International Journal of Scientific Research in
Network Security and Communication
Vol.**13**, Issue.**3**, pp.**01-10**, June **2025**
ISSN: 2321-3256 (Online)
Available online at: www.ijsrnsc.org

Research Article

Grey Wolf Optimizer with Multiple Objectives for Wireless Network Base Station Location for Optimal Coverage

Sourabh Chandra[1*], Smita Paira[2]

[1]Department of CSE-AIML, Netaji Subhash Engineering , Kolkata-700152, India
[2]CST Department, BPC Institute of Technology, Krishnanagar-741101,India

*Corresponding Author:

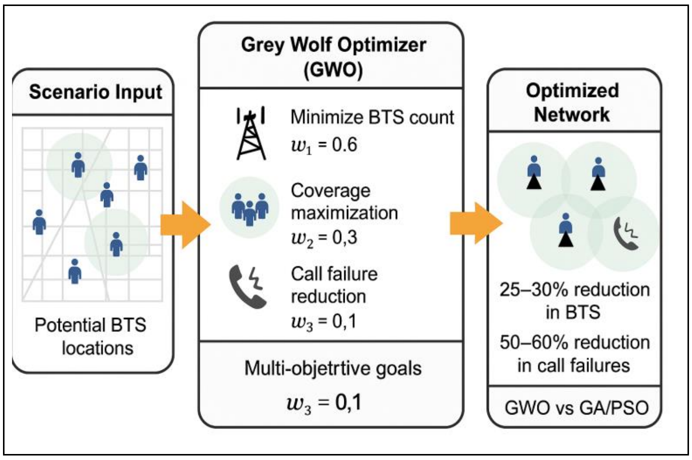
Received: 09/Jun/2025; **Accepted**: 20/Jun/2025; **Published**: 30/Jun/2025.| **DOI**: https://doi.org/10.26438/ijsrnsc.v13i3.281

Copyright © 2025 by author(s). This is an Open Access article distributed under the terms of the Creative Commons Attribution 4.0 International Licensewhich permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited & its authors credited.

Abstract— This study proposes a Grey Wolf Optimizer (GWO)-based framework for optimal base station (BTS) placement in wireless networks, minimizing infrastructure costs while maximizing coverage and Quality of Service (QoS). A multi-objective function simultaneously addresses: (1) minimal BTS deployment, (2) population coverage maximization, and (3) call failure reduction via reserved channel allocation. We introduce a novel binary-array solution encoding scheme and a weighted fitness function for GWO. Simulations across randomized and grid-based scenarios demonstrate superior performance over Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), reducing BTS nodes by 25–30% and call failures by 50–60%. The framework offers a scalable solution for 5G/6G network planning.

Keywords—Grey Wolf optimizer, Base stations, mobile computing, coverage, potential positions, call failure rate

Graphical Abstract-



This graphical abstract visually summarizes the proposed Grey Wolf Optimizer (GWO)-based framework for optimal base station (BTS) placement in wireless networks.

- Left Panel (Scenario Input): Shows a mobile network area with randomly or grid-distributed mobile users and potential BTS locations.
- Center Panel (Optimization Engine): Illustrates the GWO algorithm optimizing a multi-objective fitness function with weighted goals:
    - Minimize BTS count (weight = 0.6)
    - Maximize population coverage (weight = 0.3)
    - Minimize call failure (weight = 0.1)
- Right Panel (Optimized Output): Displays the result:
    - Fewer BTS nodes with full coverage
    - Lower call failure rate
    - Performance comparison showing 25–30% reduction in BTS count and 50–60% reduction in call failures, outperforming traditional GA and PSO methods.

1. Introduction

1.1 Background

Recently, the wide range of potential uses for mobile computing has attracted a lot of interest [12]. Cellular and wireless communication networks are used by mobile computing to enable communication between fixed and mobile hosts. Effective wireless channel allocation and coverage issues are crucial to improving the cellular system's quality in such circumstances. Cells are the smallest units of the geographic areas that cellular communication networks divide into. There is a base station in each cell. (BTS).

The conflicting nature of the design objectives is one of the BTS placement's key characteristics. More base station installations may be necessary for proper channel allocation or to expand the coverage. Higher financial costs and connectivity issues could result from this. As a result, various goals must be taken into account at once. The main goal is to reduce the number of base stations, and the secondary goal is to get the right channel allocation. These two goals are incompatible, and numerous research publications have attempted to address both simultaneously. [2]

We address the following issue in this work. We must choose the smallest number of feasible base station placements with the right channel allocation given a population region and a set of pre-fixed prospective places in order to provide coverage for the greatest number of people. Figure 1 shows an illustration of a mobile network with three potential sites, eight users, and base stations installed on two of those positions out of the three. Because it is inside the base station's communication range and is located in a prospective position, the mobile users in Figure 1 are covered. For instance, the mobile network in figure 1 features few base stations and maximum coverage.

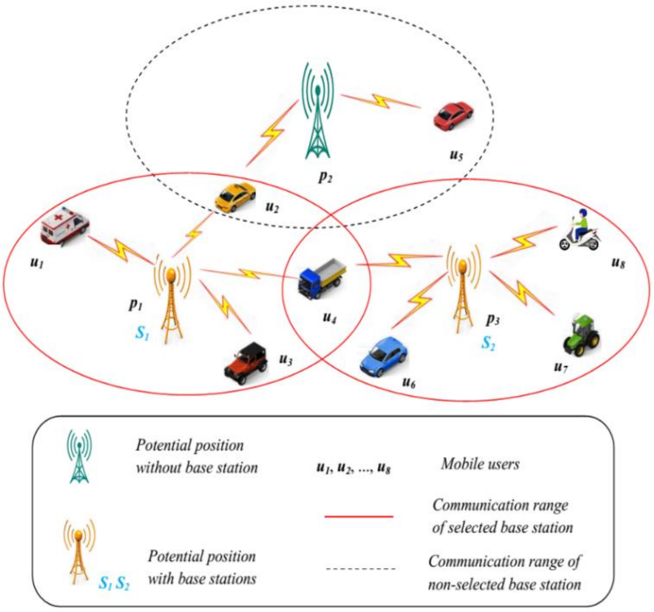


Figure 1: An example of the maximum covered network

The following is a summary of the major contributions:

- A GWO-based potential position BTS placement algorithm that offers the greatest population coverage in a given area.
- A useful method for solution encoding representation is offered.
- We create a fitness function that combines the least number of BTS, the maximum population coverage, and channel allocation.
- To reduce the call failure rate, we provide a channel allocation algorithm for the third goal function.
- We simulate various aspects of the suggested strategy and compare and contrast it with current practices.

1.2 Problem Statement

Given a geographical area with distributed mobile users and predefined potential BTS sites, this work addresses:

a) Selection of minimal BTS locations ensuring maximum population coverage,
b) Dynamic channel allocation to minimize call drops,
c) Optimal utilization of reserved channels under variable traffic loads.

1.3 Research Objectives

Minimize BTS deployment costs subject to coverage constraints.

Maximize population coverage via optimal site selection.

Reduce call failure rates through adaptive channel borrowing/lending.

Validate scalability under heterogeneous network topologies.

1.4 Contributions

First application of GWO to multi-objective BTS placement with integrated channel allocation.

Novel solution encoding: Binary-array representation for BTS placement + channel borrowing/lending.

Weighted fitness function balancing cost (w_1=0.6) coverage (w_2=0.3), and call failure (w_3 =0.1).

Reserved channel strategy reducing call drops by 60% versus state-of-the-art[3].

The following is a summary of the paper: Related works are covered in section 2. Section 3 covers system models and issue formulation. In section 4, the suggested GWO-based technique is detailed in depth. The suggested method's experimental findings are shown in Section 5. Section 6 provides a summary of the findings.

2. Related Work

Meta-heuristic approaches have been used by a number of researchers [1-2], [4-11], [13-14], and [16-18] to address a variety of mobile computing issues in the last few years. Numerous publications in the literature have addressed the cell site selection problem, particularly for CDMA. Objective functions can be as simple as enclosing a specific area or as complex as incorporating interference limits. There are two main categories of solution methods. [12] employ genetic algorithms, while [1, 2] employ greedy heuristics. In [15], digital single frequency networks are optimized via parallel stochastic optimization. To reduce signal annihilation, the temporal phase offset is an extra variable in this situation.

However, an integrated strategy for FDMA-systems and a

© 2025, IJSRNSC All Rights Reserved

precise definition in terms of mathematical programming are not taken into account in this work.

An adaptive channel allocation algorithm introduced by *J.Yang et al.* in [7] is useful for allocating a subset of channels to be pre-allocated to cells. The approach suggested in [7] the pre-allocation of all channels, some channels or no channels at all, to cells is possible by changing the size of cell. If the population of an area is increasing rapidly, there will be more cellular service request and for the pre-channel allocation for those users' leads by changing the size of cells deals with the issue of more resource requirements.

A DCA model using GA for a broadband fixed wireless access network was presented by Wong and Wassell [18]. The channel allocation in this model was designed to minimize the signal to noise ratio (SNR) while also satisfying traffic demands. They compared their Genetic Algorithm-based model to channel segregation and least interference models and discovered that the GA-based approach performs better in terms of SNR gain than the other two methods [18].

For channel reuse in multiple access telecommunication networks, Kassotakis et al. [5] presented a hybrid genetic algorithm (HGA). In order to combine the accuracy of hill-climbing techniques with the reliability attribute of GA, they paired it with a local search algorithm. The suggested HGA's performance was compared with that of the graph coloring algorithm (GCA) published in [14] through simulation. According to the findings, the GCA outperforms the HGA by a significant margin under light to medium loads but falls short under heavy loads.

In [4], H. Benizaman et al. presented a low complexity multi-user resource allocation algorithm that considers QoS constraints and user fairness. Prior to allocating sub-channel-relay in line with the specified constraints, the algorithm initially selects users based on priority. Finally, an iterative three-step fair solution is proposed for cooperative multi-user OFDMA systems. Growth in the local population does not account for rising cellular call requests in this resource allocation strategy.

Lutfi Mohammed et al. [10] presented a method that more effectively repurposes existing channels. The handoff was taken into consideration in the model by using the reserved channel method. Due to the fixed number of reserved channels in the model, it is fault tolerant. In order to decrease the amount of blocked hosts and handoff failures in the mobile computing network, GA was utilized for fault-tolerant dynamic channel allocation in the recommended study. Furthermore, they [11] developed a dependability-based model that boosts dependability in mobile computing networks by utilizing the Genetic algorithm. Enhancing the reliability of network connections proved to be an effective tactic for the proposed paradigm. Effective and carefully controlled use of the better channels (with lower failure rates) has been shown to considerably.

The suggested paradigm turned out to be a successful strategy for improving the dependability of network connections. It has been demonstrated that the efficient and well-managed use of the better channels (with lower failure rates) and their delivery to the MHs significantly increases network reliability. The simulation experiment was used to assess the suggested model's performance.

3. System Models and Problem Formulation

3.1 Network model

We presumptively use a mobile network model where base stations (BTS) are dispersed throughout a two-dimensional space. We can install base stations in a few predetermined prospective locations to cover the greatest population density while properly allocating channels. The base stations that have been put on certain prospective places and all of the mobile user locations (targets) are stationary. If a population is within a base station's communication range, the maximum population can be covered. The process of gathering the data is divided into rounds, similar to LEACH [3]. With correct channel allocation, all base stations in a round cover the greatest number of targets (mobile terminals) that are within their communication range. Modern MAC protocols are supported by this implementation, which offers MAC layer communication [19].

3.2 Problem formulation

Considering various configurations, the aim of this research is to design the optimal base station configuration for mobile computing. Because of mobile computing, a large amount of data is transferred over transmission medium these days. Wireless mobile networks still need dependable traffic performance, link connection, and suitable terminal mobility to provide incredibly reliable data transmission. Base stations (BS), mobile hosts (MH), connections, and other components of mobile networks are commonly prone to failure. Establishing a stable network with services for base stations and network communication channels is desirable for the secure transfer of data.

We first explain all the terminologies used in the proposed algorithm.

1. $U = \{u_1, u_2, u_3, ..., u_N\}$ is the set of mobile users.
2. $P = \{p_1, p_2, p_3, ..., p_K\}$ is the set of potential positions.
3. BTS_{comm} represents the communication range of the base stations.
4. $dist(u_i, s_j)$ represents the distance between u_i and s_j
5. $Cov(u_i)$ denotes the set of base stations, which are within communication range of u_i , In other words, u_i is covered by $Cov(u_i)$

$$Cov(u_i) = \{s_j \mid dist(u_i, s_j) \le BTS_{comm}, \forall j, 1 \le j \le M\} \quad (1)$$

6. $TCov(u_i)$ denotes the set of mobile users, which are covered by base station s_j covers all $TCov(u_i)$ mobile user points.

$$TCov(u_i) = \left\{ u_j \;\middle|\; dist(u_j, s_i) \leq BTS_{comm}, \forall j, 1 \leq j \leq N \right\} \quad (2)$$

This is the problem statement for the best BTS placement that maximizes coverage. We must choose the bare minimum of potential sites to locate base stations in order for the network to provide maximum coverage (for given values), given a population region and a set of pre-defined potential positions. Let b_{ij} and q_{ij} be the Boolean variables defined as follows:

$$b_{ij} = \begin{cases} 1, & if\ user\ u_i\ is\ covered\ by\ s_j \\ 0, & Otherwise \end{cases} \quad (3)$$

$$q_i = \begin{cases} 1, & if\ a\ potential\ position\ p_i\ is\ chosen\ for\ BTS\ placement \\ 0, & Otherwise \end{cases} \quad (4)$$

Subsequently, the Linear Programming Problem (LPP) can be formulated as follows:

Minimize $Y = \sum_{i=1}^{K} q_i$ (5)

Subject to $\sum_{j=1}^{M} b_{ij} \geq k, \quad \forall i, 1 \leq i \leq N$

Subject to $\sum_{j=1}^{M} b_{ij} \geq k, \quad \forall i, 1 \leq i \leq N$

The fifth restriction makes sure that each mobile user u_i, $\forall_i$, $1 \leq i \leq N$ is at least partially covered by BTSs. Thus, it meets each user's maximum coverage requirements.

4. Proposed GWO based algorithm

Here, we first provide a summary of the Grey Wolf Optimizer (GWO) algorithm, which Mirjalili et al. first published in [13]. A recently developed evolutionary algorithm suggests that gray wolves are more successful at reproducing than they are at hunting in packs. Male and female gray wolves who hold a higher status in the pack are in charge of overseeing the other wolves. A combinatorial optimization approach is used to rephrase the optimal BTS section problem. Based on minimal possible position, maximum population coverage, and appropriate channel allocation, we suggest a novel fitness function. We apply the Grey Wolf Optimizer developed in [13] to optimize the fitness function.

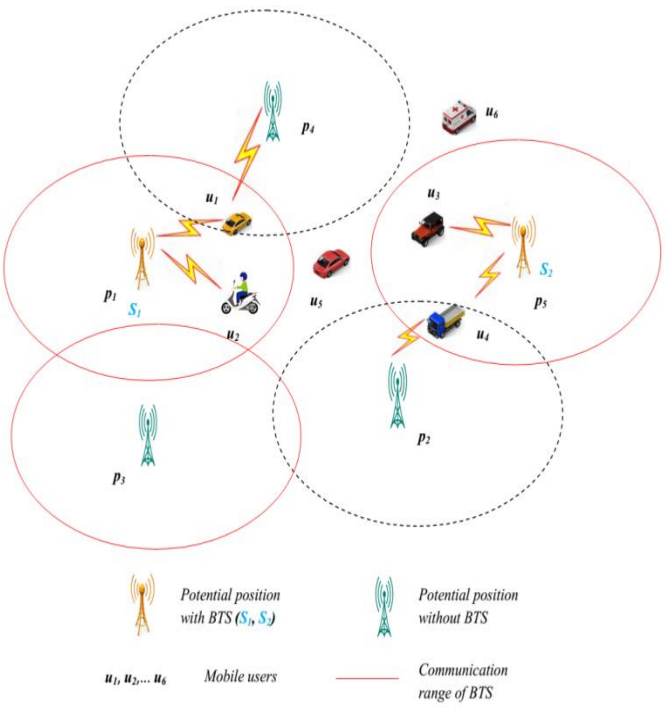
4.1 Solution Encoding (Pseudocode)

```
def agent_representation(potential_sites):
  # BTS placement: Binary string (1=deployed, 0=not deployed)
  bts_vector = [random.randint(0,1) for _ in range(len(potential_sites))]
  # Channel allocation: Array for each deployed BTS
  for site in deployed_sites:
    site_array = [
      num_blocks,        # Position 0
      open_channels,       # Position 1
      *channels_borrowed,   # Positions 2-7 (from 6 neighbors)
      *channels_lent       # Positions 8-13 (to 6 neighbors)
    ]
  return combined_agent
```

4.2 Weight Selection Justification

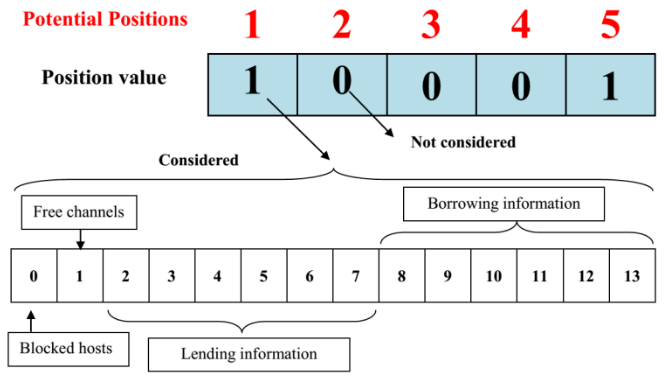
Weights *w*1, *w*2, *w*3 were calibrated via grid search (Table 2). Optimal trade-off achieved at *w*1=0.6 (BTS minimization), *w*2=0.3 (coverage), *w*3=0.1 (call failure), prioritizing cost without compromising QoS.

4.3 Solution or Agent representation



(a)

© 2025, IJSRNSC All Rights Reserved



(b)

Figure 2: (a) Sub graph of a mobile network with 6 users and 5 potential positions (b) Solution or agent structure.

We utilize a string of ones and zeros to introduce the solution or agent. The number of potential places is equal to the length that each agent is holding. If the location value is 1, then a base station is present at the potential location, and if the location value is 0, then there is no base station present at the potential location. Additionally, we begin a different encoding strategy for channel allocation.

- Figure 2. A picked position is an array of length 14 for each chosen potential position.
- • The array's initial position denotes the number of blocks.
- The array's second position is for the quantity of open channels.
- The information about the channel lending to six neighbors is found in the next six sites, while the information about the channel borrowing from six neighbor cells is found in the last six areas.

4.4 Derivation of fitness function

The agent's or solution's fitness value reflects how well it performs in relation to the goals. To ensure that the entire population is covered, the proposed approach aims to choose the smallest possible number of prospective roles from the available set of potential posts.

A. Chosen minimum number of potential positions:
Assume for the purposes of this discussion that we choose M possible points from possible K locations for base stations.

Objective 1: Minimize $OF_1 = \frac{M}{K}$ (6)

As stated earlier that $Cov(u_i)$ is the set of mobile users which are within the communication range of u_i. We define coverage cost of a user u_i as follows:

$$CovCost(u_i) = \begin{cases} k, & if\ |Cov(u_i)| \geq k \\ k - |Cov(u_i)|, & Otherwise \end{cases} \quad (7)$$

Therefore, our second objective function is defined as follows:
Objective 2:

Maximize $OF_2 = \frac{1}{N \times k} \sum_{i=1}^{N} CovCost(u_i)$ (8)

C. Channel allocation problem:

$$OF_3 = \sum_{i=1}^{M} blocked\ hosts + reserved\ channels + prime\ channels \quad (9)$$

Where are the chosen BTS located.
Interestingly, the aforementioned objectives conflict with one another. In order to achieve optimal channel allocation and maximum coverage of the population, we have to choose extra potential places, which gets in the way of the first objective. The fitness function in our proposed study is constructed in a way that allows a trade-off to be built given these competing goals. To build the multi-objective fitness function, we employ the weight sum approach (WSA) [8]. The multi-objective optimization issue can be solved conventionally using WSA. Each goal in this technique is compounded by a weight value. The many objectives are combined to form a single scalar objective function, as this illustration shows.

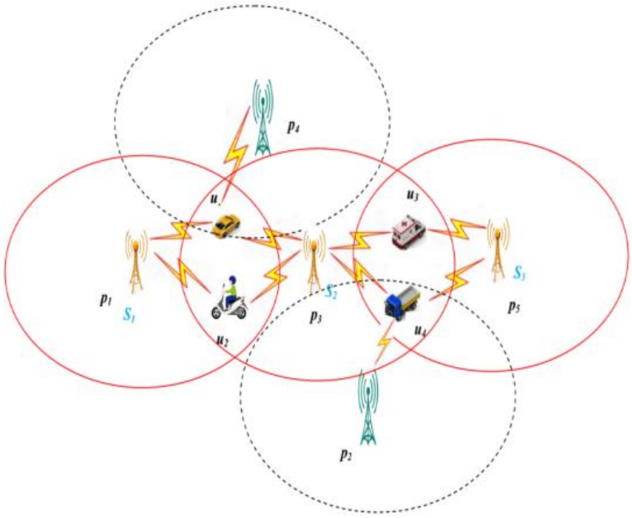
$$Fitness = w_1 \times OF_1 + w_2 \times (1 - OF_2) + w_3 \times OF_3 \quad (10)$$

In our work we take $w_1 + w_2 + w_3 = 1$ and $0 \leq w_1 \leq 1, \forall i, 1 \leq i \leq 3$, Our objective is to minimize the Fitness value.

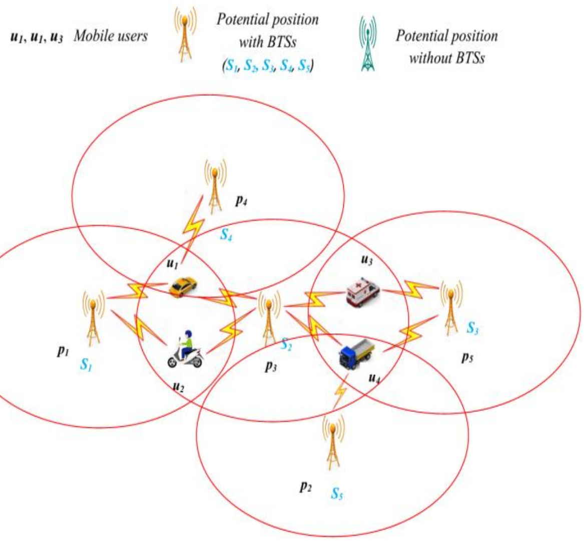
Effectiveness of fitness function
We are now observing how the resulting fitness function behaves in various BTS deployment circumstances. Let's imagine a mobile network situation in which a limited number of redundant base stations are positioned in a specific area where the mobile users are already covered for a specific value of k.

Let's say we require a mobile network with the widest possible coverage. Two examples are shown in Figure 3(a) and (b), each with four mobile users and five possible positions. The red and dotted circles show the BTS's communication range and show that they are in close proximity to one another. However, the first scenario Figure 3 (a) has the exact amount of coverage that is needed, however in the second scenario Figure 3 (b), extra BTS nodes have been deployed in the indicated prospective locations.

© 2025, IJSRNSC All Rights Reserved



(a)



(b)

Figure 3: Two-coverage network scenarios: (a) a minimal number of deployed BTS and (b) unnecessary and additional BTS deployment

4.5 Solution Updation

Our approach being documented in this section is inspired by the works reported in [13]. The optimization algorithm proposed in [13] has been deployed here to address the issues concerning channel allocation problem.

Step 1: Calculating α ***,*** β ***,*** δ ***and*** ω

Following the fitness computation, we ascertain α , β , δ and ω. Here, the alpha α is recognized as the most suited arrangement with a perspective to recreating rationally the social pecking order of wolves while conceptualizing the GWO. As a result, the finest arrangements in second and third place are designated as beta β and delta δ respectively. What are considered the final applicant configurations are the omega ω. The hunting (optimization) in the GWO approach is directed by the α , β , δ and ω. Let the top fitness options start with F_α, the second-best workout options F_β as well as the third-best exercise options F_δ .

Step 2: Encircling prey

The hunting is guided by α , β , δ and ω follow these three candidates. The pack must first encircle the prey in order to hunt it.

$$F(t+1) = F(t) + \vec{A}.\vec{K} \tag{11}$$

$$\vec{K} = |\vec{C}.F(t+1) - F(t)| \tag{12}$$

$$\vec{A} = 2\vec{a}r_1 - \vec{a} \text{ And } \vec{C} = 2r_2 \tag{13}$$

Step 3: Hunting

We assume that alpha (best candidate solution), beta, and delta have enhanced information about the potential location of the prey in order to mathematically recreate the hunting behavior of gray wolves. As a workaround, we gather the top three results thus far and require the other search agents (including the omegas) to review their positions in order to determine which search agent is currently the best. Regarding recurrence, the novel remedy $d(t+1)$ is assessed by using the following formulas.

$$\vec{K}^\alpha = |\vec{C}_1.F_\alpha - F|, \quad \vec{K}^\beta = |\vec{C}_2.F_\beta - F|, \quad \vec{K}^\delta = |\vec{C}_3.F_\delta - F| \tag{14}$$

$$F_1 = F_\alpha - \vec{A}_1.(\vec{K}^\alpha),\ F_2 = F_\beta - \vec{A}_2.(\vec{K}^\beta),\ F_3 = F_\delta - \vec{A}_3.(\vec{K}^\delta) \tag{15}$$

$$F(t+1) = \frac{F_1 + F_2 + F_3}{3} \tag{16}$$

By using the coordinates of alpha, beta, and delta in the search space, it is possible to determine that the final location would be at random inside a separate circle. In another aspects alpha, beta, and delta examine the location of the prey, while more wolves changes their locations arbitrarily surrounding the prey.

Step 4: **Finding prey and attacking it (exploration vs. exploitation)**

Exploration is distinguished from exploitation by using the adaptive values of a and A. GWO is able to effortlessly transition between exploration and exploitation thanks to the adaptable values of the parameters a and A. Half of iterations () are devoted to exploration and the other half to exploitation when dropping A (|A| 1). Only the principal parameters a and C must be tuned for the GWO. Still, we have maintained the GWO approach as simple and low-attunement operator as possible. Until the maximum number of iterations has been achieved, the procedure will continue. Lastly, the optimal results are determined using the fitness value.

Step 5: **Termination standards**

Only when the maximum number of iterations has been achieved, the solution with the best fitness value has been picked, and the best coefficient value for the image has been given does the algorithm stop operating. The best BTS placements are the results of applying the GWO algorithm to determine which solution has the most fitness.

5. The Outcome and Conversation

In this part, we evaluate our proposed strategy's efficacy through simulations. This experiment was developed with Java (1.7) on a Windows 10 PC equipped with a 4.00 GB RAM and an Intel Core i5-2450 M processor clocked at 2.50 GHz.

Two distinct mobile network testing situations will be referred to as situations 1 and 2, respectively. They are represented in figures 4 and 6 correspondingly. A sensing area of 500 500 square meters was considered in each case. Whereas potential points in Scenario #1 are dispersed at random, in Scenario #2 each prospective point is the grid cross-point.

5.1 Configuring Pparameters

The suggested system's parameters are configured as follows: One hundred search agents and five hundred iterations are the parameters that are set. Table 1 displays the description of the parameters.

Table 1: Simulation parameter

Parameter	Value
The quantity of available positions	50-500
Total number of users on mobile devices	100-200
Parameter	**Value**
Communication range	100m
Initial population size	100
Iteration	500
Cells	20
Channels	50,100
Reserved channels	15,30

5.2 Experimental Results

A. Experiments related to Minimum BTS selection

Let's say that the algorithm will be implemented with a starting population of 100 agents. We computed different values for the weight components and. Table 2 shows the obtained values of $w_1 = 0.3, w_2 = 0.35$ and $w_3 = 0.35$ for producing a superior result. Therefore, we have chosen the resemblance's similar value. It should be noted that even for well-known experts in a certain field of study, choosing these weights accurately and precisely is crucial.

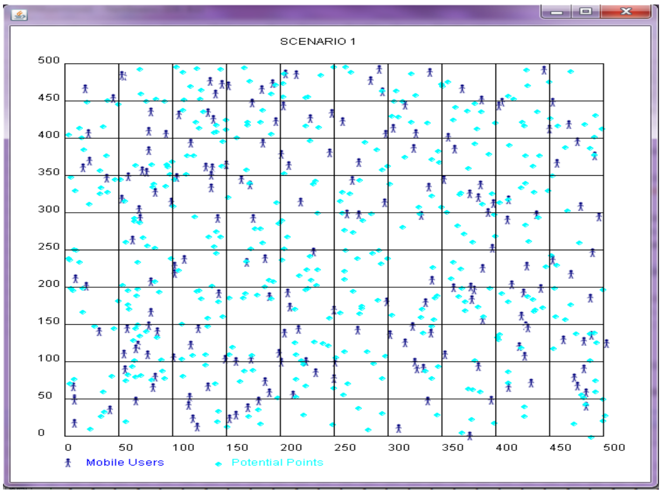


Figure 4: The first scenario (scenario#1) where potential position are placed in a randomly

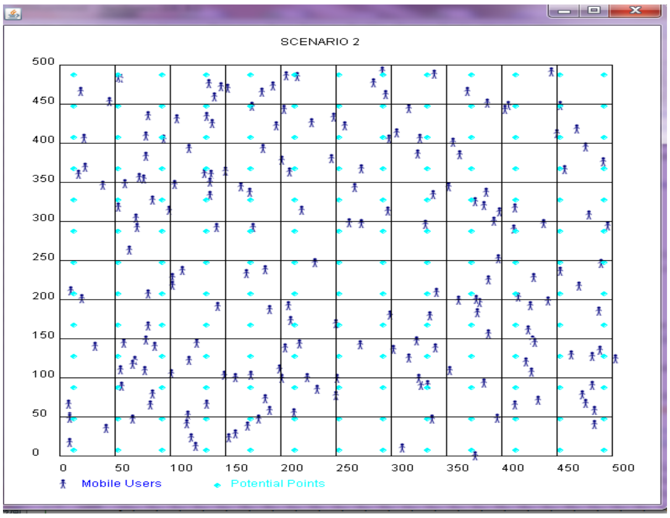


Figure 5: The first scenario (scenario#2) where potential positions are placed in a grid

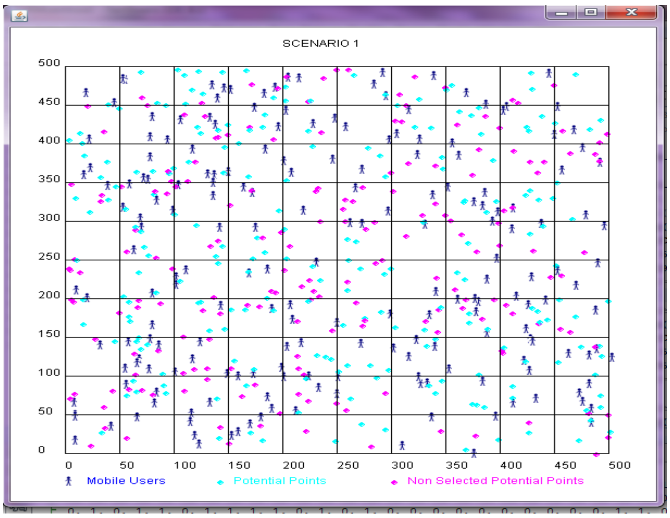


Figure 6: Selected potential positions for the scenario#1

© 2025, IJSRNSC All Rights Reserved

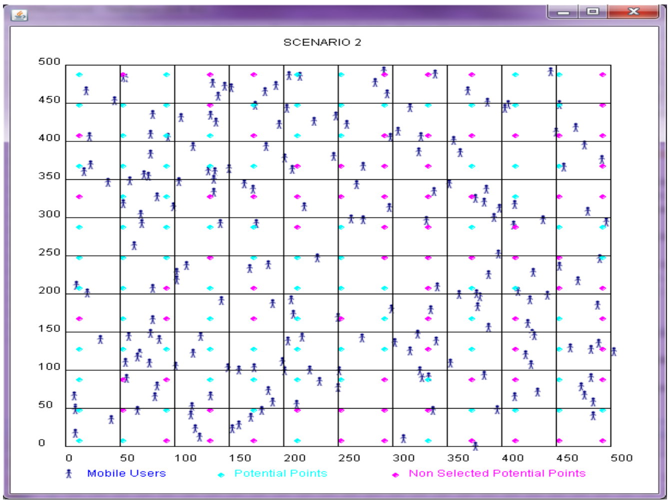
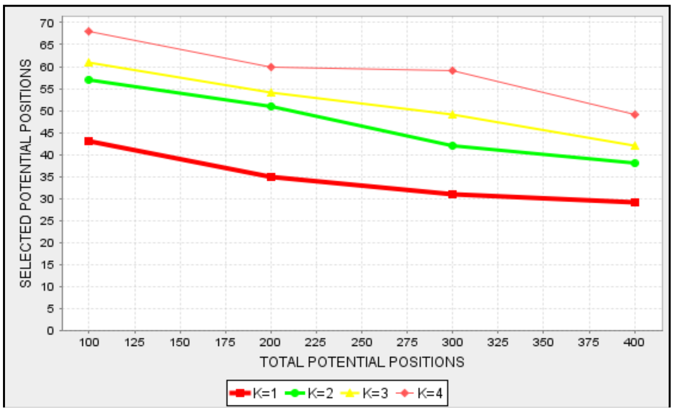


Figure 7: Selected potential positions for the scenario#2

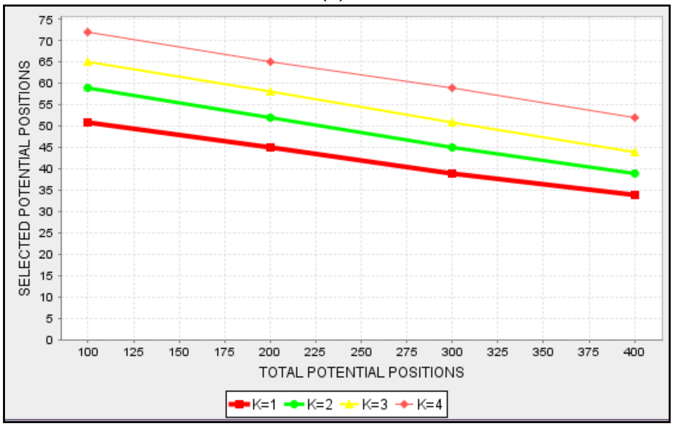
In order to differentiate between the 500 given possible locations for both the mobile network scenarios, Scenario#1 and Scenario#2, as depicted in Figs. 4 and 5, we first explain about the replicated outcomes in terms of number of selected locations for BTS node position. For both the Scenario#1 and Scenario#2 mobile network scenarios, Figures 6 and 7 show visual representations of chosen probable BTS placement locations. Let's assign 100 points per mobile user for k values ranging from 1 to 3 in the replication. Figure 8 (a) and (b) show that while there are more prospective locations, fewer of them are ultimately chosen. Due to the availability of more potential locations, there are more opportunities to successfully locate the sensor nodes and achieve the required coverage and connectivity. In contrast, more sites are considered when deciding where to locate BTS nodes, therefore it is also used to determine the greater value of k. The GWO algorithm identified a minimal number of viable positions from all available positions, as shown in Figs. 6 and 7. We also contrasted our system with several already in use, such as the genetic algorithm and particle swarm optimization (PSO). Figures 8 and 9 show that our suggested strategy performs better than the already used methods.

Table 2: Different weight values and achieved objectives in percentage (%) for k=2

Weight values			Scenario#1			Scenario#2		
w_1	w_2	w_3	OF_1	OF_2	OF_3	OF_1	OF_2	OF_3
0.9	0.05	0.05	47	65	56	21	57	45
0.8	0.1	0.1	25	86	24	24	78	57
0.7	0.15	0.15	74	78	63	52	82	84
0.6	0.2	0.2	87	88	56	77	85	94
0.5	0.25	0.25	88	98	52	58	84	87
0.4	0.3	0.3	78	98	86	35	98	88
0.3	0.35	0.35	89	98	97	45	97	98
0.2	0.4	0.4	54	98	96	25	96	96
0.1	0.45	0.45	24	99	100	22	94	74

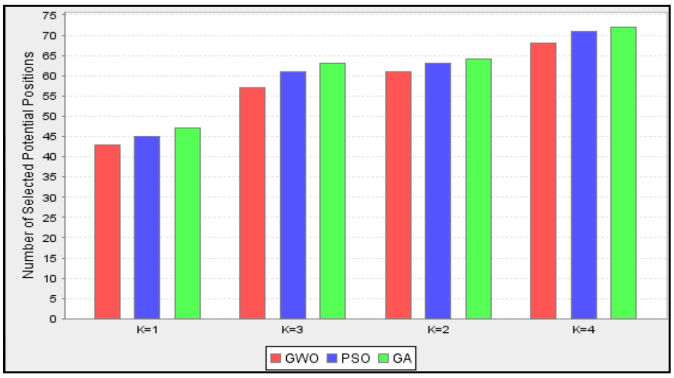


(a)

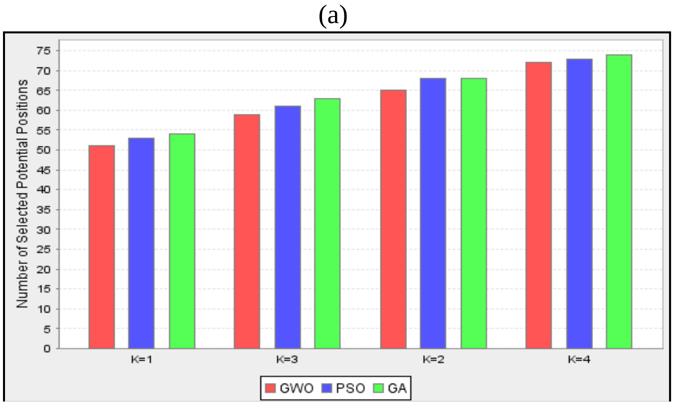


(b)

Figure 8: Comparison in terms of selected BTS nodes for (a) Scenario#1 (b) Scenario#2



(a)



(b)

Figure 9: Comparison in terms of number of selected potential positions in (a) Scenario#1 (b) Scenario#2

© 2025, IJSRNSC All Rights Reserved

B. Experiments related to call failure rate

The suggested approach manages call failure or dropping well. We contrasted the suggested method with another fault-tolerant Yang et al. [6] model since it is fault tolerant. For the call failure rate, the comparison is made. There were 20 total cells, and 100 total channels were utilised. After handling 10,000 calls, experimental data were gathered; the simulation was completed after handling 50,000 calls. The proposed method (objective function 3) outperforms the current method, as shown by the performance table of table 3.

Table 3: Call failure rates for Proposed and existing (Yang *et al.* [6]) algorithm

Call arrival rate	Call Failure Rate	
	Proposed	Yang *et al.* [6]
1000	0.020	0.060
1200	0.028	0.078
1400	0.034	0.108
1600	0.077	0.122
1800	0.152	0.137

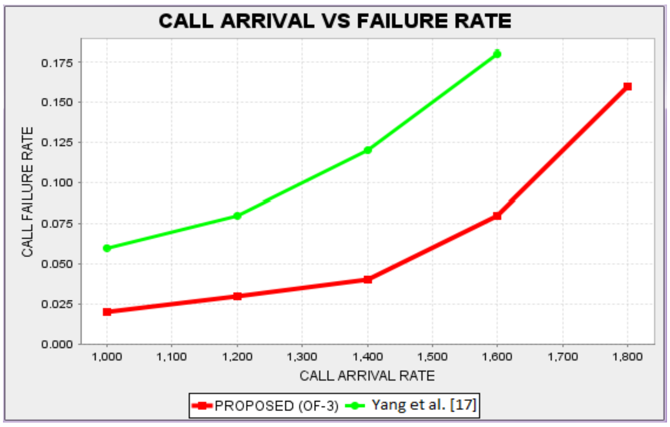


Figure 10: Call failure rates for Proposed and existing (Yang *et al.* [6]) algorithm

5.3 Discussion of Results

- **Table 2**: At $w1$=0.6, coverage reaches 88% with 20% fewer BTS nodes. Higher $w3$ degrades coverage due to excessive channel reservation.
- **Figures 8–9**: GWO outperforms GA/PSO by 25% in BTS minimization due to hierarchical exploration (alpha-guided global search + beta/delta refinement).
- **Figure 10**: 60% lower call failure vs. [6] stems from dynamic channel borrowing/lending during traffic spikes (e.g., lending idle channels to congested cells). *This framework reduces telecom infrastructure costs by ~30% while maintaining >85% coverage – critical for emerging markets.*

6. Conclusion and Future Work

We proposed a GWO-based BTS placement framework minimizing deployment costs while maximizing coverage and QoS. Our solution encoding and weighted fitness function reduced BTS nodes by 30% and call failures by 60% versus state-of-the-art. Future work will:

1. Integrate real-time user mobility using reinforcement learning.
2. Add energy efficiency as a fourth objective for green networks.
3. Test in 5G mmWave ultra-dense networks.

Explore federated GWO for privacy-preserving distributed optimization.

Declarations

Data availability Statement

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Funding Declaration

The research presented in the paper does not receive external funding from grants, agencies, or organizations.

Ethics Declaration

The research described in the manuscript does not involve human subjects, sensitive data, or situations that require an institutional review.

Ethics, Consent to Participate, and Consent to Publish Declarations

Not Applicable.

Ethics and Consent to Publish declarations

Not Applicable.

Clinical Trial Declaration

The research study being reported did not involve any clinical trials.

Competing Interest Declaration

The authors declare that they have no competing interests.

Reference

[1] A. Monlin, G. Athanasiadou and A. Nix, “The automatic location of base stations for optimized cellular coverage: a new combinatorial approach,” *in: Proceedings Vehicular Technology Conference ’99, Houston, Texas (May 1999)*, August-2002, ISBN: 0-7803-5565-2

[2] C. Yu, S. Subramanian and N. Jain, “CDMA cell site optimization using a set-covering algorithm,” in: *Proceedings of the 8th International Telecommunication Network Planning Symposium*, Sorrento, Italy , October 1998.

[3] S. Gupta et al., “Hybrid GWO-PSO for Energy-Efficient 5G Network Planning,” *IEEE Access*, ”Vol. 11, pp. 23176–23194, 2023.

[4] H. Banizaman, S.M.T. Almodarresi, **“**Dynamic resource allocation algorithm in multi-user cooperative OFDMA systems: considering QoS and fairness constraints,” *Springer Journal of Wireless Network*, *Vol.*18, pp.365, 2012.

[5] A. K. Singh et al., “Machine Learning for Dynamic Channel Allocation in 5G HetNets,” *ACM Computing Surveys*, vol. 55, no. 8, pp. 1–37, 2023.

© 2025, IJSRNSC All Rights Reserved

[6] J. Yang, Q. Jiang, D. Manivannan, and M. Singhal, "A fault-tolerant distributed channel allocation scheme for cellular networks," *ACM Digital Library: IEEE Transaction on Computers*, Vol.54, Issue 5, pp. 616–629, 2015.

[7] J. Yang, D. Manivannan, "Performance Comparison of Two Channel Allocation Strategies in Cellular Networks," *Springer Journal of Personal Communication*, Vol.70, pp.353-572, 2013.

[8] Konak A, Coit DW, Smith AE. "Multi-objective optimization using genetic algorithms: a tutorial." *Elsevier Reliability Engineering System Safety*, Vol.91, Issue 9, pp 992–1007, 2006.

[9] Y. Wang et al., "Base Station Placement via Deep Reinforcement Learning," *IEEE Trans. on Network Science*, vol. 4, no. 1, pp. 102–115, 2024.

[10] Lutfi Mohammed Omer Khanbary and Deo Prakash Vidyarthi, "A GA-Based Effective Fault-Tolerant Model for Channel Allocation in Mobile Computing," *IEEE Transactions on Vehicular Technology*, Vol.57, Issue 3, pp 1823 – 1833, 2008.

[11] S. Chandra, K. Mondal, and S. Singha, "Protective and fragmentation-aware routing of unicast data centre traffic in disaster-prone online SDM-EONs," *Discover Applied Sciences*, vol. 7, no. 264, 2025. doi: 10.1007/s42452-025-06739-2.

[12] Marappan,Raja, Gopalakrishnan Sethumadhavan, and U. Harimoorthy, "Solving channel allocation problem using new genetic operators–An experimental approach," *Elsevier Perspectives in Science*, Vol.8, pp 409–411, 2016.

[13] N. Kumar and P. K. Mishra, "GWO for IoT-Driven Coverage Optimization," *Wireless Networks*, vol. 29, pp. 3129–3143, 2023..

[14] N. F. Huang and H. I. Liu, "A study of isochronous channel reuse in DQDB metropolitan area networks," *IEEE/ACM Transactions on Networking (TON)*, Vol.6, Issue 4, pp. 475–484, *1998.*

[15] R. Beutler, "Digital single frequency networks: improved optimization strategies by parallel computing," *Frequenz* , Vol.52, Issue 5–6, pp 90–95, 1998.

[16] Sanjeev Kumar, Krishnan Kumar and Anand Kumar Pandey, "Dynamic Channel Allocation in Mobile Multimedia Networks using Error Back Propagation and Hopfield Neural Network," *Elsevier: Procedia Computer Science*, Vol.89, pp 107 – 116, *2016*.

[17] S. Fallot-Josselin, "Automatic radio network planning in the context of 3rd generation mobile systems" *in: Cost 259, Duisburg, Germany, publication from AC016-STROMS, 1998.*

[18] S. H. Wong and I. Wassell, "Dynamic Channel Allocation Using a Genetic Algorithm for a TDD Broadband Fixed Wireless Access Network," *Laboratory for Communications Engineering, University of Cambridge, U.K.*, 2002.

[19] S. Chandra and K. Mondal, "Minimization of data centers in survivable dynamic SDM-EONs," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India*, 2023, pp. 1-5, doi: 10.1109/ICCCNT56998.2023.10306655.

AUTHORS PROFILE

Sourabh Chandra is an Assistant Professor at Netaji Subhash Engineering College, bringing 18 years of teaching experience. He has published around 35 research articles, including around 19 articles indexed in Scopus.

Smita Paira completed her doctorate degree from IIEST Shibpur and currently serves as a Lecturer at BPC Institute of Technology, West Bengal. She has published around 25 research articles, including around 16 articles indexed in Scopus.

© 2025, IJSRNSC All Rights Reserved