Solving the Mesh Router Nodes Placement in Wireless Mesh Networks Using Coyote Optimization Algorithm

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ABSTRACT Wireless Mesh Networks (WMNs) have rapid real developments during the last decade due to their simple implementation at low cost, easy network maintenance, and reliable service coverage. Despite these properties, the nodes placement of such networks imposes an important research issue for network operators and influences strongly the WMNs performance. This challenging issue is known to be an NP-hard problem, and solving it using approximate optimization algorithms (i.e. heuristic and meta-heuristic) is essential. This motivates our attempts to present an application of the Coyote Optimization Algorithm (COA) to solve the mesh routers placement problem in WMNs in this work. Experiments are conducted on several scenarios under different settings, taking into account two important metrics such as network connectivity and user coverage. Simulation results demonstrate the effectiveness and merits of COA in finding optimal mesh routers locations when compared to other optimization algorithms such as Firefly Algorithm (FA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Genetic Algorithm (GA), Bat Algorithm (BA), African Vulture Optimization Algorithm (AVOA), Aquila Optimizer (AO), Bald Eagle Search optimization (BES), Coronavirus herd immunity optimizer (CHIO), and Salp Swarm Algorithm (SSA).

INDEX TERMS Coyote optimization algorithm, mesh router nodes placement, meta-heuristics, network design, wireless mesh networks.

I. INTRODUCTION

Wireless Mesh Network (WMN) is considered as an emerging communication technology that has seen an accelerated deployment since 2005 all over the world [1]–[3]. The main reasons behind this accelerated deployment are due to its easy implementation at a low cost, dynamic self-organization, self-configuration, and self-adaptive nature. In addition, WMN becomes a very attractive technology for several

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applications such as broadband home networking, education, healthcare, corporate networks, industrial automation, disaster management, military, and rescue operations [4], [5]. WMN is composed of three types of nodes (i.e. Mesh Routers (MRs), Mesh Gateways (MGs), and Mesh Clients (MCs)) as illustrated in Figure 1. MCs such as desktops, mobiles, laptops, PDAs, and Pocket-PCs connect to the internet through MRs, MRs relay traffic to and from MGs which are connected to internet infrastructure.

Despite the desirable features of WMNs, there are still a number of problems and issues that prohibit them from
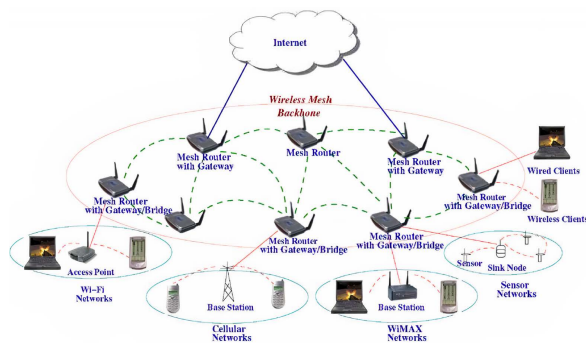
FIGURE 1. Wireless Mesh Network architecture [6].

being broadly deployed on a big scale. The most important issues are namely nodes placement problem [7]–[9] and security [10]–[14]. These issues have gotten a lot of attention in the literature.

The performance of WMN is mostly influenced by the bad positioning of mesh nodes (MR and/or MG) [15]. Consequently, many interferences and congestion are resulted causing considerable packet loss, high delays, and low throughput. To overcome these drawbacks, network operators must adopt efficient optimization techniques for WMN nodes placement.

WMN nodes placement is known to be an NP-hard problem [9]. So meta-heuristics have been presented as successful optimization algorithms to solve it providing acceptable solutions in a reasonable execution time.

Several works based on meta-heuristics have been proposed in the literature to solve the nodes placement problem in WMNs. Most of the proposed works considered stationary topology [3], [16]–[25] while others investigated the dynamic placement of mesh nodes subject to client mobility [26]–[29].

To deal with the static variant of the WMNs nodes placement problem, three algorithms have been proposed by Xhafa *et al.*, including Simulated annealing (SA) [16], Hill Climbing (HC) [17], and Tabu Search (TS) [18]. The three algorithms were evaluated in terms of user coverage and network connectivity. The evaluation is done based on 48 benchmark instances using different mesh clients distributions with different grid sizes.

In the work of Nouri *et al.* [3], an accelerated PSO algorithm (APSO) was also proposed to tackle the mesh routers placement problem in a static environment. APSO was validated in terms of coverage and connectivity and results confirmed its effectiveness when compared with the linearly decreasing weight PSO algorithm.

In the same context, Sayad *et al.* proposed three new algorithms based on Chemical Reaction Optimization (CRO) algorithm [19], Firefly optimization (FA) algorithm [20], and Electromagnetism-like Mechanism (EM) meta-heuristic [21]. These algorithms were validated using many generated instances with various number of mesh clients and mesh routers, taking into account the coverage and

connectivity metrics. Obtained results confirmed the superiority and effectiveness of these algorithms in terms of user coverage and connectivity.

Evolutionary algorithms (e.g. Genetic Algorithm (GA)) have been popular optimization algorithms in this area too [22]–[25]. For instance, the mesh router nodes placement problem was solved by Xhafa *et al.* [22] as a facility location problem using GA. It took into account user coverage and network connectivity metrics. In [23], an improved GA based on coupling GA with Minimum Spanning Tree (MST) was proposed to optimize cost and coverage metrics. Authors in [24] have proposed an enhanced GA, called MOGAMESH, for optimizing WMN topology by maximizing the user coverage percentage and minimizing the nodes degree. Similarly, two other variants of GA were applied in [25] namely the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Multi-Objective Genetic Algorithm (MOGA), where cost, coverage, and reliability are taken into account as performance metrics. These have been some of the best attempts to employ the multi-objective algorithm to simultaneously optimize multiple objectives in this area [30]–[32].

In [26]–[29], several methods have been proposed to tackle the dynamic variant of the mesh nodes placement issue. An improved PSO algorithm based on the integration of restriction coefficient into PSO was proposed in [26] to deal with this problem. In another similar work, Lin *et al.* [27] proposed an improved BA based on the incorporation of the dynamic search scheme into the original BA. The improved BA was validated based on 10 instances, taking into account the coverage and connectivity parameters. In [28], authors focused on the so-called social-aware dynamic router nodes placement in WMNs. They solved this problem using an enhanced PSO including a social-supporting vector, called a social-based-PSO. SA approach was applied in [29] to find the dynamic placement of mesh routers. In addition to user coverage and network connectivity, this approach reduces the average distance traveled by routers. Table 1 summarizes some representative works using meta-heuristics for solving the WMNs nodes placement problem. According to the No Free Lunch (NFL) theorem [33], [34], there is no optimization algorithm that can solve all optimization problems effectively. In fact, most optimization algorithms are able to solve some optimization problems while they fail to solve other problems.

COA is precisely, one of the recent meta-heuristics introduced by Pierezan and Coelho in 2018 [35]. It is characterized by the use of few tuning parameters and the strong capability of exploration and exploitation phases. It was applied to solve a large variety of difficult optimization problems such as image segmentation [36], feature selection [37], economic load dispatch [38], wireless sensor networks [39], and heavy-duty gas turbine operation [40]. For each one of these applications, COA proved its successfulness and merits. All these advantages motivate us to apply COA for solving the mesh routers placement problem in WMNs, which is, to the best of our knowledge, never solved with this meta-heuristic.

TABLE 1. Summary of some existing WMNs nodes placement representative works.

Algorithms	References	Environment	Location	Metrics		
				Cost	Coverage	Connectivity
SA	Xhafa et al. [16]	Static	Discrete		x	x
HC	Xhafa et al. [17]	Static	Discrete		x	x
TS	Xhafa et al. [18]	Static	Discrete		x	x
APSO	Nouri et al. [3]	Static	Continuous		x	x
CRO	Sayad et al. [19]	Static	Continuous		x	x
FA	Sayad et al. [20]	Static	Continuous		x	x
EM	Sayad et al. [21]	Static	Continuous		x	x
GA	Xhafa et al. [22]	Static	Discrete		x	x
Improved GA	Tang et al. [23]	Static	Discrete	x	x	x
MOGAMESH	De marco [24]	Static	Discrete	x	x	x
MOGA and NSGAII	Bello et al. [25]	Static	Discrete	x	x	x
Enhanced PSO	Lin [26]	Dynamic	Continuous		x	x
Improved BA	Lin et al. [27]	Dynamic	Continuous		x	x
Social based-PSO	Lin et al. [28]	Dynamic	Continuous		x	x
SA	Sayad et al. [29]	Dynamic	Continuous		x	x
COA	Proposed method	Static	Continuous		x	x

In this paper, we present the implementation of COA for solving the mesh router nodes placement issue. We evaluate the performance of COA using many generated instances under various settings, taking into account the coverage and the connectivity metrics. The major contribution of this paper is given below:

- Implementation of COA, FA, PSO, WOA, GA, BA, AVOA, AO, BES, CHIO, and SSA to tackle the mesh router nodes placement issue;
- Assessment and comparison of the performance of the proposed COA with FA, PSO, WOA, GA, BA, AVOA, AO, BES, CHIO, and SSA using various scenarios under different settings.

The remainder of this paper is organized as follows. We describe the formulation of the mesh router nodes placement problem in section 2. In section 3, We propose the new bio-inspired meta-heuristic COA to solve the formulated problem. Furthermore, we evaluate the performance of our approach and we provide results in section 4. Finally, we give the main findings and the potential perspectives in section 5.

II. MESH ROUTER NODES PLACEMENT PROBLEM FORMULATION

In this section, we describe the system model and the formulation of the mesh router nodes placement problem. For better readability, the main notations used in this paper are summarized in Table 2.

A. SYSTEM MODEL

WMN can be described mathematically as an undirected graph $G = (V, E)$ where V is the set of network vertices (nodes) and E is the set of edges (links) between these vertices. The network G is formed by a set of disjoint sub-networks. In this paper, we consider the WMN with two types of nodes such as mesh clients and mesh routers. Thus $V = MR \cup MC$ where:

- MR is the set of m mesh routers: $MR = \{mr_1, mr_2, \ldots, mr_m\}$, Each mesh router is equipped with radio interface

TABLE 2. The main notations used in this paper.

Parameter	Description
$G = (V, E)$	Undirected graph topology
V	Set of mesh nodes
E	Set of links between mesh nodes
MR	Set of mesh routers
MC	Set of mesh clients
m	Number of mesh routers
n	Number of mesh clients
mr_i	The i-th mesh router
mc_i	The i-th mesh client
CR_i	Coverage radius of the i-th mesh router
$G_i = (V_i, E_i)$	The i-th sub-network
$|G_i|$	Size of the i-th sub-network
$\phi(G)$	Network connectivity
$\psi(G)$	User coverage
D	Dimension of search space
W	Width of the dimension
H	Height of the dimension
ub, lb	Upper and lower bound of the decision variable in search space
$d(mr_i, mr_j)$	Distance between mesh router mr_i and mesh router mr_j
λ	Control parameter
σ_{ij}	Defines if the mesh client mc_i is covered by the mesh router mr_j
G_p	Number of groups in a population
C_c	Number of coyotes in each group
$SC_c^{p,t}$	The social condition of the c-th coyote in the p-th group at iteration t
$new\_SC_c^{p,t}$	The new social condition of the c-th coyote in the p-th group at iteration t
$ft_c^{p,t}$	Fitness function of the c-th coyote in the p-th group at iteration t
$new\_ft_c^{p,t}$	Fitness function of the new c-th coyote in the p-th group at iteration t
$\alpha^{p,t}$	Alpha coyote in the p-th group at iteration t
$cultr_j^{p,t}$	The cultural tendency of the p-th group at iteration t
$R^{p,t}$	The ranked social condition of the coyote in the p-th group at iteration t
$age_c^{p,t}$	Age of the c-th coyote in p-th group at iteration t
P_α	Probability of leaving a group
P_s	Scatter probability
P_z	Association probability
r_1, r_2, r_j, K_j	Random numbers in the range [0 1]

with the same coverage radius $CR_1 = CR_2 = \ldots = CR_m$. Two mesh routers mr_i and mr_j can be connected if and only if the distance between them does not exceed two time the coverage radius CR i.e. $d(mr_i, mr_j) \leq 2CR$.

- MC is the set of n mesh clients $MC = \{mc_1, mc_2, \ldots, mc_n\}$, we assume that mesh clients are randomly distributed in $2D$ rectangle area of dimension $W \times H$. A mesh client mc_i is said covered by a mesh router mr_j if it is within the coverage radius of this router: $d(mc_i, mr_j) \leq CR$. It can be associated at most to one router. It can be within coverage radius of various routers but it is associated with the closest router.

B. PROBLEM FORMULATION

As per the nature of studied environments (static or dynamic) and the nature of deployment spaces (discrete or continuous), several variants of the WMN router nodes placement problem can be found. In this paper, the static continuous mesh routers nodes placement problem was considered. Therefore, the main goal is to find the optimal placement of m mesh routers in a $2D$ area of dimensions $W \times H$, depending on the location of n mesh clients.

The problem studied in this work considers two main objectives that need to be optimized:

- User coverage: It represents the number of covered users by at least one mesh router according to the following equation:

$$\Psi(G) = \sum_{i=1}^{n} (max_{j \in \{1,\ldots m\}} \sigma_{ij}) \tag{1}$$

where σ_{ij} defines the coverage variable represented as follows:

$$\sigma_{ij} = \begin{cases} 1 \text{ if mesh client } c_i \text{ is covered by mesh router } r_j, \\ 0 \text{ Otherwise.} \end{cases} \tag{2}$$

- Network connectivity: It is defined as the geant sub-network among k formed sub-networks with regard to the number of mesh nodes (mesh routers and mesh clients). It is calculated as follows:

$$\Phi(G) = Max_{i \in \{1,\ldots k\}} |G_i| \tag{3}$$

where $|G_i|$, $i \in \{1, k\}$ is the size of ith sub-network and $G = G_1 \cup G_2 \cup \ldots \cup G_k$.

III. COYOTE OPTIMIZATION ALGORITHM

The Coyote Optimization Algorithm (COA) was introduced by Pierezan and Coelho [35] as a population-based meta-heuristic for solving global optimization problems. This optimization algorithm is inspired by the social behaviors of the Canis Latrans species that reside mainly in North America. The population of coyotes is partitioned into G_p groups with C_c coyotes in each group. Therefore, the population size can be defined by the multiplication of G_p*C_c. Every coyote is considered as a possible (candidate) solution and its social condition refers to the objective function or decision variable. In this regard, the social condition of the *c-th* coyote in the *p-th* group at iteration t can be represented mathematically
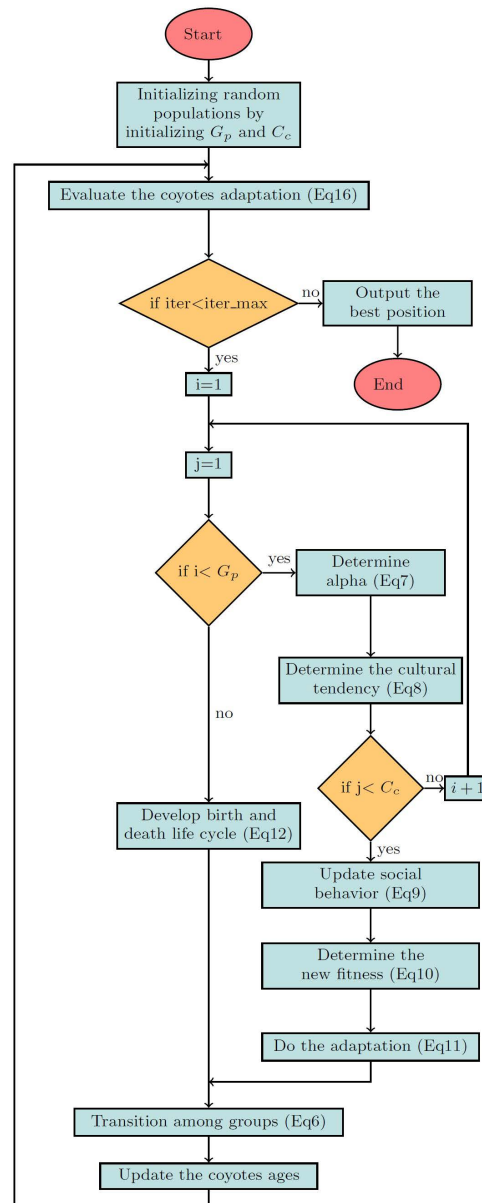
FIGURE 2. Flowchart of the COA.

as follows:

$$SC_c^{p,t} = X = (x_1, x_2, \ldots, x_D) \tag{4}$$

where D is the search space dimension.

This social behavior involves adapting coyotes to the environment named $ft_c^{p,t} \in R$. The adaptation of the coyote to its respective current social condition is validated using the following equation:

$$ft_c^{p,t} = f(SC_c^{p,t}) \tag{5}$$

At the beginning of the process, the coyotes are randomly assigned to the groups. However, coyotes have sometimes a tendency to abandon their groups in order to join other groups

or to become solitary. The probability P_a that a coyote leaves its group is given as follows:

$$P_a = 0,005 * C_c^2 \qquad (6)$$

As the value of P_a cannot exceed unity, the number of coyotes per group is limited to 14. This mechanism increases the cultural exchange between all the coyotes in the global population. In each group, the leader of the coyotes, also called the alpha coyote, is the coyote that achieves the best objective function. Considering a minimization problem, the alpha coyote can be determined mathematically by the following equation:

$$alpha^{p,t} = \{SC_c^{p,t} | arg_{c=\{1,2,...,C_c\}} min f(SC_c^{p,t})\} \qquad (7)$$

The cultural tendency of each group is expressed as follows:

$$cultr_j^{p,t} = \begin{cases} R_{\frac{C_c+1}{2},j}^{p,t}, & C_c \text{ is odd} \\ \frac{R_{\frac{C_c}{2},j}^{p,t} + R_{(\frac{C_c}{2}+1),j}^{p,t}}{2}, & Otherwise \end{cases} \qquad (8)$$

where $R^{p,t}$ is the ranked social condition of the coyote inside the *p-th* group at iteration t for every j in the search space D.

After determining the global best $alpha^{p,t}$ and the cultural tendency $cultr^{p,t}$ of each group, new social conditions of coyotes are updated using the following equation:

$$new\_SC_c^{p,t}$$
$$= \{SC_c^{p,t} + r_1(alpha^{p,t} - SC_{cr_1}^{p,t}) + r_2(cultr^{p,t} - SC_{cr_2}^{p,t}\} \qquad (9)$$

where $SC_{cr_1}^{p,t}$ and $SC_{cr_2}^{p,t}$ are social conditions of random coyotes cr_1 and cr_2, respectively. r_1 and r_2 are random numbers in the range [0, 1].

The fitness value of the new social condition is calculated as follows:

$$ft_c^{p,t} = \begin{cases} new\_ft_c^{p,t}, & if \ new\_ft_c^{p,t} < ft_c^{p,t} \\ ft_c^{p,t}, & Otherwise \end{cases} \qquad (10)$$

The selection of final social conditions is based on the computation of new solutions. Each one is compared with the worst solution in each group and the best one is then kept as it is shown in the following equation:

$$SC_c^{p,t} = \begin{cases} new\_SC_c^{p,t}, & if \ new\_ft_c^{p,t} < ft_c^{p,t} \\ SC_c^{p,t}, & Otherwise \end{cases} \qquad (11)$$

In COA, the two main biological events of life (i.e. the birth and the death) are modeled considering the age of each coyote $age_c^{p,t} \in N$ in the group p. The new coyote is born by combining two parents $SC_{r_1,j}^{p,t}$ and $SC_{r_2,j}^{p,t}$ chosen randomly. The process of birth can be mathematically given as follows:

$$pp_j^{p,t} = \begin{cases} SC_{r_1,j}^{p,t}, & r_j < P_s \ or \ j = j_1 \\ SC_{r_2,j}^{p,t}, & r_j \geq P_s + P_z K_j, \ Otherwise \end{cases} \qquad (12)$$

where r_1 and r_2 are the parents coyotes selected randomly from the group p. j_1 and j_2 are two random dimensions of the problem. r_j and K_j represent random numbers in the

range [0, 1]. P_s and P_z denote the scatter and the association probabilities, respectively. They are calculated as follows:

$$P_s = \frac{1}{D} \qquad (13)$$

$$P_z = \frac{1 - P_s}{2} \qquad (14)$$

The main steps of COA are given below:

Step 1: Generate randomly $G_p * C_c$ solutions and evaluate the adaptive function.

Step 2: Execute the following operations inside each group

- Detect the alphas of the group.
- Compute the cultural tendency of the group.
- Update the social conditions of the coyotes in the group.
- Evaluate the new social conditions.
- Do the adaptation.
- Develop birth and death life cycle.

Step 3: Transition of coyotes among random groups.

Step 4: Repeat step 2 until the stop criterion is reached.

Step 5: Output the best social condition of the adapted coyote.

The corresponding flowchart of COA is given in Figure 2.

IV. COA ALGORITHM APPLIED FOR SOLVING THE MESH ROUTER NODES PLACEMENT PROBLEM

The mesh router nodes placement problem is known to be an NP-hard problem, and several meta-heuristics have proven their success in this field. As part of the permanent search for the optimal solution to cope with this issue, we choose the application of COA on WMN for the following reasons:

TABLE 3. Similarities between COA theory and mesh routers placement problem.

COA system	Mesh routers placement problem
Search space	Deployment area
Social condition of coyotes	Position of routers
Solution	Set of optimal mesh routers locations
Coyotes' adaptation	Objective function value
Cultural interaction inside the packs	Generating new solutions

- COA has been successfully implemented to solve a large variety of difficult optimization problems such as image segmentation [36], feature selection [37], economic load dispatch [38], and wireless sensor networks [39].
- COA is a population-based meta-heuristic that is easy to implement with only two control parameters.
- COA has shown good results when solving several placement problems such as sizing and location of renewable distributed generations [41]–[43], optimal placement of photovoltaic distributed generations [44]–[47], and perfect position of static compensators [48].
- Presence of some similarities between the mesh routers placement problem and the COA theory as illustrated in Table 3.

A. OBJECTIVE FUNCTION

Our approach aims to find the optimal placement of a given number of mesh routers that maximizes simultaneously the user coverage and network connectivity metrics. As defined earlier, user coverage refers to the number of mesh clients covered by at least one router, whereas, network connectivity is defined by the size of the biggest sub-network among k formed sub-networks in terms of the mesh nodes number. These metrics are involved to define the fitness function f used to assess the quality of solutions. The objective function is given as follows:

$$f(SC_c^p) = \lambda \cdot \frac{\Psi(G)}{n} + (1 - \lambda) \cdot \frac{\Phi(G)}{m+n} \quad (15)$$

where G is the graph corresponding to the solution SC_c^p and λ is a floating parameter in the range [0, 1] which is used to control the importance of metrics. So, according to this objective function formulation, the tackled problem is then considered as a problem of maximization of $f(SC_c^p)$.

However, the original version of COA given by Pierezan and Coelho [35] was defined for problem of minimization. Thus, it is essential to turn our objective function into a minimization function. Consequently, we have defined another function g as follows:

$$g = 1 - f(SC_c^p) \quad (16)$$

B. SOLUTION REPRESENTATION

The resolution of a mesh routers placement problem consists of determining the placement of all mesh routers. In this paper, the solution of each coyote, which is a mesh routers placement solution, is represented by an array $SC_c^p = \{x_{c1}^p, y_{c1}^p, x_{c2}^p, y_{c2}^p, \ldots x_{cm}^p, y_{cm}^p\}$, where (x_{ck}^p, y_{ck}^p) are the

TABLE 4. Solution representation of deploying four mesh routers.

p_1	p_2	p_3	p_4
(100, 200)	(150, 400)	(300, 700)	(1400, 1900)

(x, y) coordinates of the mesh router c_k, with $0 \leq x_{ck}^p \leq W$ and $0 \leq y_{ck}^p \leq H$; $\forall m \in \{1, 2, \ldots m\}$. The array illustrated in Table 4 represents the solution of deploying four mesh routers in an area of 2000×2000.

C. INSTANTIATING OF COA TO THE MESH ROUTERS PLACEMENT PROBLEM

As described earlier, COA is a population-based metaheuristic for solving global optimization problems. It has proven to be an effective method for solving several placement problems. So in this section, we will describe how COA is adapted to solve the mesh routers placement problem as illustrated in Algorithm 1:

V. SIMULATION RESULTS AND DISCUSSION

In this section, we study the performance of the proposed COA in solving the mesh router nodes placement problem in WMNs. Thus, COA is compared with ten algorithms

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Algorithm 1: The Proposed COA for the Mesh Routers Placement Problem

Input:
    m: Number of mesh routers
    n: Number of mesh clients
    CR: Coverage radius
    G_p: Number of groups
    C_c: Number of coyotes in each group
    P_α: Probability of leaving a pack
    P_s: Scatter probability
    P_z: Association probability
    lb: Lower bound
    ub: Upper Bound

Output:
    SC_{best} the best social conditions
    $f(SC_{best})$ the objective function value of SC_{best}

  // Initialization
1 **for** $i \leftarrow 1$ **to** $G_p * C_c$ **do**
2   **for** $j \leftarrow 1$ **to** m **do**
3   Randomly place the j-th mesh router of coyote SC_i in the deployment area

4 **for** $i \leftarrow 1$ **to** n **do**
5   Randomly place the i-th mesh client in the deployment area
  // Evaluate the coyotes adaptation
6 **for** $i \leftarrow 1$ **to** $G_p * C_c$ **do**
7   Compute the objective value of the coyote SC_i (Eq.16)

8 **while** *stopping criterion is not achieved* **do**
9   *Update the years counter*
    // Execute operations inside each group p
10   **for** $p \leftarrow 1$ **to** G_p **do**
11   *Detect the alpha according to the costs in group p (Eq.7)*
12   *Determine the cultural tendency of the group p (Eq.8)*
13   *Update the coyotes' social condition*
      // Execute operations for each coyote c inside the group p
14   **for** $c \leftarrow 1$ **to** C_C **do**
15   *Generate the new social conditions (Eq.9)*
16   *Evaluate the new social conditions (new fitness) (Eq.10)*
17   *Check the adaptation of the social conditions (Eq.11)*
18   *Birth of new coyote from random parents (Eq.12)*
19   *Random transition of coyote among groups (Eq.6)*
20   *Update the age of all coyotes*

21 *Return the best social condition*

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namely FA [20], GA [49], PSO [28], WOA [50], BA [27], AVOA [51], AO [52], BES [53], CHIO [54], and SSA [55]. Its performance is assessed considering three metrics: i) user coverage; ii) network connectivity; iii) objective function value. The proposed COA and the ten compared algorithms are implemented in MATLAB and all experiments are

TABLE 5. Algorithms parameters.

Parameter	Value
COA	
Number of groups in a population G_p	10
Number of coyotes in each group C_c	5
Probability of leaving a group P_α	0.125
Scatter probability P_s	0.025
Association probability P_z	0.48
FA	
Light absorption coefficient γ	1
Initial light intensity coefficient I_0	2
Initial attractiveness coefficient β_0	2
Mutation coefficient	0.2
Mutation coefficient damping ratio	0.98
Uniform mutation range	100
GA	
Crossover probability p_c	0.8
Mutation probability p_m	0.2
PSO	
Parameter $c1$ in updating velocity	2
Parameter $c2$ in updating velocity	2
Maximum velocity	200
Minimum velocity	-200
BA	
Minimum frequency f_{min}	0
Maximum frequency f_{max}	2
Constant α for loudness update	0.5
Constant γ for emission rate update	0.5
Initial Loudness A_0	Random
Initial pulse emission rate r_0	0.001
WOA	
Control parameter a_{max}	2
Control parameter a_{min}	0
AO	
Exploitation adjustment parameter α	0.1
Exploitation adjustment parameter β	0.1
AVOA	
Control parameter $P1, P3$	0.6
Control parameter $P2$	0.4
Control parameter α	0.8
Control parameter β	0.2
Control parameter γ	2.5
BES	
Control parameter α	2
Control parameter R	1.5
Control parameter a	10
CHIO	
Basic reproduction rate BR_r	0.05
Maximum infected cases age Max_{age}	100
SSA	
Control parameter $C1$	2 to 0
Control parameter $C2, C3$	Random

TABLE 6. Parameters values considered in our simulations.

Parameter	Value	Default value
n	[50 300]	100
m	[5 40]	20
CR	[50 400]	200 m
W	2000	2000 m
H	2000	2000 m
λ	[0 1]	0.5
Population size	50	50
Number of run	50	50
Number of iteration	1000	1000

FIGURE 3. The optimal placement of mesh routers obtained using COA.
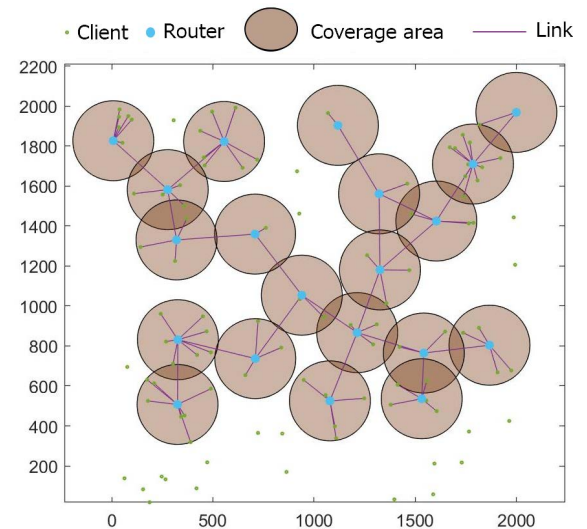
FIGURE 4. The optimal placement of mesh routers obtained using FA.

carried out on a Core i7 2.5 GHz-CPU machine. A rectangle deployment area of 2000*m* x 2000*m* is considered in all simulations. The number of mesh routers is varied from 5 to 40 for covering 50 to 300 mesh clients. Mesh clients are randomly distributed in the deployment area. The total number of iterations is 1000. The results presented in this section

are obtained after an average of 50 runs. The parameters used during the simulation are summarized in Table 6, and algorithms' parameters are described in Table 5. We evaluate and analyze the performance results of the proposed COA

FIGURE 5. The optimal placement of mesh routers obtained using GA.

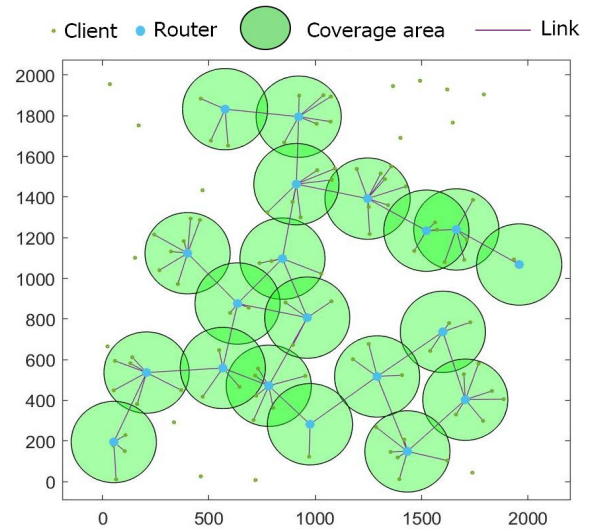**FIGURE 7.** The optimal placement of mesh routers obtained using WOA.

FIGURE 6. The optimal placement of mesh routers obtained using PSO.

FIGURE 8. The optimal placement of mesh routers obtained using BA.

by investigating the impact of varying the number of mesh clients, number of mesh routers, and coverage radius values.

Figures 3-13 report examples of a planned WMN using COA, FA, GA, PSO, WOA, BA, BES, AO, AVOA, SSA, and CHIO respectively. The planned network is a solution of network instance with 20 mesh routers and 100 clients (distributed randomly in a rectangle deployment area of $4km^2$). Yellow circles represent installed mesh routers whereas purple circles represent mesh clients. A solid line between two mesh routers indicates that these routers are within the transmission of each other.

A. IMPACT OF VARYING THE NUMBER OF MESH CLIENTS

In this scenario, we varied the number of mesh clients from 50 to 300 with a fixed number of mesh routers. Table 7 illustrates the impact of increasing the number of mesh clients

on user coverage, network connectivity, and fitness function. Its graphical representation is shown in Figure 14.

Figure 14(a) shows the users' coverage while varying the number of mesh clients. It is observed that the users' coverage increases when increasing the number of mesh clients. It is also shown that our approach covers up to 10.6%, 9%, 14.22%, 32.42%, 41.48%, 13.62%, 37.59%, 20.42%, 7.69%, and 20.56% more clients than FA, GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, and SSA, respectively.

In terms of connectivity, Figure 14(b) shows that the connectivity increases when increasing the number of mesh clients. It is demonstrated that the network connectivity is increased considerably by our approach. More precisely, connectivity is increased by up to 8.74%, 6.4%, 10%, 35%, 37.40%, 13.35%, 33.65%, 15%, 6.85%, and 16.81% when compared to FA, GA, PSO, WOA, BA, AVOA, AO,

TABLE 7. Coverage, connectivity, fitness under various number of mesh clients.

		50	100	150	200	250	300
Coverage	COA	**46.74**	**87.12**	**120.32**	**157.88**	194	226
	FA	41.44	78.74	113.82	151.63	194	226.12
	GA	42.26	78.6	118.86	151.1	187.13	225.33
	PSO	39.63	74.56	115.33	148.53	190.66	**228.03**
	WOA	30.53	59.3	112.26	125.06	155.1	175.2
	BA	26	48.93	73.4	98.63	126.46	157.76
	AVOA	40.23	73.5	107.5	132.76	169.93	197.06
	AO	30	49.53	75.16	93.73	119.8	163.16
	BES	36.53	69.33	101	137.23	170.3	194.7
	CHIO	44.86	79.43	113.7	148.5	184	221.4
	SSA	36.46	70.26	95.9	132.13	166.53	200.2
Connectivity	COA	**66.5**	**107.12**	**140.32**	**177.5**	214	246
	FA	60.38	98.24	132.8	170.1	210.16	244.84
	GA	62	98.6	138.86	171.1	207.13	245.33
	PSO	59.63	94.4	135.33	168.53	210.66	248.03
	WOA	48	77.86	105.66	100.6	123.46	153.23
	BA	42.6	60.5	79.13	104.9	124.8	153.23
	AVOA	58.5	91.1	126.73	152.03	188.5	216.03
	AO	43	66.73	89.26	109.66	139.8	165.03
	BES	55.5	89.13	120.43	156.56	188.83	213.63
	CHIO	63.56	98.9	133.33	167.2	204	241.13
	SSA	54.73	90.06	113.23	150.36	185.63	217.3
Fitness	COA	**0.94**	**0.88**	**0.81**	**0.79**	**0.78**	**0.76**
	FA	0.84	0.80	0.77	0.76	0.76	0.75
	GA	0.86	0.80	0.80	0.76	0.75	0.75
	PSO	0.82	0.76	0.78	0.75	0.77	0.76
	WOA	0.64	0.62	0.61	0.61	0.62	0.57
	BA	0.56	0.49	0.47	0.47	0.48	0.50
	AVOA	0.82	0.74	0.73	0.67	0.68	0.66
	AO	0.60	0.52	0.51	0.48	0.49	0.52
	BES	0.76	0.71	0.69	0.69	0.69	0.65
	CHIO	0.90	0.80	0.77	0.75	0.74	0.74
	SSA	0.75	0.72	0.65	0.67	0.67	0.67

TABLE 8. Coverage, connectivity, fitness under various number of mesh routers.

		5	10	15	20	25	30	35	40
Coverage	COA	**32.96**	**57.7**	**69.9**	87	**96**	99	100	100
	FA	29.86	52	65.2	80.6	89.8	94.6	98.06	99.36
	GA	31.23	49.93	62.43	78.6	92.23	96.26	98.53	99.36
	PSO	31.33	49.86	65.2	82.33	89.06	92.86	97.33	97.86
	WOA	29.83	44.96	59.96	59.3	70.1	78.46	87.06	88.13
	BA	23.83	40.03	46.66	48.93	62	62.76	71.9	76.1
	AVOA	30.63	49.66	65.1	73.5	82.36	85.66	94.26	97.56
	AO	24.66	33.46	39.16	53.1	60.66	70.8	74.43	83.63
	BES	27.96	45.86	64.8	69.03	82.03	83.76	88.13	92.86
	CHIO	29	53	66.4	80.03	86.7	95.06	99	100
	SSA	31.16	45.3	57.43	70.13	79.96	84.76	92	93.03
Connectivity	COA	**37.42**	**67.43**	**84.9**	107	121	129	135	140
	FA	30.86	56	75	100.6	114.8	124.6	133	139.76
	GA	26.46	59.43	77.43	98.6	117.23	124.8	133.53	139.36
	PSO	29.86	58.58	77.96	102.2	113.8	122.86	132.33	137.86
	WOA	16.06	42.16	58.93	77.86	93.6	105.63	120.53	118
	BA	21	35	43	60.6	83	80	106.83	116.1
	AVOA	26.7	53.46	64.8	91.1	106	112.83	128.1	136.3
	AO	25.23	36.93	53.53	73.1	77.2	100.8	104.93	123.63
	BES	32.43	55.26	77	88.5	106.56	113.06	122.86	132.53
	CHIO	29.26	60.66	81.26	99.53	111.3	125	133.93	140
	SSA	30.03	50.76	68.9	88.13	103.63	114.23	126.76	132.9
Fitness	COA	**0.34**	**0.59**	**0.71**	**0.88**	**0.96**	**0.99**	1	1
	FA	0.29	0.51	0.65	0.82	0.90	0.95	0.98	0.99
	GA	0.28	0.51	0.64	0.80	0.93	0.96	0.98	0.99
	PSO	0.29	0.51	0.66	0.83	0.90	0.93	0.97	0.98
	WOA	0.22	0.41	0.55	0.62	0.72	0.79	0.88	0.89
	BA	0.16	0.30	0.42	0.49	0.60	0.63	0.75	0.79
	AVOA	0.28	0.49	0.60	0.74	0.83	0.86	0.94	0.97
	AO	0.24	0.33	0.42	0.57	0.61	0.74	0.76	0.85
	BES	0.29	0.48	0.65	0.71	0.83	0.85	0.89	0.93
	CHIO	0.28	0.53	0.68	0.81	0.87	0.95	0.99	1
	SSA	0.29	0.45	0.58	0.71	0.81	0.86	0.92	0.93

TABLE 9. Coverage, connectivity, fitness under various coverage radius values.

		50	100	150	200	250	300	350	400
Coverage	COA	**38.88**	**44.6**	**63.78**	**87.12**	**98.72**	100	100	100
	FA	29.9	42.76	57.2	81.2	95.13	99.66	100	100
	GA	21.73	36.36	60.53	78.6	96.76	99.16	100	100
	PSO	21.63	29.9	57.1	76.93	96.26	99.86	100	100
	WOA	5.9	21.06	46.66	59.3	84.96	96.43	99.2	100
	BA	8.6	20.73	35.06	46	68	88	90.96	98.13
	AVOA	11.26	31.26	51.93	73.5	90	99.4	99.9	100
	AO	5.13	14.7	28.1	54	71.6	92.2	96.8	99.1
	BES	8.43	24.76	47.3	70.1	91.1	98.9	100	100
	CHIO	28.9	42.2	58.53	81.2	96.86	100	100	100
	SSA	11.63	25.63	43.63	70.13	88.86	97.66	99.9	100
Connectivity	COA	8.26	42.88	78.72	**107.12**	**118.72**	120	120	120
	FA	9	35.73	70.83	101.2	115.13	119.2	120	120
	GA	22.63	**51.63**	**80.1**	98.6	116.76	119.16	120	120
	PSO	11.63	34.96	76.63	96.93	116.26	119.86	120	120
	WOA	23.4	32.63	50.96	77.86	104.4	116.43	119.2	120
	BA	5.9	30.83	54	85.63	108	110.96	118.13	
	AVOA	23.86	34.96	61.66	91.1	109.86	119.13	119.56	119.73
	AO	25.06	31.5	45.76	66.26	91.6	112.2	115.4	119.1
	BES	**26.36**	40.7	65.56	88.16	110.83	118.9	120	120
	CHIO	7.9	31.93	71.33	100.46	116.86	120	120	120
	SSA	25.06	38.7	52.6	88.13	108.73	117.16	119.9	120
Fitness	COA	**0.22**	0.38	**0.64**	**0.88**	**0.98**	1	1	1
	FA	0.18	0.36	0.58	0.82	0.95	0.99	1	1
	GA	0.2	**0.39**	0.63	0.80	0.97	0.99	1	1
	PSO	0.15	0.29	0.60	0.78	0.96	0.99	1	1
	WOA	0.12	0.24	0.44	0.62	0.85	0.96	0.99	1
	BA	0.065	0.15	0.30	0.45	0.69	0.89	0.91	0.98
	AVOA	0.15	0.30	0.51	0.74	0.90	0.99	0.99	0.99
	AO	0.13	0.20	0.33	0.54	0.73	0.92	0.96	0.99
	BES	0.15	0.29	0.50	0.71	0.91	0.98	1	1
	CHIO	0.17	0.34	0.58	0.82	0.97	1	1	1
	SSA	0.16	0.28	0.43	0.71	0.89	0.97	0.99	1

FIGURE 9. The optimal placement of mesh routers obtained using BES.

BES, CHIO, and SSA, respectively. Results illustrated in Figure 14(c) demonstrate that the fitness value decreases with the increase of the number of mesh clients. In fact, more routers are needed to cover the added mesh clients. However, the number of mesh routers is fixed. Consequently, the new added mesh clients may be not covered by the deployed routers leading to a decrease in coverage and connectivity that constitute the fitness value. The obtained results revealed that COA gives better results than FA, GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, and SSA.

B. IMPACT OF VARYING THE NUMBER OF MESH ROUTERS

The impact of varying the number of mesh routers (from 5 to 40 mesh routers) on coverage, connectivity, and fitness value are given in Table 8 and Figure 15.
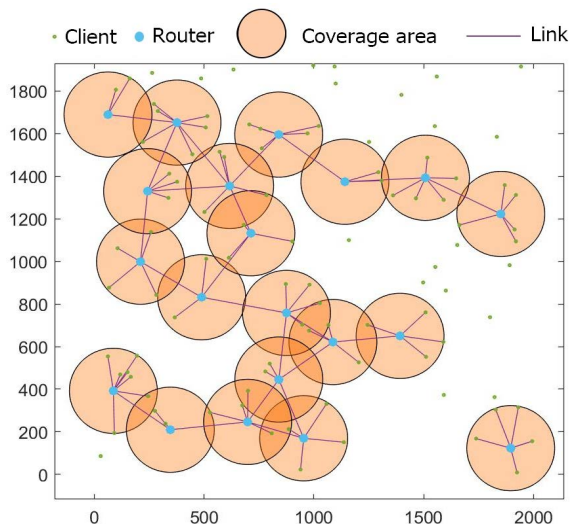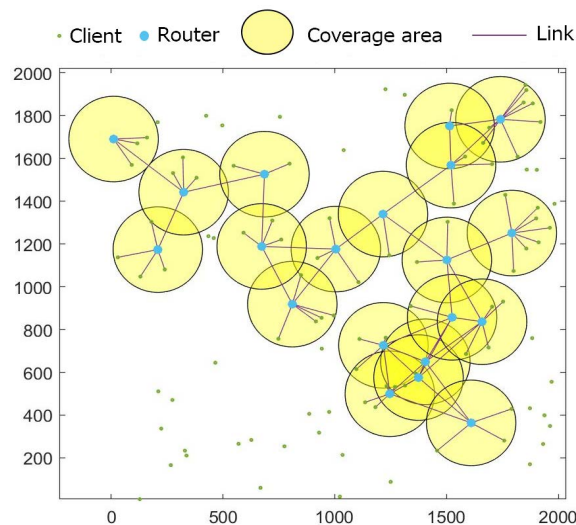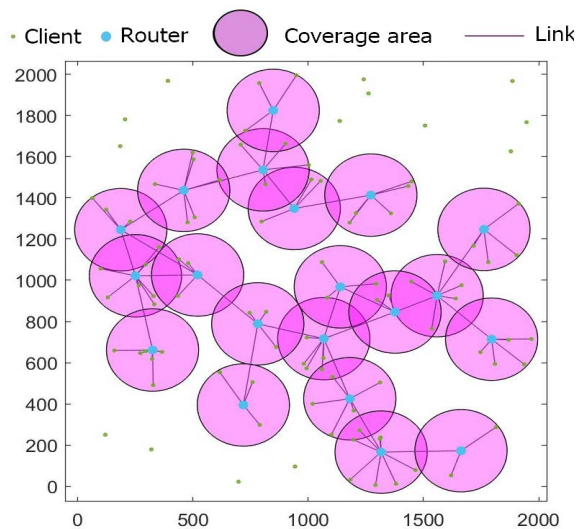
FIGURE 10. The optimal placement of mesh routers obtained using AO.

FIGURE 12. The optimal placement of mesh routers obtained using SSA.

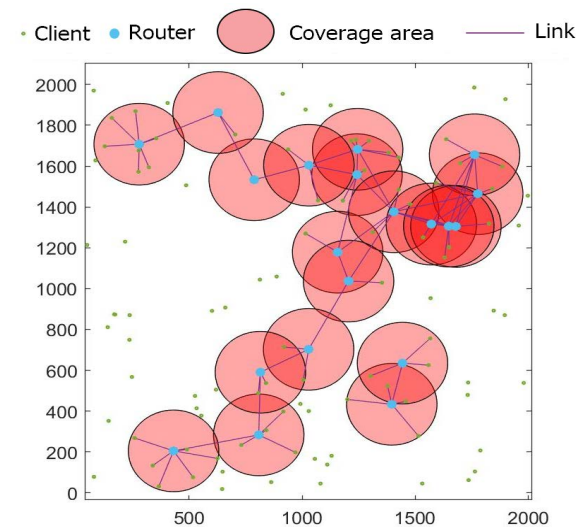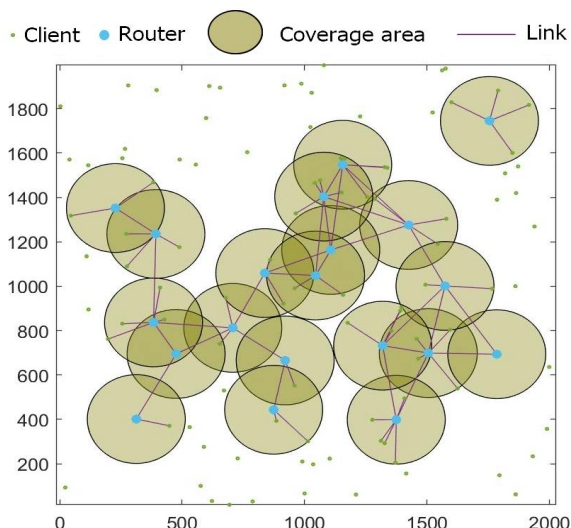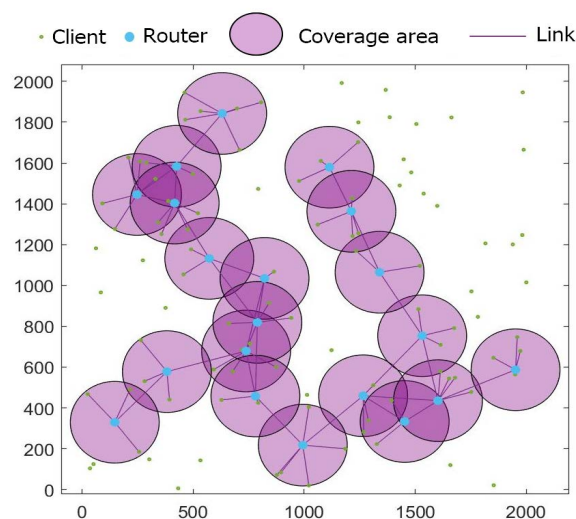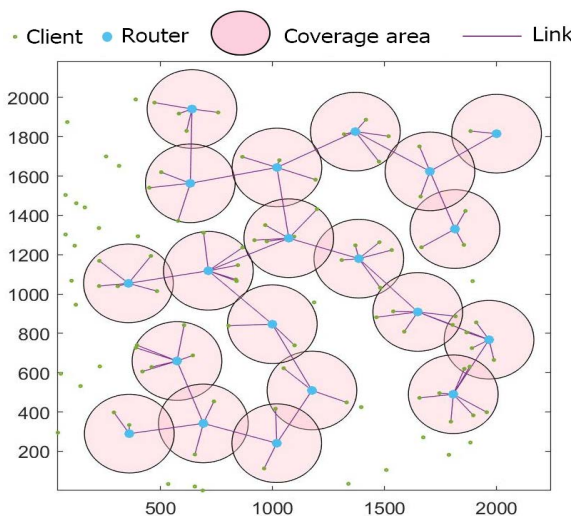**FIGURE 11.** The optimal placement of mesh routers obtained using AVOA.
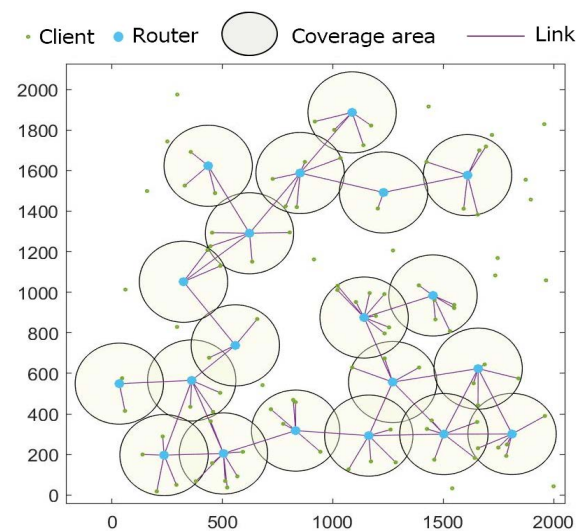

FIGURE 13. The optimal placement of mesh routers obtained using CHIO.

Figure 15(a) shows the evolution of users' coverage when varying the number of mesh routers. It is observed that the number of covered clients increases while increasing the number of mesh routers. More precisely, the coverage is increased by our approach up to 6.4%, 8.4%, 7.84%, 25.9%, 38%, 14.34%, 35.34%, 18%, 9.7%, and 16.87% when compared with FA, GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, and SSA, respectively.

The effect of varying the number of mesh routers on network connectivity is shown in Figure 15(b). It is clearly seen that the network connectivity increases when increasing the number of mesh routers. In fact, when adding more routers, the number of formed sub-networks will be decreased by connecting some sub-networks to form bigger sub-networks. Consequently, the size of the biggest sub-network will be increased until including all mesh nodes. It is also demon-

TABLE 10. Network instances considered in convergence analysis.

Instance	$W \mathbf{x} H$	m	n	CR
$Instance_1$	1000x1000	5	50	200
$Instance_1$	1500x1500	10	100	200
$Instance_3$	2000x2000	15	150	200
$Instance_4$	2500x2500	20	200	200

strated that COA forms the biggest sub-network in all cases. More precisely, the network connectivity using COA is increased up to 10.39%, 10.43%, 8%, 25.71%, 39.2%, 17.47%, 35%, 15.41%, 15.41%, 7.77%, and 17.37% more than FA, GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, and SSA, respectively.

Results illustrated in Figure 15(c) show that the fitness value is proportional to the number of mesh routers. Thus, as the number of mesh routers increases, the fitness value
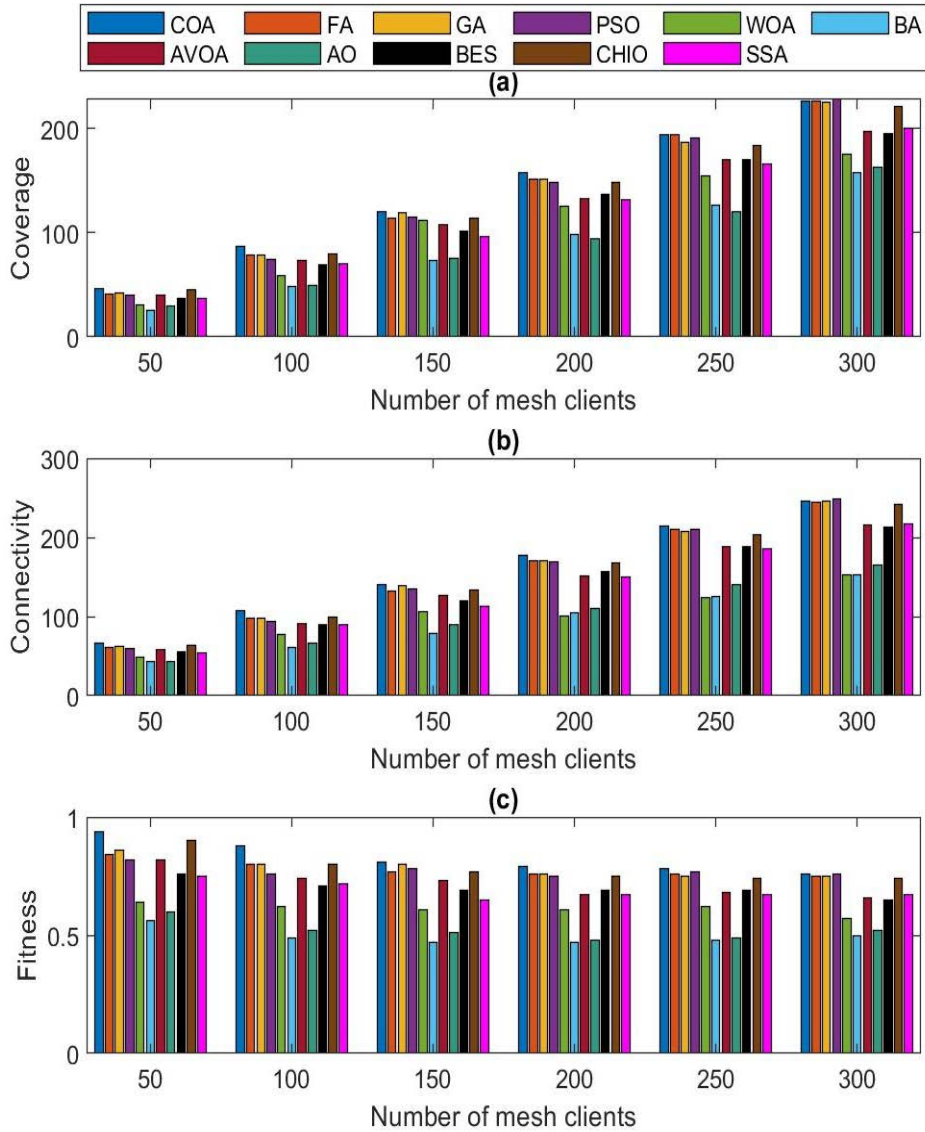
FIGURE 14. Impact of varying number of mesh clients on: (a) Coverage (b) Connectivity (c) Fitness.

TABLE 11. Convergence analysis between COA, FA, GA, PSO, WOA, and BA algorithms.

Instance	$Instance_1$		$Instance_2$		$Instance_3$		$Instance_4$	
	Fitness	Iteration	Fitness	Iteration	Fitness	Iteration	Fitness	Iteration
COA	0.85	308.67	**0.77**	721.6	**0.68**	817.26	**0.61**	911.46
FA	0.80	10.63	0.75	27.3	0.67	49.16	0.57	63.65
GA	0.76	347.93	0.73	668.5	0.66	837.23	0.58	847
PSO	**0.89**	134.9	0.68	345.3	0.66	432.7	0.52	545
WOA	0.69	17.36	0.57	4.56	0.5	4.3	0.40	36.75
BA	0.55	248.83	0.45	144.46	0.37	203.63	0.30	235.25
AVOA	0.77	322.63	0.65	524.2	0.60	622.43	0.52	688.26
AO	0.68	684.96	0.54	736.46	0.40	673.03	0.34	685.33
BES	0.87	192.9	0.71	471.76	0.61	721.9	0.47	812.2
CHIO	0.80	611.36	0.71	812.53	0.65	888.96	0.56	913.23
SSA	0.80	427.06	0.69	533.33	0.57	513.73	0.49	588.8

will increase for all algorithms. Again, the proposed COA outperforms FA, GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, and SSA algorithms when the number of mesh routers exceeds 5.
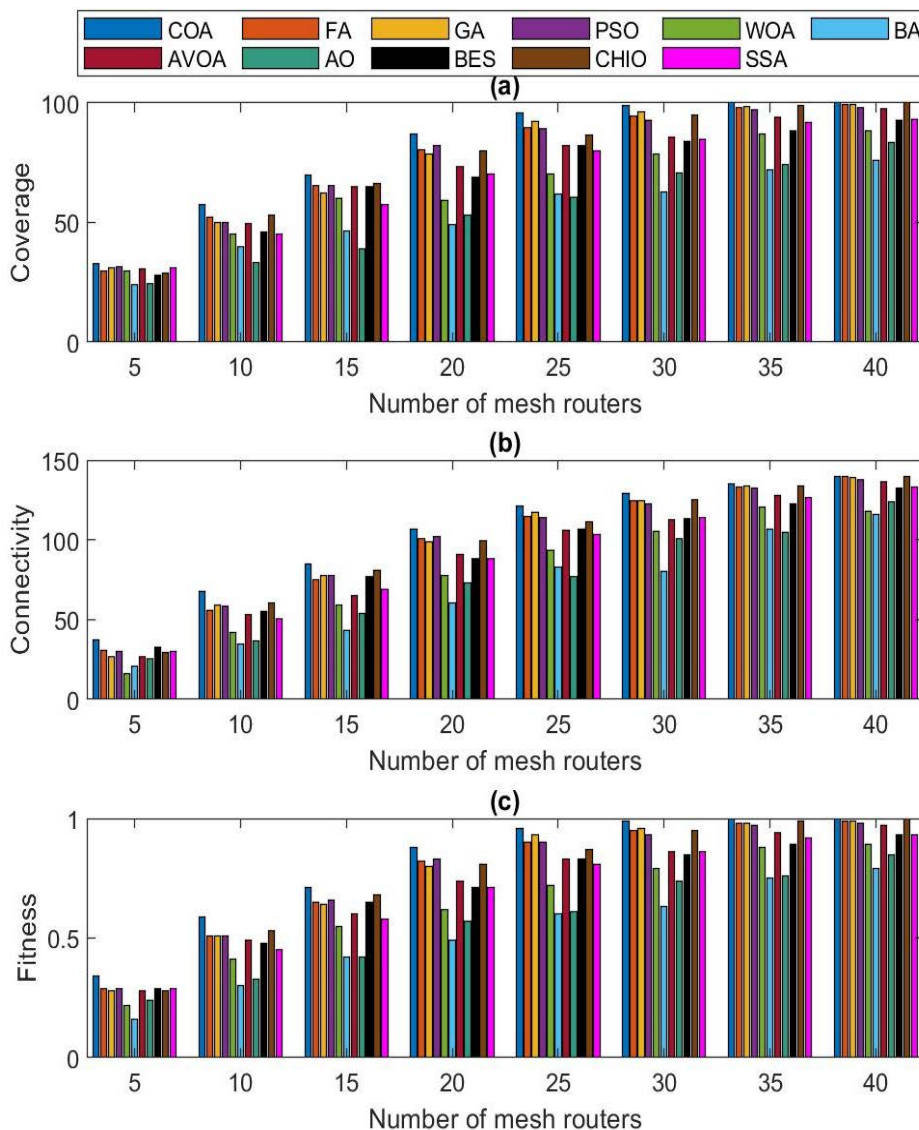
FIGURE 15. Impact of varying number of mesh routers on: (a) Coverage (b) Connectivity (c) Fitness.

C. IMPACT OF VARYING THE ROUTER COVERAGE RADIUS

The impact of varying the router coverage radius (from 50 m to 400 m) on coverage, connectivity, and fitness value is illustrated in Table 9. Its graphical representation is shown in Figure 16.

Figure 16(a) illustrates the influence of varying the mesh router coverage radius on coverage. Results presented in this figure show that when increasing the radius coverage of every mesh router, the coverage metric will increase automatically. In fact, when increasing the radius coverage, mesh routers cover a large area until covering approximately all mesh clients (when coverage radius exceeds 300 m for most of the algorithms). Moreover, COA outperforms other algorithms for all cases. More precisely, it covers up to 9%, 17.15%, 13.25%, 33%, 41.12%, 27.62%, 33.75%, 30.45%, 9%, and 27.25% more clients than FA,

GA, PSO, WOA, BA,AVOA, AO, BES, CHIO, and SSA, respectively.

Results presented in Figure 16(b) demonstrated that the network connectivity is proportional to the mesh router coverage radius. When increasing the radius coverage of every mesh router, the network connectivity will increase too. In fact, when increasing the radius coverage, each mesh router has the capability to cover more clients and to connect to other mesh routers. Consequently, the size of the biggest sub-network will increase until connecting approximately all mesh nodes. COA performs better than other algorithms when the coverage radius exceeds 50 m. More precisely, it increases the network connectivity up to 7.89% (8.52%, 8.46%, 29.26%, 53.12%, 17%, 40.86%, 19%, 11% and 26.12%) than FA (GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, and SSA, respectively).
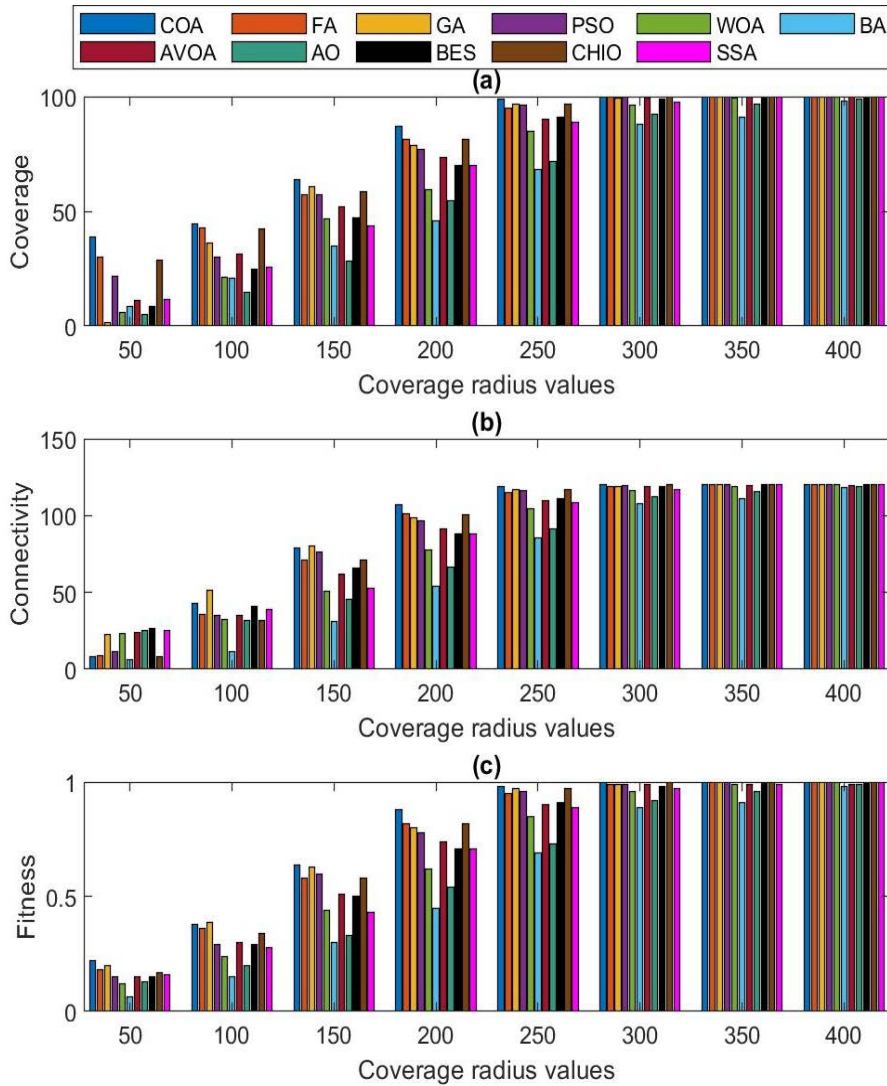
FIGURE 16. Impact of varying coverage radius values on: (a) Coverage (b) Connectivity (c) Fitness.
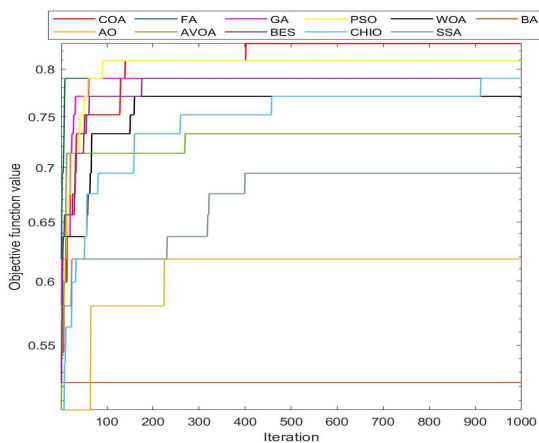
FIGURE 17. Convergence analysis using instance1.
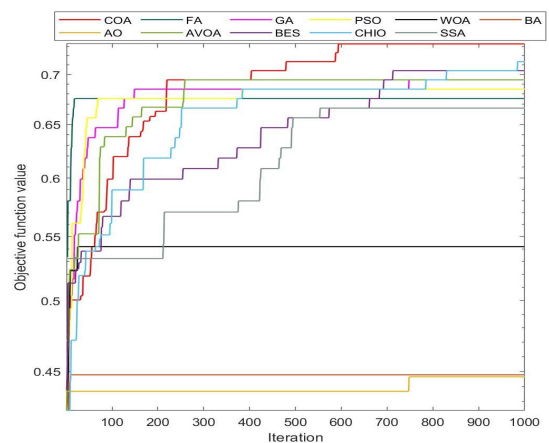
FIGURE 18. Convergence analysis using instance2.

Results described in Figure16(c) showed that the fitness value is increased when increasing the mesh router coverage radius. It is revealed that our approach COA outperforms FA, GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, SSA algorithms.
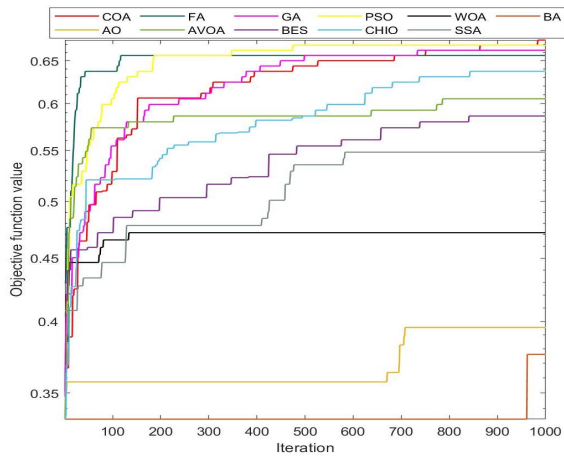
FIGURE 19. Convergence analysis using instance2.
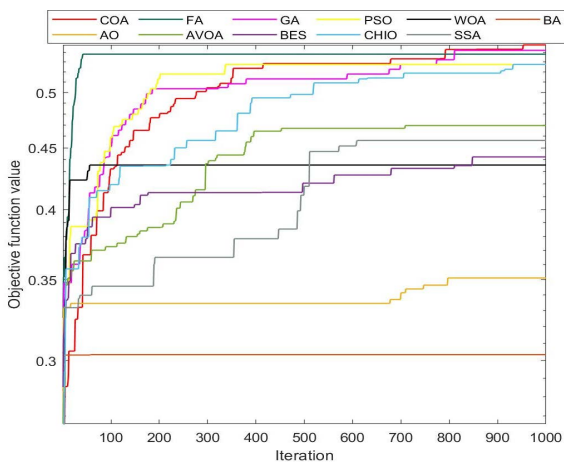
FIGURE 20. Convergence analysis using instance2.

D. CONVERGENCE ANALYSIS

The convergence analysis of COA, FA, GA, BA, WOA, PSO, AVOA, AO, BES, CHIO, and SSA algorithms is shown in Figure [17-20] and Table 11. We considered four network instances of different sizes (i.e. (a) *Instance*$_1$, (b) *Instance*$_2$, (c) *Instance*$_3$, (d) *Instance*$_4$) as described in Table 10. The convergence process is done according to two parameters: convergence speed and convergence efficiency (fitness value). Each obtained result is an average of 50 experiments.

Results reported in Table 11 show that WOA converges more quickly than other algorithms. However, it provides less interesting solutions when compared to COA, GA, FA, PSO, AVOA, AO, BES, CHIO, and SSA algorithms. The fitness value obtained by COA is the best. This is due to its unique structure and search mechanisms. For instance, the random transition of coyotes among groups promotes the population diversity. In addition, using alphas dictates the movement of other coyotes during the cultural interaction phase providing a good balance between exploration and exploitation phases. Furthermore, the biological events (birth and death) serve as a mechanism to retain good solutions and eliminate weaker ones as the algorithm progresses.

VI. CONCLUSION

In this work, we have proposed the application of COA to tackle the mesh router nodes placement problem in WMNs. Its performance was analyzed and evaluated by investigating the impact of varying the number of mesh clients, the number of mesh routers, and coverage radius values. Obtained results revealed the superiority and the effectiveness of COA when compared to other optimization algorithms such as FA, GA, PSO, WOA, BA, AVOA, AO, BES, CHIO, and SSA in terms of network connectivity and user coverage. For future works, we plan to apply the COA meta-heuristic to solve the joint design process including gateway deployment, antenna placement, routing, and channel assignment. We also suggest implementing other meta-heuristics, especially hybrid solutions to take advantage of each algorithm.

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