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# Optimally DBS Placement In 6G Communication Networks Using Improved Gray Wolf Optimization Algorithm to Enhance Network Energy Efficiency

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**Abstract**

The transition to sixth-generation (6G) networks demands highly energy-efficient solutions for large-scale IoT services. Drone Base Stations (DBSs) offer flexible coverage, but their three-dimensional placement must be optimized to reduce both transmission and hovering energy. This paper, model DBS deployment as a power-minimization problem and introduce an Improved Grey Wolf Optimization (IGWO) algorithm that integrates adaptive control parameters, exponential weighting of leader contributions (alpha/beta/delta), and a dynamic control structure that progressively favors elite solutions. This design improves search efficiency in high-dimensional, nonlinear spaces and reduces the risk of premature convergence. Extensive MATLAB simulations across multiple propagation environments demonstrate that IGWO achieves lower network power consumption and faster convergence compared to standard metaheuristics, while preserving coverage and connectivity. Specifically, the simulation results demonstrate that the proposed method achieves a remarkable superiority over other optimization algorithms, showing more than a 2% improvement compared to the best among them the standard GWO algorithm—thereby confirming its effectiveness and efficiency in low-power network scenarios.

**Keywords:** 6G Communication Networks; Drone Base Stations (DBSs); Internet of Things (IoT); Improved Gray Wolf Optimization (IGWO); Energy Efficiency.

## 1- Introduction

The emergence of 6G communication networks is a significant step forward in wireless technology, which provides ultra-high capacity, ultra-reliable low-latency communication and these technological advancements have been accompanied by the use of DBSs which have offered a practical means of addressing the growing and geographically dispersed needs for wireless services, especially in areas where conventional tower-based networks are constrained or unable to adjust [1-3]. Incorrect positioning may lead to signal losses, higher energy needs, and degraded network capabilities, particularly in areas with numerous constructions. Thus, it is necessary to implement a thoughtful and organized strategy for the three-dimensional distribution of DBSs in order to optimize the potential capabilities of 6G networks [4,5]. Conventional optimization works often fail to provide globally optimal solutions because of the intricate, ever-changing, and multi-layered nature of DBS placement. Conversely, metaheuristic algorithms inspired by the dynamics of nature and society are gaining increasing attention for their reliability and efficiency in the face of the intricacies of optimization problems [6].

Authors in [7] propose an optimized method for DBS placement using the Marine Predators Algorithm (MPA), which is good at avoiding local optima. Through simulation, their approach outperforms previous techniques, with an average path loss of 56.13 dB, which significantly improves path loss mitigation and user access. The work in [8] describes the quasi-opposition-based lemurs optimizer (QOBLO), a new method of using lemur foraging strategies with quasi-opposition learning to optimally deploy DBS in NG-I. QOBLO outperforms other swarm methods, as per thorough simulations and statistical analysis, markedly increasing connectivity, coverage, and energy efficiency, and providing a strong scalable solution for 6G network problems. In [9], researchers present a two-layer optimizer using a pre-trained VGG-19 model and micro-swarms to optimize network performance by means of non-orthogonal multiple access. It is demonstrated that after statistical testing, the method obtains a 98% accuracy of results

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when compared to Cuckoo Search, Grey Wolf, and Particle Swarm Optimization.

In [10], an analysis of a wireless architecture where aerial and terrestrial base stations serve respective users is carried out, with emphasis on how ABS height and transmit power alter rates for downlink and uplink communication. The results show that optimal ABS configurations are often at the maximum or minimum extremity, and factors like user distance affect performance. Based on [11] where a multi-UAV communication setting is addressed, the authors formulate a multi-objective optimization problem, CUEMOP, to pursue improved coverage and energy saving. The authors propose the Improved Multi-objective Grey Wolf Optimizer (ImMOGWO) which includes the clustering, hybrid initialization techniques, and innovations related to the Levy flight algorithms. It is demonstrated that trial simulations show that ImMOGWO has better efficiency and solution quality than benchmark algorithms.

In [12], researchers conduct systematic mapping analysis of 3D placement in communication systems with UAVs, analyzing goals of optimization, system models, and solution techniques. The study indicates that there is a focus on optimizing data rate, power and coverage using large scale fading models, heuristic algorithms dominate, and there is a lack of significant work on outage probability, cost, and quality of experience and spectrum optimization. In [13], the researchers propose a Mixed-Integer Non-Linear Programming method for coordinating DBS location optimization and minimization of their number, using a modified PSO algorithm that begins with K-means-based initialization. A unique communication protocol is established and simulation results prove the approach offers low packet loss, minimized latency, and extensive user coverage across various environments.

In [14], the DBS placement problem is addressed using P-median optimization; fuzzy clustering is used to generate candidate positions and a bisection algorithm is used to determine the optimum number of DBSs. The optimization solution yields better results than rival approaches, especially when the clustering parameters are adjusted with high precision. The authors in [15] perform an assessment of a variety of existing swarm intelligence algorithms including Cuckoo Search (CS), Elephant Herd Optimization (EHO), Grey Wolf Optimization (GWO), Monarch Butterfly Optimization (MBO), Salp Swarm Algorithm (SSA), and Particle Swarm. They examine how well and productively these algorithms solve a specified problem, carrying out tests in various scenarios. To systemically assess the algorithms, the authors use the Friedman and Wilcoxon tests. Through the use of these tests, the study creates a foundation for performance disparities evaluation and identifies the most effective swarm intelligence methods for dealing with the problem.

This study employs an Improved Grey Wolf Optimization (IGWO) algorithm for the optimal placement of drone base stations (DBSs) within 6G cellular networks, with the primary objective of minimizing network power consumption. Owing to its high capability in navigating complex, high-dimensional search spaces, the IGWO algorithm rapidly converges toward optimal solutions. This characteristic proves particularly advantageous for the placement of DBSs, as it significantly reduces computational time while achieving near-optimal configurations. Furthermore, the IGWO algorithm maintains a balance between local exploitation and global exploration. This adaptive balance mitigates the risk of entrapment in local optima and facilitates the discovery of more globally efficient placement strategies for the DBSs.

The key contributions of this study include:

An optimization framework is formulated to minimize the average power consumption of ground users by strategically deploying DBSs. Given the high-dimensional and nonlinear nature of the problem space, the Improved Gray Wolf Optimization (IGWO) algorithm, rooted in swarm intelligence, is utilized. The algorithm adaptively maintains a dynamic balance between exploration and exploitation, thereby reducing the likelihood of premature convergence and enhancing the algorithm's ability to approximate the global optimum effectively.

A dynamic weighting mechanism is introduced to reinforce gradual exploitation. In this mechanism, the weights assigned to the alpha, beta, and delta wolves are updated iteratively using exponential functions. As the iterations progress, increased emphasis is placed on the alpha wolf's position, thereby enhancing the algorithm's ability to exploit the most promising solution discovered thus far and leading to more precise convergence behavior.

A dynamic control structure is also developed to gradually intensify the influence of elite solutions over time. Unlike conventional approaches that uniformly aggregate the guidance from all reference wolves, this method employs a targeted weighting strategy. This allows the search process to be progressively steered toward more reliable regions of the solution space. Such structural modification in information aggregation significantly enhances the algorithm's performance in complex and dynamic wireless communication environments.

The efficacy of collective intelligence-based techniques for identifying the optimal position of drone base stations has been assessed through extensive simulations. The superiority of the suggested approach in reducing average power consumption has been demonstrated by a comparative analysis conducted under various environment circumstances, search agent counts, and user densities.

The remainder of this paper is organized as follows: The suggested methodology is presented in Section 2. The simulation settings and performance evaluation processes are described in Section 3, and the paper's conclusion and future research prospects are outlined in Section 4.

## 2- Proposed Method

The primary objective of this study is to propose an effective methodology for the optimal placement of drone base stations (DBSs) within 6G cellular networks, aiming to minimize overall network power consumption. To achieve this, an Improved Gray Wolf Optimization (IGWO) algorithm is employed. The IGWO algorithm maintains an effective trade-off between local exploitation and global exploration. This balance significantly contributes to avoiding local optima and facilitates the discovery of more efficient deployment strategies for DBSs. Owing to its high flexibility, IGWO exhibits strong adaptability to dynamic network environments and variable conditions—such as fluctuating user densities and evolving network demands—allowing it to consistently determine optimal base station locations in real time. Moreover, compared to conventional metaheuristic approaches, the IGWO algorithm demonstrates greater stability in producing reliable solutions and shows robust performance under the diverse challenges inherent in 6G communication networks.

### 2-1- System Model

This section outlines the system model used for evaluating the service provisioning capabilities of DBSs to Internet of Things (IoT) devices. The conceptual system architecture is illustrated in Figure 1. In the presented structure $S_{device}$={1,2,...,s} denotes the set of IoT devices randomly distributed within a two-dimensional area, and $K_{DBS}$={1,2,...,k} represents the set of DBSs deployed to serve these devices. Each DBS hovers above the device layer.

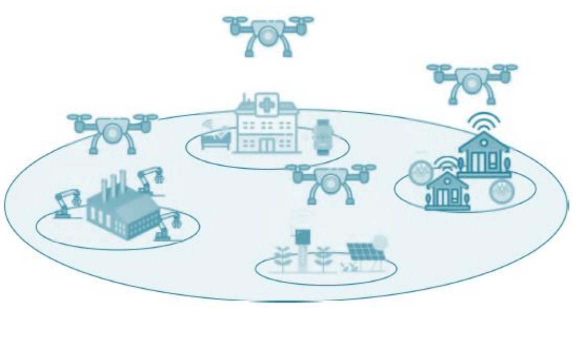

Fig.1. Conceptual System Model

Traditional channel models are insufficient for accurately simulating air-to-ground (AtG) communication due to the altitude variability of DBSs. Instead, two primary link types are considered for modeling the relationship between DBSs and IoT devices: Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) connections.

### 2-2- Air-to-Ground Propagation Model

The probability of establishing a Line-of-Sight (LoS) link between the $k$-th DBS and the $s$-th IoT device is given by the following expression:

$$P\left(h_k . d_{k,s}\right) = \frac{1}{1+\alpha \exp\left[-\beta\left(\arctan\left(\frac{h_k}{d_{k.s}}\right)-\alpha\right)\right]}, \quad (1)$$

where $\alpha$ and $\beta$ are environment-dependent parameters, $h_k$ denotes the k-th DBS altitude, and $d_{k.s}$ is the horizontal distance between the DBS and the IoT device, defined as:

$$d_{k.s} = \sqrt{(x_k - x_s)^2 + (y_k - y_s)^2}. \quad (2)$$

Here, $(y_k . x_k)$ and $(y_s . x_s)$ represent the 2D coordinates of the k-th DBS and the IoT device, respectively.

Using the LoS and NLoS probabilities, the path loss can be modeled as:

$$\mathrm{PL}\ (h_k . d_s) = 20\log\left(\sqrt{h_k^2 + d_{k.s}^2}\right) + AP(h_k . d_{k.s}) + B \quad (3)$$

where:

$$A = \eta_{LoS} - \eta_{NLoS}, \quad (4)$$

$$B = 20\log\left(\frac{4\pi f_c}{c}\right) + \eta_{NLoS}. \quad (5)$$

In these equations:

- $\eta$ represents the mean additional path loss;
- $A$ is the differential loss between LoS and NLoS conditions;
- $f_c$ is the carrier frequency (in Hz);
- $c$ denotes the speed of light.

### 2-3- Objective Function for Optimal DBS Placement

The central goal of this research is to determine optimal placements for the DBSs that minimize the total power consumption of the network. This objective is formulated as an optimization problem and is addressed using the proposed IGWO metaheuristic algorithm. Given that the objective function plays a pivotal role in the design of any metaheuristic optimization strategy, it is formally defined in this section to guide the optimization process effectively.

#### 2-3-1 Minimizing Network Power Consumption

The objective of this section is to present a comprehensive model for calculating the total power consumption of the network, incorporating the energy required for electronic processing, average data transmission time, path loss, and other real-world parameters. To this end, the transmitter's power consumption can be considered to comprise two components: a fixed amount of electronic energy required for processing, and the transmission energy component, which depends on the path loss. Consequently, the average power consumption for communication between the $s$-th user device and the $k$-th Drone Base Station (DBS) can be expressed as:

$$P_{cons_{ave}}(h_k.d_s) = \left(E_{elec} + \varepsilon_{amp-tx} \cdot \text{PL}\,(h_k.d_s)\right) \cdot \frac{K}{T_{Ave}} \quad (6)$$

where, $E_{elec}$ is the energy required for processing each bit electronically and is measured in joules (J), $\varepsilon_{amp-tx}$ represents the amplifier efficiency needed to compensate for the path loss during transmission and is also expressed in joules (J), $K$ is the number of bits transmitted, and $T_{Ave}$ denotes the average data transmission time in seconds (s).
It is important to note that $\varepsilon_{amp-tx}$ quantifies the energy consumed per bit to overcome the attenuation in the signal path and is determined based on the path loss intensity PL. Accordingly, the total average energy consumed across the network—borne by the devices—can be minimized by optimizing the placement of DBSs. Assuming that $s$ indexes the devices and $k$ indexes the DBSs, and that each device connects to the nearest DBS, the optimization problem can be formulated as follows:

$$\begin{aligned} &\underset{\{x.y.h\}}{\text{minimize}} \frac{\sum_{k=1}^{K}\sum_{S=1}^{S} P_{cons_{ave}}\,(h_k.d_s)}{S} \\ &\text{subject to: } \mathcal{C}1: x_{min} \le x_D^k \le x_{max}.\forall k \\ &\qquad\qquad \mathcal{C}2: y_{min} \le y_D^k \le y_{max}.\forall k \\ &\qquad\qquad \mathcal{C}3: h_{min} \le h_D^k \le h_{max}.\forall k \end{aligned} \quad (7)$$

Here, $x$, $y$ and $h$ represent the 3D spatial coordinates of every DBS, while $x_{min}/x_{max}$ , $y_{min}/y_{max}$ and $h_{min}/h_{max}$ define the boundaries of the deployment region.

## 2-4- Optimal Placement of Drone Base Stations Using the Improved Grey Wolf Optimization (IGWO) Algorithm

In this study, the Improved Grey Wolf Optimization (IGWO) algorithm is employed to determine the optimal positioning of drone base stations (DBSs), with the aim of minimizing the power consumption of Internet of Things (IoT) user devices as defined by the objective functions.
The Grey Wolf Optimizer (GWO) is a nature-inspired metaheuristic algorithm that mimics the social hierarchy and hunting behavior of grey wolves in the wild. It is particularly effective for solving complex optimization problems. In this algorithm, a population of "wolves" represents candidate solutions in the search space. The optimization process begins with evaluating each wolf's position and identifying the top solutions, referred to as the alpha, beta, and delta wolves. The leaders direct the other wolves as they iteratively update their positions based on these until certain termination conditions are satisfied, like a convergence threshold or maximum number of iterations. The final position of the alpha wolf is considered the optimal solution. Due to its simplicity and efficiency, GWO has attracted considerable interest in both academic and industrial optimization tasks. The main procedural steps of the IGWO algorithm are as follows:

**Step 1: Initialization of Parameters**

Initially, key factors including the number of wolves (*N*), number of variables (problem dimensions, *D*), number of iterations (*T*), and the control vector (*a*) are defined. The control vector *a*, which linearly decreases from 2 to 0 over the iterations, balances the exploration and exploitation phases of the algorithm. The decrease in the value of *a* enables the algorithm to initially conduct a wide-ranging search (exploration), and later to focus on the best regions (exploitation). This vector is defined as follows:

$$\vec{a}(t) = 2 - \frac{2t}{T}\,. \quad (8)$$

**Step 2: Population**

After initializing the parameters, a population of grey wolves—representing potential solutions—is randomly generated within the search space. The initial position of each wolf is determined as follows:

$$X_{i.j} = rand(0.1)\ \cdot \left(ub_j - lb_j\right) +\ lb_j, \quad (9)$$

where:

- $X_{i.j}$ is the j-th variable for the i-th wolf,
- $ub_j$ and $lb_j$ are the upper and lower bounds of the j-th variable, and
- $rand(0.1)$ is a uniformly distributed random number between 0 and 1.

**Step 3: Evaluation of Objective Function**

Each wolf's position is evaluated using the objective function:

$$f_i = f(X_i)\ . \quad (10)$$

**Step 4: Social Hierarchy Assignment**

This step reflects the social behavior of grey wolves in nature, where the leader directs the hunting group. In this stage, based on the fitness values obtained in the previous step, the wolves are divided into four categories: Alpha, Beta, Delta, and Omega. The Alpha, Beta, and Delta wolves act as the leaders of the hunt, while the Omega wolves follow the leaders. Therefore, the wolf with the best fitness value is selected as the Alpha wolf $X_\alpha$, and the wolves with the second and third best fitness values are selected as the Beta $X_\beta$ and Delta $X_\delta$ wolves, respectively. The remaining wolves are classified as Omega wolves $X_\omega$.

**Step 5: Modeling the Hunting Behavior and Position Update of Grey Wolves**

The alpha, beta, and delta wolves' positions are used to update the wolves' positions at this point. To facilitate this, the control vectors A and C are defined as follows:

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r}_1 - \vec{a} \ , \tag{11}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \ . \tag{12}$$

Here, $\vec{r}_1$ and $\vec{r}_2$ are randomly generated vectors of $[0,1]^D$. Next, the relative distance and estimated positions with respect to the alpha, beta, and delta wolves are calculated using the following relations:

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \ \Rightarrow \ \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \ , \tag{13}$$

$$\vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \ \Rightarrow \ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \ , \tag{14}$$

$$\vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \ \Rightarrow \ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta . \tag{15}$$

Finally, the wolves' final positions are updated according to following equation:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \ . \tag{16}$$

As evident in the Eq. (16) above, the influence of the alpha, beta, and delta wolves is equally weighted in determining the optimal position. However, since the alpha wolf typically represents a better solution than the beta, and the beta better than the delta, assigning adaptive weights to each of their contributions can lead to more effective convergence toward the global optimum.

In the proposed IGWO algorithm, the initial weights assigned to the alpha, beta, and delta wolves are equal, which supports the exploration phase by allowing the algorithm to broadly search the solution space. To enhance the exploitation phase over time, these weights are adaptively adjusted throughout the iterations. Specifically, the weight of the alpha wolf gradually increases, directing more focus on the region near the current best solution, while the weights of the beta and delta wolves decrease, thus reducing their influence. This adaptive weighting strategy ensures a balanced transition from exploration to exploitation, allowing the algorithm to converge effectively to an optimal or near-optimal solution by the end of the search process. The updated position equation with adaptive weighting becomes:

$$\vec{X}(t+1) = \frac{w_\alpha(t)\vec{X}_1(t) + w_\beta(t)\vec{X}_2(t) + w_\delta(t)\vec{X}_3(t)}{3}, \tag{17}$$

where $w_\alpha$, $w_\beta$, and $w_\delta$ are the time-dependent adaptive weights for the alpha, beta, and delta wolves, respectively, defined as:

$$w_\alpha(t) = w_{\alpha\_ini} + (1 - w_{\alpha\_ini}) \cdot (1 - e^{-\frac{5t}{T}}) \ , \tag{18}$$

$$w_\beta(t) = w_{\beta\_ini} \cdot e^{-\frac{2t}{T}}, \tag{19}$$

$$w_\delta(t) = w_{\delta\_ini} \cdot e^{-\frac{4t}{T}} \ . \tag{20}$$

Here, $w_{\alpha\_ini}$, $w_{\beta\_ini}$, and $w_{\delta\_ini}$ represent the initial weights for updating the positions of the Alpha, Beta, and Delta wolves. At the beginning of the algorithm, these initial weights are considered equal, following the standard GWO procedure. However, as the algorithm progresses, the weights $w_\alpha(t)$, $w_\beta(t)$ and $w_\delta(t)$ change over time to enhance the algorithm's exploitation capability. Specifically, the weight for the Alpha wolf, which has the best position, increases exponentially. Meanwhile, the weights for the Beta and Delta wolves gradually decrease as the algorithm advances. The exponential coefficients are tuned such that the slope of the decrease in $w_\beta(t)$ is less steep than the slope of the decrease in $w_\delta(t)$.

**Step 6: Iterative Execution Until Convergence Criterion Is Met**

Steps 3 through 5 are executed iteratively until the stopping condition—typically the maximum number of iterations—is satisfied. Upon termination, the final position of the alpha wolf $\vec{X}_\alpha$, representing the optimal coordinates of the drone base stations, is returned as the best solution obtained by the Improved Grey Wolf Optimization algorithm.

The pseudo-code of proposed method is illustrated in Algorithm 1.

### 2-4-1Computational complexity of the proposed IGWO

The computational complexity of the proposed IGWO algorithm is determined by the population size N, search space dimension D, and maximum number of iterations T. In each iteration, the algorithm evaluates the objective function for all search agents and updates their positions, leading to a total complexity of **O(N×D×T)**. The additional adaptive weighting and parameter control mechanisms require only simple arithmetic operations, resulting in negligible extra cost. Hence, the proposed IGWO maintains a linear computational complexity similar to the standard GWO.

Algorithm 1: Improved Grey Wolf Optimization (IGWO)

```
Input:
  - Objective function f(x)
```

- Search space dimension D
- Population size N
- Maximum iterations T

Output:
- Best solution $x_\alpha$ (corresponding to minimum power consumption)

1: Initialize positions of N grey wolves {xi}, i = 1,...,N randomly within bounds
2: Evaluate fitness f(xi) for all wolves
3: Identify three best solutions: α (best), β (second best), δ (third best)
4: Set iteration counter t = 1
5: while (t ≤ T) do
6: Update control parameter a(t) using adaptive rule
7: For each wolf i = 1 to N do
8: Compute coefficient vectors $A = 2ar_1 - a,\ C = 2r_2$
9: Calculate distances to leaders:
$$D_\alpha = |C_1 \cdot X_\alpha - X_i|$$
$$D_\beta = |C_2 \cdot X_\beta - X_i|$$
$$D_\delta = |C_3 \cdot X_\delta - X_i|$$
10: Update candidate position:
$$X_1 = X_\alpha - A_1 \cdot D_\alpha$$
$$X_2 = X_\beta - A_1 \cdot D_\beta$$
$$X_3 = X_\delta - A_1 \cdot D_\delta$$
11: Update position:
$$X_i(t+1) = \frac{w_\alpha(t)X_1 + w_\beta(t)X_2 + w_\delta(t)X_3}{3}$$
(where $w_\alpha$, $w_\beta$, $w_\delta$ are dynamic weights)
12: end for
13: Evaluate new fitness values f(xi)
14: Update α, β, δ if better solutions are found
15: t = t + 1
16: end while
17: Return $x_\alpha$ as the best solution

## 3- Performance Evaluation

The effectiveness of the suggested approach in determining the best location for drone base stations (DBSs) under varied parameter settings is thoroughly evaluated in this section. The proposed approach is assessed through numerical results derived from extensive software-based simulations. The conducted experiments investigate the impact of several key factors, including the number of users, the number of search agents (population size), the number of iterations (generations), and different propagation environments—namely suburban, urban, dense urban, and high-rise urban—on path loss and power consumption in the Improved Grey Wolf Optimization (IGWO) algorithm. Table 1 provides a summary of the different parameters related to various environments. It should be noted that the parameters related to environmental modeling, simulation parameters, and parameters related to optimization algorithms are inspired by reference [15], which deals with the optimal location of DBSs using meta-heuristic algorithms in telecommunication networks. Also, the simulations were carried out using MATLAB 2023a. In addition all simulation results presented in the paper are obtained by averaging over 50 independent runs of the proposed algorithm to account for its stochastic nature and ensure reliability.

Table 1: Propagation Parameters in Different Environments

| ***Environment*** | $\boldsymbol{\alpha}$ | $\boldsymbol{\beta}$ | $\boldsymbol{\eta_{Los}}$ | $\boldsymbol{\eta N_{Los}}$ |
|---|---|---|---|---|
| Urban | 9.61 | 0.16 | 1 | 20 |
| Suburban | 4.88 | 0.43 | 0.1 | 21 |
| Dense Urban | 12.08 | 0.11 | 1.6 | 23 |
| High-raise Urban | 27.23 | 0.08 | 2.3 | 34 |

### 3-1- Path Loss Evaluation

In this section, the effect of four different factors on path loss is investigated: population size in optimization algorithms, maximum number of iterations, type of propagation environment, and the number of users.

**Experiment 1: Impact of Propagation Environment on Path Loss**

This experiment evaluates the impact of different propagation environments on the average path loss. For this purpose, the number of users is set to 20, the maximum number of iterations is 100, and the population size (number of search agents) is 25. The detailed parameters of this experiment are represented in Table 2.

Table 2: Experiment 1 Simulation Parameters

| ***Parameter*** | ***Value*** |
|---|---|
| Number of Users | 20 |
| Maximum number of iterations | 100 |
| Various Environments | Urban- suburban- dense urban, high-rise urban |
| Number of Search Agent | 25 |

Figure 2 illustrates the effect of different propagation environments—suburban, urban, dense urban, and high-rise urban—on the path loss within the network. As shown in the figure, suburban environments exhibit the lowest path loss across all optimization algorithms, while dense urban environments result in the highest path loss. Moreover, it is observed that the proposed IGWO method consistently yields lower path loss compared to other optimization techniques across all environment types, indicating the algorithm's robustness and adaptability to diverse propagation conditions.

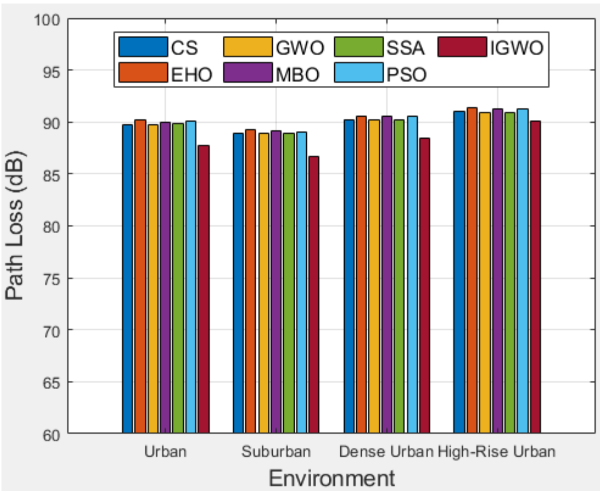


Fig.2. Effect of Path Loss in Various Environments for Different Approaches

**Experiment 2: Impact of Maximum Number of Iterations on Path Loss**

This investigation assesses how varying the maximum number of iterations (generations) affects the overall path loss. The simulation parameters used in this experiment are listed in Table 3.

Table 3: Experiment 2 Simulation Parameters

| ***Parameter*** | ***Value*** |
|---|---|
| Number of Users | 20 |
| Maximum number of iterations | 50, 100, 200, 500 |
| Various Environments | Urban |
| Number of Search Agent | 25 |

As illustrated in Figure 3, the path loss decreases with an increasing number of iterations for all metaheuristic algorithms. This demonstrates that increasing the number of iterations enhances the convergence and performance of optimization methods. Furthermore, the lowest recorded path loss of 86.8 dB is achieved by the proposed Improved Grey Wolf Optimization (IGWO) when the number of iterations reaches 500, highlighting the superior efficiency of the proposed algorithm in minimizing power consumption compared to alternative approaches.

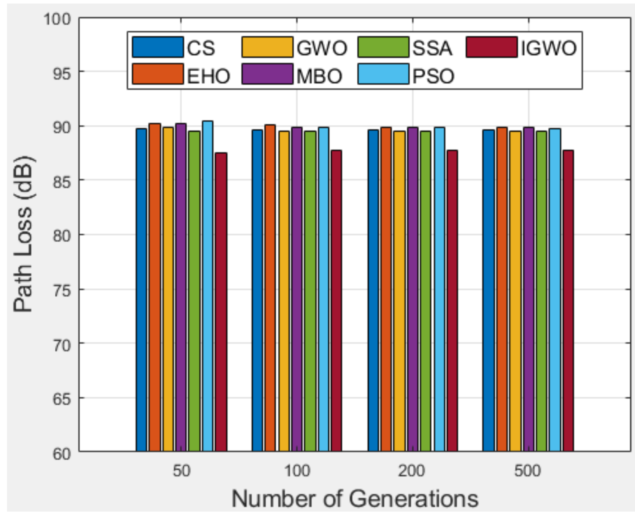


Fig.3. Effect of the Maximum Iterations on Path Loss for Different Methods

**Experiment 3: Impact of the Number of Search Agents on Path Loss**

The third investigation investigates the effect of varying the count of search agents on path loss for different metaheuristic algorithms, including the proposed IGWO method. The simulation considers 20 users, a maximum of 100 iterations, and an urban propagation environment. The detailed parameters of this experiment are shown in Table 4.

Table 4. Experiment 3 Simulation Parameters

| ***Parameter*** | ***Value*** |
|---|---|
| Number of Users | 20 |
| Maximum number of iterations | 100 |
| Various Environments | Urban |
| Number of Search Agent | 5, 25 ,50, 75, 100 |

Figure 4 depicts the effect of the number of search agents on the path loss. As seen in the figure, increasing the number of agents generally results in a reduction in path loss. The proposed IGWO method consistently achieves the lowest path loss across various population sizes compared to the other approaches.

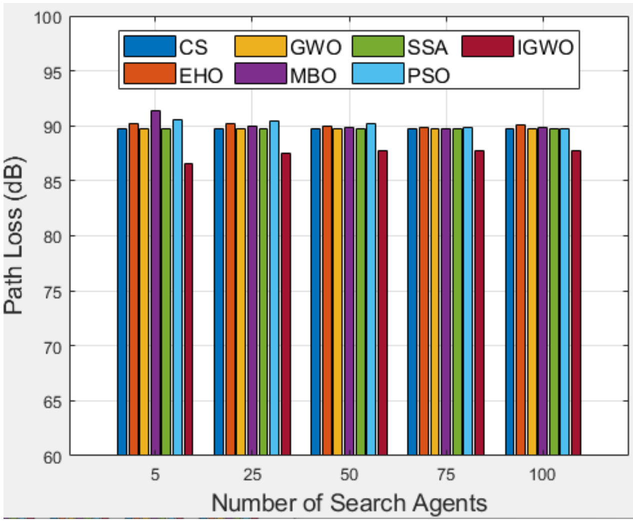


Fig.4. Effect of the Number of Search Agents on Path Loss for Different Methods

**Experiment 4: Impact of User Counts on Path Loss**

Based on the first simulation scenario, this investigation assesses how the count of users affects the suggested method's performance. While keeping the maximum number of iterations, propagation environment, and number of search agents constant, the number of users is varied to assess its impact on the path loss. The simulation parameters are summarized in Table 5.

Table 5: Experiment 4 Simulation Parameters

| ***Parameter*** | ***Value*** |
|---|---|
| Number of Users | 10, 20, 30, 40, 50 |
| Maximum number of iterations | 100 |
| Various Environments | urban |
| Number of Search Agent | 25 |

As shown in Figure 5, the path loss increases with the number of users. Additionally, it is observed that the proposed IGWO algorithm consistently yields the lowest path loss, particularly for 10 users, further demonstrating its ability to adapt and scale across different user densities.

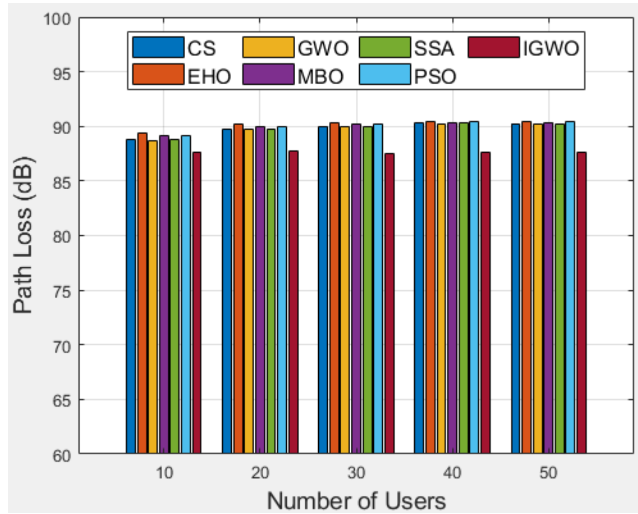


Fig.5. Effect of the User Counts on Path Loss for Different Methods

## 3-2- Evaluation of Average Power Consumption

This section investigates how various factors influence the average power consumption of deployed drones across four experiments. These include population size, number of iterations, propagation environment, and number of users.

**Experiment 1: Effect of Propagation Environment on Power Consumption**

Figure 6 presents the average power consumption for various propagation environments. The results show that the proposed IGWO algorithm consumes the least energy across all environments, with the lowest power consumption of 44 mW observed in the suburban scenario. Conversely, the highest power consumption (45.8 mW) is observed for the PSO algorithm in high-rise urban areas. Specifically, the simulation results demonstrate that the proposed method achieves a remarkable superiority over other optimization algorithms, showing more than a 2% improvement compared to the best among them—the standard GWO algorithm—thereby confirming its effectiveness and efficiency in low-power network scenarios. Furthermore, power consumption in suburban environments is generally lower for all algorithms, confirming the lower propagation loss in such environments.

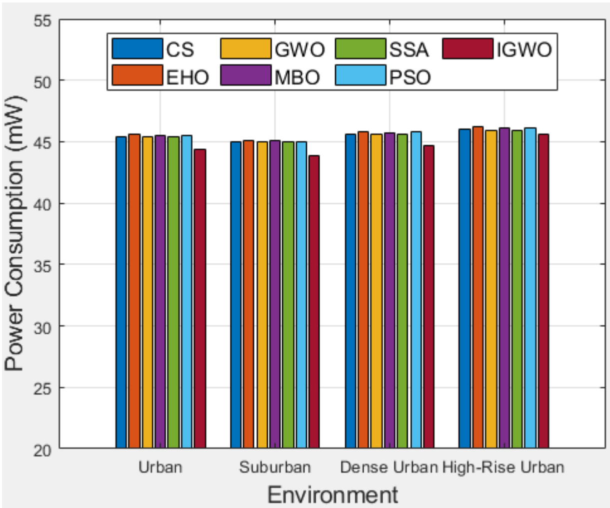


Fig.6. Effect of the Propagation Environment on Average Power Consumption for Different Methods

**Experiment 2: Effect of Maximum Number of Iterations on Power Consumption**

As shown in Figure 7, increasing the number of iterations significantly reduces average power consumption for all algorithms. The IGWO method achieves the minimum value of 44.6 mW at 500 iterations, while PSO shows the highest power consumption of 45.3 mW at 50 iterations. The results confirm that more iterations allow the optimization process to converge toward more energy-efficient deployments.


Fig.7. Effect of Maximum Iterations on Power Consumption for Different Methods

**Experiment 3: Effect of Number of Search Agents on Power Consumption**

In Figure 8, the results reveal that increasing the number of search agents reduces the average power consumption, as more agents improve the search space exploration and chances of finding optimal solutions. The IGWO consistently outperforms other methods, maintaining the lowest power consumption across all population sizes, demonstrating its efficient exploration and exploitation balance.

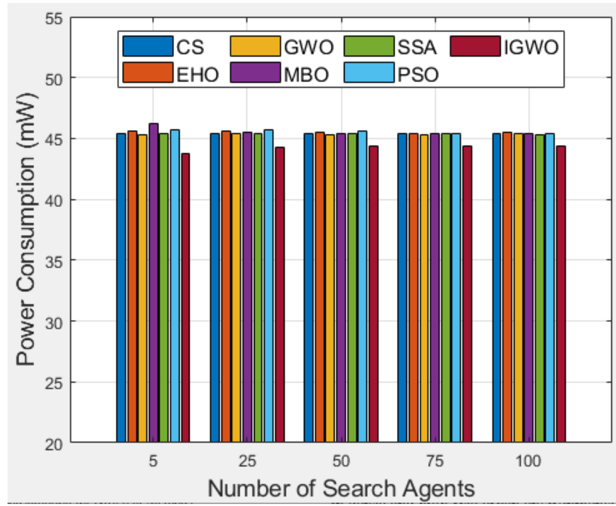


Fig.8. Effect of the Number of Search Agents on Power Consumption for Different Methods

**Experiment 4: Effect of Number of Users on Power Consumption**

As depicted in Figure 9, power consumption increases with the number of users, which is expected due to the higher communication and coverage demands. Nevertheless, the IGWO algorithm consistently consumes less energy than other methods across all user counts. This underscores the method's scalability and adaptability, primarily due to its dynamic balance between exploration and exploitation.

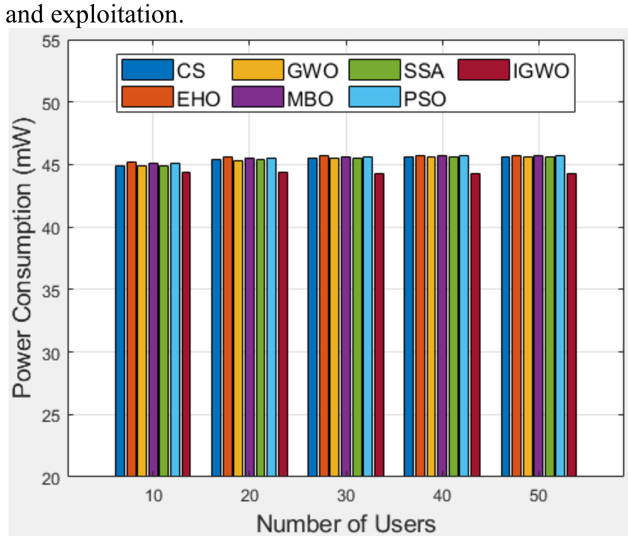


Fig.9. Effect of User Count on Average Power Consumption for Different Methods

## 4- Conclusion

In this study, an improved Gray Wolf Optimization (IGWO) algorithm was developed to address the urgent challenge of energy-efficient deployment of Drone Base Stations (DBSs) in 6G networks. The proposed IGWO algorithm, featuring adaptive weighting mechanisms and dynamic control structures, demonstrated enhanced capacity to explore the complex, multivariate search spaces required for effective DBS deployment. Several simulation experiments were conducted under varying conditions, including different propagation environments, population sizes, iteration counts, and user densities. The presented strategy consistently exhibited strong performance and stability across all simulations. Notably, the IGWO algorithm achieved the lowest path loss values across all propagation environments, with suburban scenarios yielding the lowest overall path loss. In the urban environment simulation, the IGWO method generated a path loss of only 86.8 dB after 500 iterations, outperforming traditional optimization methods. Analysis of average power consumption further confirmed that IGWO enables significant energy savings. The algorithm achieved an average power consumption of 44 mW in suburban areas, while also maintaining strong performance in dense and high-rise urban environments.

Increasing the number of search agents and iterations further improved the algorithm’s performance, demonstrating its scalability and convergence efficiency. Even as user demand increased, the power consumption of IGWO remained systematically lower than that of all other optimization approaches. Future research could explore mobility models, examine temporal variations in user distribution, and investigate integrated optimization strategies to further enhance overall network performance.

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