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Research paper

Innovative Drone Base Station Placement in 6G Networks: A Marine Predators Algorithm Approach

Hussein Aad Hassan Alaboodi and Saeed Khosroabadi*

Department of Electrical Engineering, Imam Reza International University, Mashhad, Iran.

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**Corresponding author: Khosroabadi@imamreza.ac.ir (S. Khosroabadi).*

Abstract

In the context of advancing sixth-generation (6G) communication networks, ensuring high-quality user coverage across varying geographic landscapes remains a paramount objective. Terrestrial base stations conventionally provide this coverage; however, they are susceptible to disruption due to adverse environmental conditions. Consequently, the integration of airborne mobile stations is pivotal for continued user coverage support. Among the viable solutions for terrestrial station augmentation, the deployment of drone base stations (DBS) emerges as the optimal substitute. Nonetheless, the establishment of a drone-based infrastructure presents challenges in terms of time and cost efficiency. Thus, the strategic positioning of DBSs, aimed at maximizing user coverage while simultaneously minimizing path loss and the number of drones required, is essential to achieving efficient and high-quality service provisioning.

This study introduces a novel and optimized DBS placement strategy utilizing the Marine Predators Algorithm (MPA)—a recent metaheuristic renowned for its potent resistance to entrapment in local optima. Through simulation, we demonstrate that our proposed methodology distinctly surpasses analogous approaches with regard to optimization of path loss and user coverage. Simulation outcomes reveal average path losses of 71.75 dB for the Gray Wolf Optimization (GWO), 75.78 dB for the Weighted Time-Based Non-Orthogonal Multiple Access (TW-NOMA), and a significantly reduced 56.13 dB for our proposed MPA-based method, thereby indicating a substantial decrease of at least 15 dB in path loss compared to current techniques.

1. Introduction

Drone base station (DBS) positioning in 6G cellular networks is a critical aspect facilitating enhanced communication and social capabilities of this advanced technology. In 6G, DBSs equipped with mobility features can be deployed in various locations, significantly increasing network coverage and improving connectivity in remote and dynamic areas. This technology not only accelerates data transmission rates and reduces communication latency but also enhances location-based services by precisely positioning DBSs, offering improved spatial and regional services [1,2]. Advanced DBS positioning capabilities are particularly crucial in emergency situations and for intelligent network resource management [3,4]. Through precise positioning, DBSs can intelligently respond to communication demands in high-traffic regions and optimize resource distribution. Furthermore, with enhanced positioning accuracy, 6G networks can support location-based services such as location-based payments, advanced navigation, and new location-centric services. DBSs can also be employed for various applications, including environmental monitoring, traffic control, and emergency communication in remote areas [5,6].

Consequently, DBS positioning in 6G plays a pivotal role in advancing future network capabilities [7].

In addition, this advanced positioning technology can be applied in fields such as industrial automation, smart agriculture, and machine-to-machine (M2M) communication [8,9]. DBSs, through precise positioning, enable increased interactions on the 6G network platform, ensuring seamless communication among smart vehicles, connected devices, and autonomous systems. Additionally, location-based intelligent tasks like efficient energy management, traffic forecasting, and urban system optimization can be realized using this technology [10,11]. Therefore, DBS positioning in 6G networks not only improves communications but also contributes to building dynamic, intelligent infrastructures across various fields.

One effective approach for DBS positioning in 6G networks involves the use of machine learning algorithms. In [12], the problem of dispatching DBSs in B5G/6G multi-cell networks is addressed, aiming to maximize system utility and provide services to the largest possible number of users with minimal cost. A reinforcement learning (RL) approach is adopted to adaptively distribute DBSs, enhancing overall operator utility. The method in [13] employs a two-layer optimizer based on the pre-trained VGG-19 model and non-orthogonal multiple access (NOMA), significantly improving network performance. This approach leverages cuckoo search, grey wolf, and particle swarm optimization algorithms, achieving high performance. In [14], the application of cellular-active drones as airborne base stations in next-generation networks is discussed. The main concepts are based on flying ad hoc networks (FANETs) as clusters of deployable relays for expanding bandwidth accessibility. In [15], an adaptive unmanned aerial migration strategy (UAMS) is proposed to enhance migration efficiency, with simulation results indicating substantial improvements in system performance. Research in [16] addresses UAV coverage in cellular networks, providing a decision-making model for UAV-BS coverage areas with simulations showing improved packet delivery and reduced latency. Study [17] examines the impact of UAV base station altitude and transmission power on downlink and uplink data rates, suggesting that in most scenarios, either the maximum or minimum achievable altitude offers optimal results. Resource allocation in B5G and 6G networks with cognitive radio (CR) capability is explored in [18], where a D-OFDMA scheduling protocol enhances network throughput, achieving up to 90% and 150% improvements over traditional methods. In [19], drones are utilized as base stations for emergency communication systems in 5G with mMTC, implementing a DDQN-based reinforcement learning technique to optimize energy efficiency and resource allocation, outperforming DQN and Q-learning models. Reference [20] reviews swarm intelligence-based optimization techniques for determining optimal DBS locations, with the grey wolf algorithm yielding the best performance. Additionally, [21] applies a two-layer TW-NOMA optimizer and the VGG-19 neural network model to address DBS placement, minimizing path loss and enhancing network efficiency.

In this study, the Marine Predators Algorithm (MPA) is utilized to optimize DBS positioning in 6G cellular networks, aiming to maximize user coverage while minimizing path loss. MPA's high capability in exploring complex, multidimensional spaces, enables rapid convergence toward optimal solutions, making it highly effective for DBS positioning, reducing computational time, and achieving efficient optimization. Moreover, MPA's mechanisms, such as migration and predation, establish a balanced trade-off between local exploitation and global exploration, preventing entrapment in local optima and yielding highly optimized DBS placement results.

The remainder of this article is organized as follows: Section 2 provides a detailed description of the proposed method, Section 3 evaluates its performance through various experiments, and Section 4 presents a general summary and conclusion.

2. Proposed Method

This study aims to present an effective method for positioning drone base stations (DBSs) within a 6G network to maximize user coverage and minimize path loss. For this purpose, the Marine Predators Algorithm (MPA) is employed. Through mechanisms such as migration and predation, the MPA establishes a balanced trade-off between local exploitation and global exploration. This characteristic helps avoid entrapment in local optima, thereby yielding more optimal DBS positioning results. Additionally, due to its high adaptability, the MPA can effectively respond to environmental changes and dynamic conditions (such as varying user numbers and network demands) by adjusting DBS locations accordingly. Moreover, compared to other optimization algorithms, MPA demonstrates greater stability in delivering optimal results and displays enhanced reliability when tackling the challenges inherent in 6G networks.

2.1. System Model

This section introduces the system model for evaluating DBS service provision to Internet of Things (IoT) devices. Figure 1 presents the system model. In this model, $S=\{1\ldots .S\}$ represents the set of IoT devices, while $K=\{1\ldots .K\}$ denotes the set of DBSs serving these devices.

The IoT devices are randomly distributed in a spatial area, with the DBSs positioned above them.

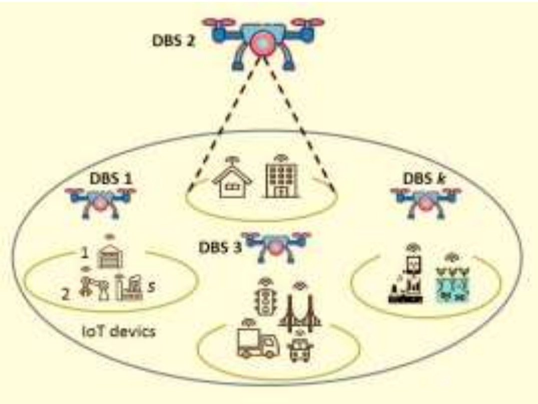

Figure 1. Conceptual System Model [19].

Conventional channel models are insufficient to simulate the relationship between DBSs and ground-based devices due to the variable altitude of DBSs. The two primary types of links utilized for modeling the relationship between DBSs and IoT devices are Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) links.

2.2. Information Propagation Model

The probability of information propagation for the air-to-ground (AtG) model between the k-th DBS and the s device in the direct LoS condition can be calculated by the following equation:

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

where the coefficients α and β depend on the environment type (e.g., urban, suburban). The horizontal distance between the k-th DBS and the s device is given by:

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

where $x_k.y_k$ and $x_s.y_s$ denote the horizontal positions of the DBS and the IoT device, respectively. Using the LoS and NLoS probabilities, the path loss can be calculated as:

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

Where:

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

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

In these equations:
- η denotes the mean additional path loss,
- A represents the difference in mean path loss between LoS and NLoS conditions,
- f_c is the carrier frequency in Hz, and
- c is the speed of light.

2.3. Objective Function for Optimal DBS Positioning

The primary objective of this study is the optimal positioning of DBSs based on two objectives: minimizing path loss and maximizing coverage for IoT devices, which will be addressed using the Marine Predators Algorithm (MPA). Since the objective function is the most critical component of a metaheuristic algorithm, we first present the objective function for this algorithm in detail.

2.3.1. Minimizing Average Path Loss

According to Shannon's equation, assuming constant bandwidth and system noise, an increase in the corresponding signal power enhances the data rate of a device. The received power at an IoT device on the ground depends on the path traversed by the wireless channel, which can be expressed as:

$$P_s^r=P_k^t-PL\left(h_k.d_s\right)-P_N \quad (6)$$

where P_k^t is the transmit power of the k-th DBS and P_N represents the additional white Gaussian noise power (AWGN). Given that P_k^t is fixed, reducing the distance between the device and DBS increases received power. Consequently, optimizing DBS positions minimizes the average path loss experienced by devices. Assuming each device is connected to its nearest DBS, the optimization problem is formulated as follows:

$$\underset{\{x.y.h\}}{minimize} \frac{\sum_{k=1}^{K}\sum_{S=1}^{S} PL\left(h_k.d_s\right)}{S} \tag{7}$$
$$\text{subject to: } C1: x_{min} \le x_D^k \le x_{max}.\forall k$$
$$C2: y_{min} \le y_D^k \le y_{max}.\forall k$$
$$C3: h_{min} \le h_D^k \le h_{max}.\forall k$$

where x, y, and h represent each DBS's location in 3D space, while $x_{\min} / x_{\max}, y_{\min} / y_{\max}$ and $h_{\min} / h_{\max}$ define the area boundaries.

2.3.2. Maximizing Device Coverage by DBSs

If the quality of service (QoS) for a device is met, it is considered covered. Another way to define a covered device is by establishing a path loss threshold T; if path loss falls below this threshold, the device is considered under coverage. The relevant optimization problem is therefore expressed as:

$$\underset{\{x.y.h\}}{maximize} \sum_{k=1}^{K}\sum_{S=1}^{S} C_{k.s}$$
$$\text{subject to: } C1: x_{min} \le x_D^k \le x_{max}.\forall k \tag{8}$$
$$C2: y_{min} \le y_D^k \le y_{max}.\forall k$$
$$C3: h_{min} \le h_D^k \le h_{max}.\forall k$$

where $C_{k.s}$ is defined as:

$$C_{k.s} = \begin{cases} 1. & PL\left(h_k.d_s\right) \le T \\ 0. & \text{otherwise} \end{cases} \tag{9}$$

The solutions to these optimization problems are challenging to obtain. Therefore, the Marine Predators Algorithm is employed as an efficient solution for DBS positioning.

2.4. Optimal Positioning of Drone Base Stations Using the Marine Predators Algorithm (MPA)

In this study, the Marine Predators Algorithm (MPA) is employed to determine the optimal positioning of DBSs according to the defined objective functions of minimizing path loss and maximizing IoT user coverage. MPA is a population-based metaheuristic method in which each population member's position serves as a candidate solution for DBS positioning. The initial population is uniformly distributed across the search space (the allowable DBS location range):

$$X_0 = X_{min} + rand\left(X_{max} - X_{min}\right) \tag{10}$$

where X_{min} and $X_{\max}$ denote the lower and upper bounds of the DBS location search space, and rand represents a uniformly random vector between 0 and 1.

According to the theory of survival of the fittest, it is assumed that the top predators in nature have a greater aptitude for locating food. Therefore, the most suitable solution is designated as the "top predator," forming a matrix known as "Elite," which holds potential solutions for the optimal DBS positions. The elements of this matrix track and update the search process based on prey location information:

$$Elite = \begin{bmatrix} X_{1.1}^I & X_{1.2}^I & \cdots & X_{1.d}^I \\ X_{2.1}^I & X_{2.2}^I & \cdots & X_{2.d}^I \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ X_{n.1}^I & X_{n.2}^I & \cdots & X_{n.d}^I \end{bmatrix}_{n\times d} \tag{11}$$

where $\vec{X}^I$ represents the vector of the top predator repeated n times to construct the Elite matrix, with n denoting the number of search agents and d the number of dimensions. Notably, both the predator and prey are considered search agents since, while the predator is seeking prey, the prey is also foraging. At the end of each iteration, if a superior predator emerges, Elite is updated accordingly.

A secondary matrix called Prey, with dimensions matching those of Elite, is also initialized. Prey assists in updating the predators' positions based on the prey's configuration, ultimately leading to the optimal (Elite) solutions:

$$Prey = \begin{bmatrix} X_{1.1}^I & X_{1.2}^I & \cdots & X_{1.d}^I \\ X_{2.1}^I & X_{2.2}^I & \cdots & X_{2.d}^I \\ X_{3.1}^I & X_{3.1}^I & \vdots & X_{3.d}^I \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ X_{n.1}^I & X_{n.2}^I & \cdots & X_{n.d}^I \end{bmatrix}_{n\times d} \tag{12}$$

where $X_{i,j}$ represents the j-th dimension of the i-th prey. It is noteworthy that the entire optimization process is primarily and directly linked to these two matrices.

Ultimately, when the termination criterion is met, and the top predator yielding the best solution (optimal DBS locations) is found, the final Elite matrix is established. The best solution is determined by optimizing the MPA objective functions. Here, the stopping criterion involves assessing factors such as network coverage, capacity, and reliability, which are compared to predefined targets or benchmarks.

In conclusion, MPA follows a sequence of stages, and the continuous optimization of these stages enables the algorithm to identify the optimal DBS locations within the 6G network, thereby enhancing network performance and efficiency.

3. Results Evaluation

This section presents a comprehensive assessment of the proposed method's performance in locating optimal DBS positions under varying parameters. The evaluation is based on numerical simulation results obtained through multiple experiments. These experiments examine the effects of factors such as the number of drones, path loss, environment type, and the number of generations in the MPA algorithm. All simulations were conducted using MATLAB 2022. The simulation parameters are shown in table 1.

Table 1. Simulation Parameters.

Parameters	Value
threshold values	100,110,120
Number of maximum iterations	5,50,100,200,500
Environments	Urban, Suburban, Dense Urban, High-rise Urban
Number of DBSs	20,40,60,80,100

3.1. Experiment 1: Effect of the Number of Drones on Coverage Probability at Different Threshold Levels

The first experiment investigates the impact of varying the number of drones on coverage probability, considering threshold values of 100, 110, and 120. Figure 2 illustrates the effect of drone count on network coverage probability at a threshold of 100. As shown, coverage probability increases as the number of DBSs rises.

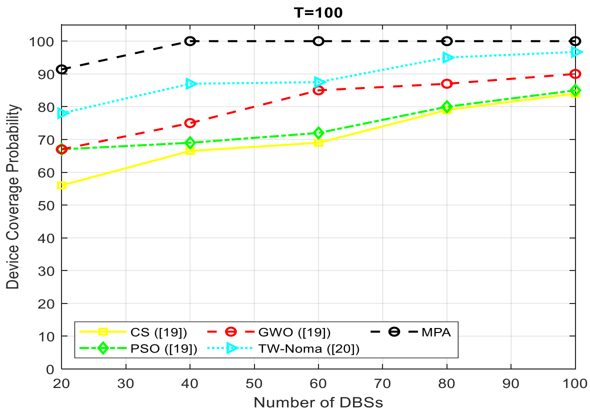

Figure 2. Coverage Probability of IoT Devices by the Proposed Method and Other Approaches at a Threshold of 100.

In the proposed method, coverage probability reaches 100% once the number of DBSs reaches 40, outperforming other methods. It is evident that even with 100 DBSs, other positioning methods fail to achieve full coverage.

Figure 3 compares the proposed method's coverage probability at a threshold of 110 with other methods. As illustrated, the proposed method achieves 100% coverage when the number of DBSs reaches 40.

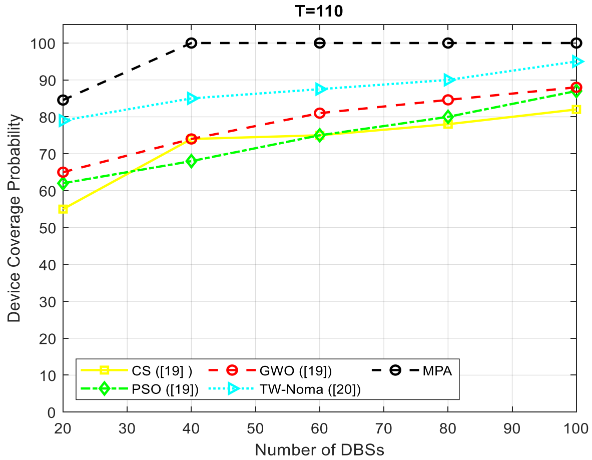

Figure 3. Coverage Probability of IoT Devices by the Proposed Method and Other Approaches at a Threshold of 110.

Similarly, Figure 4 presents a comparison at a threshold level of 120. As depicted, the proposed method achieves full coverage with 60 DBSs. Figures 2 through 4 illustrate DBS coverage probabilities for IoT devices using various methods, including the proposed MPA-based approach, across threshold values of 100, 110, and 120 with different DBS counts.

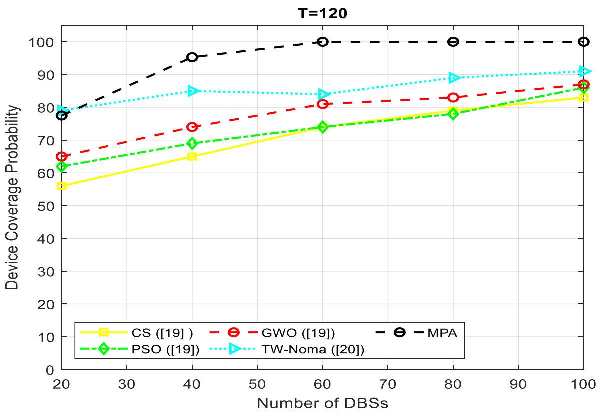

Figure 4. Coverage Probability of IoT Devices by the Proposed Method and Other Approaches at a Threshold of 120.

These results reveal an increase in coverage probability with additional DBSs. Notably, the proposed MPA-based optimization for DBS positioning yields higher coverage probability than all other evaluated methods.

3.2. Experiment 2: Impact of the Number of Generations on Average Path Loss

In this experiment, the effectiveness of the proposed method in reducing path loss is evaluated in relation to the number of iterations of various metaheuristic algorithms.

Figure 5 illustrates the path loss values for different approaches across varying iteration counts in metaheuristic algorithms. Evidently, the proposed method (MPA algorithm) yields the lowest path loss values. Additionally, it is clear that path loss decreases with an increase in the number of algorithmic cycles.

This result stems from the fact that the convergence of a metaheuristic algorithm towards the desired solution becomes more refined with a greater number of iterations.

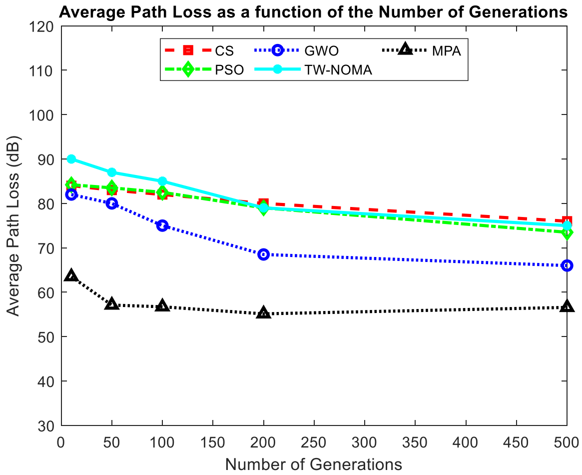

Figure 5. Comparison of Path Loss in Optimal DBS Positioning by Several Metaheuristic Methods across Different Iteration Counts.

3.3. Experiment 3: Impact of Different Environments on Average Path Loss

The third experiment considers four propagation environments: suburban, urban, dense urban, and high-rise urban. The propagation parameters for each environment are provided in Table 2.

Table 2. Propagation Parameters in Various Environments

Environment	α	β	η_{Los}	ηN_{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

Figure 6 illustrates the average path loss in different environments, where lower path loss signifies more effective DBS positioning.

For example, in urban environments, the proposed method achieves an average path loss of 57, compared to 80, 82, 78, and 80 for the CS, PSO, GWO, and TW-NOMA methods, respectively.

As shown, the results obtained from the proposed method based on the Marine Predator Optimization Algorithm (MPA) indicate the superiority of this method in reducing Pathloss in Urban, Dense Urban, and High-rise Urban environments.

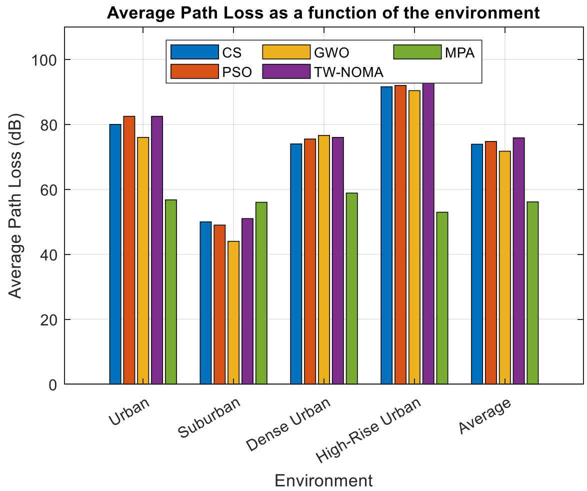

Figure 6. Comparison of Path Loss in Optimal DBS Positioning by Several Metaheuristic Methods across Different Environments.

This superiority is due to the special features of the MPA algorithm and its ability to adapt to complex environmental conditions. The MPA algorithm, by utilizing three stages of exploration, transfer, and exploitation, establishes a good balance between local and global search. This feature, together with inspiration from the behavior of marine predators, allows the algorithm to more effectively achieve optimal locations for base stations in dense and complex environments (such as Dense Urban and High-rise Urban). In these environments, there are many challenges such as the presence of many obstacles and multi-path signals, but MPA identifies the best points with an energy-efficient mechanism and the use of multi-dimensional random movements and significantly reduces Pathloss. However, in the Suburban environment, the performance of the proposed method was weaker than in other environments. The reason for this difference can be attributed to the characteristics of the Suburban environment, where the density of buildings and obstacles is lower and signal propagation is relatively simpler. In such environments, simpler algorithms that are less dependent on the precise exploitation of the search space can provide similar or even better performance than MPA. Since the MPA algorithm is designed for more complex environments and performs more effective optimization in the face of conditions such as high density of obstacles, its performance in the Suburban environment has been observed with less difference than other methods. This difference indicates that the main advantage of MPA is in conditions where the system needs to adapt more to obstacles and complex environmental conditions. However, in order to examine the average efficiency of the proposed method in all environments compared to other works, the average path loss is compared in Table 3, which indicates the overall better performance of the proposed method considering all environments. In Figure (7), the path losses are illustrated for various numbers of search agents and different methods. The results indicate that the proposed MPA algorithm achieves the lowest path loss, measuring 84.5 dB for 100 search agents. Furthermore, as the number of search agents in optimization algorithms increases, the average path losses decrease. This reduction occurs because a higher number of search agents in metaheuristic algorithms enhances the likelihood of identifying optimal points, leading to lower average path losses.

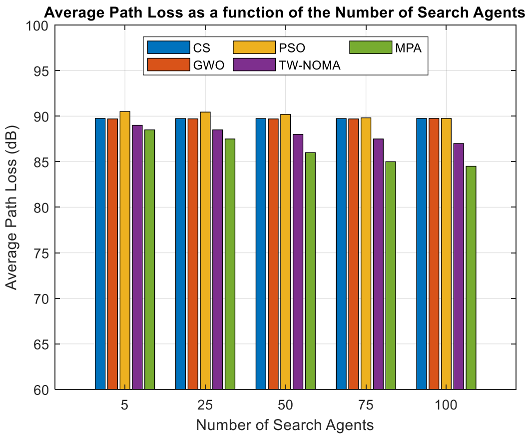

Figure 7. Comparison of Path Loss in Optimal DBS Positioning by Several Metaheuristic Methods across Different Number of Search Agents.

3.4. Comparative Results

This section compares the average path loss of the proposed approach against other methods, as presented in Table 3. The average path loss across different environments for the proposed method is calculated and compared with previous methods. As shown in Table 3, the proposed method achieves an average path loss of 56.13. By comparison, the TW-NOMA method in [19] yielded 75.78, while the Grey Wolf Optimization (GWO) algorithm in [20] produced 71.75. This comparison highlights a reduction of 19.65 and 15.62 units in path loss for the proposed method relative to TW-NOMA and GWO, respectively. In the proposed method, the marine predator algorithm, which is a novel metaheuristic algorithm, is used to locate UAV base stations. This algorithm, using three main stages (discovery, transfer, and exploitation), establishes a suitable balance between local and global search, which prevents the possibility of getting stuck in local optima and ensures faster convergence towards the optimal solution. Features inspired by the adaptive behaviors of predators such as chasing prey, ambushing, and group cooperation, along with the energy efficiency mechanism, have increased the efficiency of the algorithm in discovering optimal areas and reducing the convergence time. In addition, high flexibility in parameter adjustment and intelligent design of multidimensional random movements have increased the ability of the algorithm to avoid getting stuck in local optima. Compared to other algorithms such as PSO, CS, and GWO, it shows superior performance in solving nonlinear and complex problems with higher accuracy, greater stability, and shorter convergence time.

Table 3. Comparison of Average Path Loss for the Proposed Method versus Other Methods.

Author	Method	Average path loss
Pliatsios et al. [20]	CS	73.9
	PSO	74.75
	GWO	71.75
Alsolai et al. [21]	TW-NOMA	75.78
Proposed	MPA	56.13

4. Conclusion

Positioning drone base stations in 6G networks is critical for optimizing network performance and enhancing connectivity. Advanced techniques such as metaheuristic algorithms, including the Marine Predators Algorithm (MPA), provide a promising approach for addressing the complex optimization challenge of DBS placement. By accounting for factors such as signal strength, coverage area, interference, and capacity, these algorithms can effectively determine optimal DBS locations. Successful DBS placement within 6G networks enhances network coverage, capacity, and overall performance, facilitating the realization of advanced wireless capabilities and the seamless integration of emerging technologies in future wireless networks. In this study, MPA was employed to determine the optimal DBS positions based on two criteria: path loss and effective coverage of IoT devices. By continually refining solutions through Elite matrix updates, the MPA yields optimal placement solutions, thereby improving network coverage and capacity. Simulation results demonstrate that the average path loss in the GWO, TW-NOMA, and proposed methods is 71.75, 75.78, and 56.13, respectively, signifying a minimum 15 dB reduction in path loss for the proposed method. This algorithm, which has shown superior performance over traditional placement approaches, provides a promising pathway for optimizing DBS positioning in 6G networks and advancing future wireless communication capabilities.

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مکان یابی ایستگاه پایه پهپاد در شبکه سلولی نسل ششم (6G) برای بهبود پوشش شبکه با استفاده از الگوریتم بهینه سازی شکارچیان دریایی

حسین العبودی و سعید خسروآبادی*

گروه مهندسی برق، دانشگاه بین المللی امام رضا علیه السلام، مشهد، ایران

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چکیده:

با توجه به توسعه شبکه‌های مخابراتی نسل ششم (6G) پوشش‌دهی با کیفیت به کاربران در محیط‌های جغرافیایی مختلف یکی امر ضروری می‌باشد. از آنجا که پوشش‌دهی به کاربران معمولا توسط ایستگاه‌های زمینی انجام می‌شود و در برخی مواقع با توجه به شرایط بد محیطی این پوشش‌دهی مختل می‌شود، باید بتوان از ایستگاه‌های هوایی متحرک برای پشتیبانی از پوشش‌دهی به کاربران استفاده کرد. بهترین گزینه برای جایگزینی ایستگاه‌های زمینی، ایستگاه‌های پایه پهپاد (DBS) می‌باشد. اما از آنجا که ایجاد زیر ساخت برای پهپادها بسیار زمان‌بر و پر هزینه است باید مکان قرار گرفتن ایستگاه پایه پهپادها به گونه‌ای باشد که با کمترین تعداد DBS بیشترین پوشش‌دهی به کاربران و کمترین تلفات مسیر به منظور خدمات دهی با کیفیت بالا، ایجاد شود. در این پژوهش، یک روش مکان‌یابی بهینه برای DBSها با استفاده از الگوریتم فراابتکاری شکارچیان دریایی (MPA) ارائه شده است. الگوریتم MPA یکی از جدیدترین الگوریتم‌های فراابتکاری است که احتمال گرفتار شدن در اکسترمم‌های محلی در آن بسیار کم می‌باشد. با توجه به نتایج شبیه سازی، روش پیشنهادی در مکان‌یابی بهینه DBSها نسبت به سایر روش‌های مقایسه شده، از نظر تلفات مسیر و میزان پوشش‌دهی کاربران عملکرد بهتری داشته است. نتایج شبیه‌سازی‌ها نشان می‌دهد میانگین تلفات مسیر در روش‌های GWO، TW-NOMA و روش پیشنهادی به ترتیب برابر ۷۱/۷۵، ۷۵/۷۸ و ۵۶/۱۳ می‌باشد که بیان‌گر کاهش حداقل ۱۵ دسیبل میزان تلفات مسیر برای روش پیشنهادی می‌باشد.

کلمات کلیدی: قرارگیری ایستگاه پایه پهپاد، مخابرات نسل ششم، الگوریتم بهینه سازی شکارچیان دریایی.