study.

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