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Post-Disaster Unmanned Aerial Vehicle Base Station Deployment Method Based on Artificial Bee Colony Algorithm

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ABSTRACT Ground-based communication facilities are at risk of being destroyed after natural disasters, such as earthquakes, floods, tsunamis, hurricanes, fires, or terrorist attacks. Unmanned aerial vehicles (UAV) can be used as air base stations to support user equipment (UE). UAV base station (UAV-BS) development plays a major part in rescue operations and post-disaster reconstruction. Improving network throughput in the UAV-BS signal coverage area and reducing deployment costs while maintaining effective communication are important issues that need to be addressed. In view of the problem, this paper demonstrates the problem of maximizing network throughput under the constraint of UAV-BS capacity by deploying UAV-BS. We proposed a UAV-artificial bee colony (U-ABC) algorithm to solve the problem of UAV-BS deployment. U-ABC algorithm can calculate the optimal flight position of each UAV-BS and maximum network throughput in the disaster area. In performance evaluation, we compared U-ABC algorithm with genetic algorithm, Greedy-ABC algorithm, PSO algorithm, DI-PSO algorithm and PSO-GWO algorithm. We analyzed the flight height altitude of UAV-BSs, the interference factor of UAV-BS, and the influence of the number of UE on network throughput. Results show that the proposed method improved the overall network throughput and achieved a high UE coverage rate under a given number of UAV-BSs.

INDEX TERMS Artificial bee colony algorithm, network throughput, post-disaster wireless communication, UAV base station.

I. INTRODUCTION

In recent years, various types of natural and sudden disasters have increased. When the ground-based communication facilities in the disaster area are destroyed, the communication between the disaster area and the outside world becomes challenging. The rational application of unmanned aerial vehicles (UAV) has played a major role in post-disaster monitoring and reconstruction. In post-disaster monitoring, UAV can immediately register the video of forest fires on a large scale, thereby measuring the wildfire geometry and tree parameters [1]. UAV is easy to operate, responsive and mobile in the communication network, and provides network access anytime and anywhere. It uses directional antennas for air-to-ground and air-to-air communication on ground targets [2], [3]. Researchers establish an emergency communication network with UAV, which has an onboard computer responsible for end-to-end communication, formation control, and autonomous navigation [4]. UAV is assisted to evaluate the efficiency of the positioning and deploy floating relay (FR) cells in a macro cell to achieve adaptive coverage [5], [6]. In addition, UAV can cover the blind spots of network signals with path planning algorithm [7]. In post-disaster communication construction, UAV can serve as a mobile base station in air to provide communication services for user equipment (UE). At the same time, reducing the overall congestion cost of network can be considered [8].

The reasons for network coverage of the disaster area by deploying UAV-BS are as follows. First, when the disaster occurred, most of the terrestrial communication facilities

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in the disaster area were destroyed and most areas had no signal [9]. If emergency communication network cannot be quickly established, the rescue and reconstruction work will face enormous difficulties. The emergency communication network established by UAV-BS has the advantages of fast deployment speed, high mobility and wide coverage. Therefore, UAV-BS is a communication tool that is very suitable for deployment in disaster areas. Second, due to the destruction of buildings and terrain in the disaster area, the ground obstacles and terrain are complicated [10]. Damaged or collapsed road makes the deployment of traditional emergency communication vehicles difficult. In addition, the antenna height of the emergency communication vehicle is also limited. Thus, large area signal coverage becomes difficult to achieve. Compared with the emergency communication vehicle, the UAV-BS is not affected by the ground conditions in the disaster area. UAV-BS can reach the place where the emergency communication vehicle cannot reach, greatly improving the signal coverage of the disaster area. Therefore, for the wide application of UAV-BS, it is an urgent task to research how to deploy UAV-BS in disaster areas. The deployment of UAV-BS is usually a non-deterministic polynomial-time (NP)-hard problem. In addition, issues, such as improving network throughput, UE coverage, and saving deployment costs, need to be addressed.

We propose a UAV-BS deployment method based on UAV-artificial bee colony algorithm (ABC) (U-ABC) to deploy UAV base station (UAV-BS) after disasters. Under certain conditions of UAV-BS deployments, the flight location of the UAV-BS is deployed to improve the network throughput in the disaster area. This paper has the following contributions:

1) We propose a post-disaster UAV-BS deployment model. The model calculates the network throughput and coverage of the covered UEs according to the Euclidean distance between the UAV-BS and the UE. The signal-to-interference-plus-noise ratio (SINR) of the covered UE is greater than a specified threshold, wherein UEs are subject to the signal interference of multiple UAV-BSs and the constraint of UAV-BS capacity.
2) We propose a heuristic U-ABC to maximize network throughput. The algorithm designs a new fitness function and uses the three-dimensional (3D) coordinates of a group of UAV-BSs as the solution of U-ABC. U-ABC effectively solves the problem of network throughput optimization and determines the optimal flight position of the UAV-BS.

The rest of this work is organized as follows. Section II reviews the existing research on UAV deployment. Section III proposes the UAV-BS deployment model. Section IV describes U-ABC. Section V shows the parameter settings of performance evaluation and discusses the results to evaluate our proposed algorithm. Finally, Section VI summarizes this work.

II. RELATED WORK

The UAV can act as a mobile air base station to provide wireless network coverage for UEs. Many scholars have conducted extensive research on the deployment of UAV-BS. Considerable number of research on UAV-BS deployments aim to increase signal coverage and network throughput. Savkin and Huang [11] proposed a distributed algorithm by investigating the problem of keeping the UAV-BS connected to the fixed base station while minimizing the average distance between UAV-BS and UE. Lyu *et al.* [12] proposed a new cyclic multiple access scheme, which was based on the location of the UAV-BS, to schedule the UAV for the maximization of the minimum throughput in a cyclically time-division manner. Lai *et al.* [13] proposed a density aware placement algorithm to maximize the number of restricted users. This algorithm is limited by the minimum data rate required by each user. Wu and Zhang [14] investigated a UAV orthogonal frequency division multiple access (OFDMA) network to maximize the minimum average network throughput for all users. Rupasinghe *et al.* [15] proposed a method to identify the optimal hovering position of a UAV-BS equipped with multiple antenna arrays and discussed the problem on maximizing the signal-to-noise ratio (SNR) at the ground node. Kalantari *et al.* [16] introduced network- and user-centric approaches to examine the effects of different types of wireless backhaul on the number of service users. They found the best 3D backhaul-aware location for UAV-BS, which enhanced network coverage and regional capacity. Mozaffari *et al.* [17] first derived the downlink coverage probability of the UAV-BS as a function. Subsequently, they used circular filling theory to determine the 3D position of the UAV-BS. Wu *et al.* [18] proposed an efficient iterative algorithm to maximize the minimum throughput of all terrestrial users in downlink communications by applying block coordinate descent and continuous convex optimization techniques. Xie *et al.* [19] first proposed an effective continuous hovering and flight path design. Subsequently, they presented local optimal solutions by applying alternating optimization and continuous convex optimization techniques. Chen and Gesbert [20] developed an algorithm based on fine-grained line of site (LOS) information to determine the optimal location of the drone to maximize end-to-end throughput. Kovalchukov *et al.* [21] constructed a new 3D model of drone-based millimeter wave communication to improve network coverage and regional capacity. Dong *et al.* [22] studied the deployment density of optimized small aircraft (DSC) and proposed an algorithm to maximize the coverage of UAV-BS. Chen *et al.* [23] proposed two networking strategies to improve network efficiency and maximize communication performance by using a greedy algorithm to determine the optimal hover point for UAV-BS in each region. Zhao *et al.* [24] proposed two algorithms based on whether knowing the UE location on the ground is necessary in determining the on-demand coverage of terrestrial UE. Huang and Savkin [25] proposed a natural distribution optimization model and developed a maximization algorithm to determine the local optimal solutions to maximize coverage and reduce interference effects. Sharma *et al.* [26] investigated the UAV allocation problem based on user demand in the geographical area of high traffic demand. They developed a neural-based cost function approach to improve coverage and increase capacity. Azari *et al.* [27] proposed a general framework for the analysis and optimization of air-to-ground (A2G) systems. The optimal altitude of the drone is obtained for maximum coverage by ensuring the minimum power outage performance in the area. Turgut and Gursoy [28] provided an analysis framework for the SINR coverage probability of UAV-assisted cellular networks with clustered UE. Liu *et al.* [29] used deep reinforcement learning (DRL) for UAV control and proposed a novel and energy efficient DRL-based approach to enhance the coverage of communication networks.

Studies also explored the fairness of UAV-BS coverage. Xi *et al.* [30] investigated the network selection problem of integrated cellular and UAV networks by proposing an efficient and fair network selection (RSG-EF) algorithm based on repetitive random games to maximize the proportional fairness function. The deployment of UAV-BS is usually a NP-hard problem. Thus, the heuristic algorithm can solve the UAV-BS deployment problem by providing a feasible solution to the combinatorial optimization problem to be solved under acceptable spatiotemporal computation. Shi *et al.* [31] proposed a UAV-BS-assisted radio access network architecture. They maximized user coverage while maintaining a given number of UAV-BSs by iterating PSO (DI-PSO) algorithm for each UAV-BS. They maintained the communication quality between UAV-BS and terrestrial base stations. However, the scenario of the above paper is not a post-disaster scenario. Chen *et al.* [32] proposed an improved multi-population genetic algorithm for horizontal size UAV-BS layout problems to maximize the number of users covered. Zhang *et al.* [33] used UAV-BS with in-band full-duplex in cellular networks to improve network throughput. They proposed two heuristic algorithms that are dynamic-DSP and fixed-DSP to solve the entire problem. Heuristic algorithms can also be used for the optimization of heterogeneous cellular networks. Lu *et al.* [34] proposed a simple greedy algorithm, a submodule greedy algorithm, and a particle swarm optimization algorithm based on the Femto-BS selection algorithm to select the best Femto-BS to maximize the average number of connected UEs in a given time. Chen *et al.* [35] developed a heuristic multicast delivery tree algorithm to optimize the delay performance and transmission cost of the video transport network.

This paper proposed a UAV-BS deployment method based on U-ABC algorithm. First, we proposed a post-disaster UAV-BS deployment model. Second, we proposed the U-ABC algorithm, where the 3D coordinates of a group of UAV-BSs were used as the solution of the U-ABC algorithm to calculate the maximum network throughput and obtain each UAV-BS's best flight location.

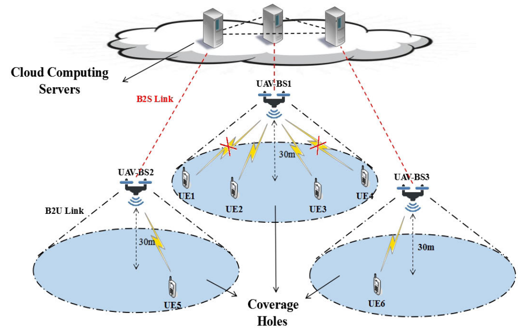


FIGURE 1. Schematic of the unified UAV-BS flight altitude deployment.

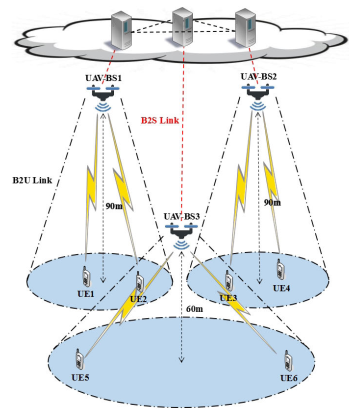


FIGURE 2. Schematic of the variable UAV-BS flight altitude deployment.

III. SYSTEM MODEL

We propose a post-disaster UAV-BS deployment model in this section to solve the deployment problem of UAV-BS. We analyze the characteristics of UAV-BS and demonstrate the problem.

A. CHARACTERISTIC ANALYSIS OF UAV-BS

The UAV-BS's unified flight altitude and variable flight altitude deployment diagrams are compared in Figures 1 and 2, where the blue area represents the signal coverage of the UAV-BS. The SINR in the area is not less than the threshold. The out-of-area indicates that the SINR is less than the threshold. Cloud computing server provides scalable computing services that are easier and more efficient to manage than physical servers. The cloud computing server receives the data of each UAV-BS and processes the data by using the method proposed therein to schedule the flight location of each UAV-BS. The B2U link is a communication connection between the UAV-BS and the UE. The B2S link is a communication connection between the UAV-BS and the cloud computing server. We assume that the capacity of each UAV-BS can accommodate up to two UE network throughput. In Figures 1 and 2, the UAV-BS heights hold a reference from experimental result in Section V. Figure 1 shows that the UAV-BS1 cannot establish normal communication with UE1 and UE4 because its capacity is limited and UE1 and

UE4 are farther away from UAV-BS1 than UE2 and UE3. In Figure 2, the heights of UAV-BS1 and UAV-BS2 are increased to 90 m, and the coverage decreased, and they covered UE1, UE2, UE3, and UE4. Meanwhile, the flight altitude of UAV-BS3 is increased to 60 m, and the coverage increased, thereby covering UE5 and UE6. The following conclusions can be drawn. First, as the flight altitude of UAV-BS increases, the transmission loss increases. When the transmission loss is greater than the received power, the coverage becomes larger first and then becomes smaller. Second, the method of variable UAV-BS flight altitude covers more UEs than the method of unified UAV-BS flight altitude in increasing network throughput. The characteristics of the UAV-BS we derived are as follows:

- Flight altitude of UAV-BS: The horizontal flight position of the UAV-BS shall not exceed the specified area, and the flight altitude should be between 20 m and 120 m. UAV-BS's variable flight altitude allows improved coverage of the UE to increase network throughput.
- Coverage of UAV-BS: The signal coverage of UAV-BS increases first, and then decreases with the increase in UAV-BS flight altitude. Therefore, coverage and transmission loss increase with UAV-BS flight altitude. If the transmission loss is greater than the received power, then the coverage will be reduced.

B. PROBLEM FORMULATION

The post-disaster UAV-BS deployment model is summarized into three steps. First, the network throughput of each UE is calculated. Second, constraints are imposed on the throughput of the UAV-BS. Third, the overall network throughput and UE coverage in the disaster area were calculated. The detailed steps are explained in the next paragraph.

In the first step, we establishe a 3D scene with a specified size and number of UEs. Afterwards, we randomly generate the coordinates of several UAV-BSs in the 3D scene and calculate the Euclidean distance between UAV-BSs and UEs. The SINR of each UE and the transmission power of the UAV-BS are also calculated on the basis of the Euclidean distance. Finally, the respective network throughput of the SINR of UEs that are not lower than the set threshold are calculated. In the second step, the network throughput of each UE covered by the UAV-BS is accumulated, and its SINR is greater than the set threshold. Then, we determine whether the network throughput of each UAV-BS is greater than the capacity of the UAV-BS. If the network throughput of the UAV-BS is greater than the capacity of the UAV-BS, the UAV-BS is disconnected from one or more UEs so that the UAV-BS does not exceed its capacity. When the UAV-BS capacity is not exceeded, the network throughput of the UAV-BS is maximized. In the final step, the network throughput of all the UAV-BSs that meet the capacity constraints is added to calculate the network throughput in the disaster area.

The received power, SINR, UE network throughput, UAV-BS network throughput, and network throughput in the proposed UAV-BS deployment model are introduced as follows.

Received Power: The received power is represented by $P_{r,ij}$, which refers to the power received by the UE i from the UAV-BS j.

$$P_{r,ij} = P_t + L_{ij}, \tag{1}$$

where P_t is the transmission power of UAV-BS. L_{ij} is the transmission loss between UAV-BS j and UE i. The average of the upper limit $L_{u,ij}$ of L_{ij} and the lower limit $L_{l,ij}$ of L_{ij} is computed as follows:

$$L_{u,ij} = L_j + 20 + \begin{cases} 25\lg(d_{ij}/R_j), & if \;\; d_{ij} \geq R_j \\ 40\lg(d_{ij}/R_j), & if \;\; d_{ij} \geq R_j \end{cases}, \tag{2}$$

$$L_{l,ij} = L_j + \begin{cases} 20\lg(d_{ij}/R_j), & if \;\; d_{ij} \geq R_j \\ 40\lg(d_{ij}/R_j), & if \;\; d_{ij} \geq R_j \end{cases}, \tag{3}$$

$$L_j = |20\lg(\lambda^2/8\pi h_j h_p)|, \tag{4}$$

In Formulas (2) and (3), d_{ij} is the Euclidean distance of the UAV-BS j and the UE i. (x_j, y_j, h_j) is the coordinates of the UAV-BS j and (x_i, y_i, h_p) is the coordinates of the UE i. In formula (4), L_j is the free space path loss of the UAV-BS j.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (h_p - h_j)^2}, \tag{5}$$

where h_j is the flight altitude of the UAV-BS j above the ground, and h_p is the height of the UE above the ground.

$$\lambda = \frac{c}{f}, \tag{6}$$

where λ is a wavelength, c is a wave speed and f is a frequency.

$$R_j \approx \frac{4\pi h_j h_p}{\lambda}, \tag{7}$$

In Formulas (6) and (7), R_j is a threshold for measuring the transmission loss radius of the UAV-BS j.

SINR: $SINR_{in}$ refers to the ratio of the received power and interference power plus channel noise of the UE i under the coverage of the UAV-BS n.

$$SINR_{in} = \frac{P_{r,in}}{I + N}, \tag{8}$$

where $P_{r,in}$ is the maximum received power of all UAV-BSs received by the UE i. We will call the UAV-BS received by UE i the maximum received power UAV-BSn. N is a constant channel noise. I is the interference power, which is the sum of the received powers received by UE from other $m - 1$ UAV-BSs.

$$I = \sum_{j=1}^{m} P_{r,ij} - P_{r,in}, \tag{9}$$

Network Throughput: The network throughput of UE refers to the maximum data rate that are actually transmitted by UE i and the UAV-BS n during network transmission. Channel capacity is the maximum information rate that the channel can transmit without error. A specific single channel is used for the communication of UE and UAV-BS. The network throughput of each UE is equal to the channel capacity of each UE. Shannon formula is used to calculate the channel capacity of each UE:

$$C_{in} = B * \log_2(1 + SINR_{in}), \tag{10}$$

where C_{in} is the channel capacity of the UE i to the UAV-BS n, and B is the channel bandwidth in units of Hz.

The formula for calculating the network throughput of UAV-BS can be defined as follows:

$$T_j = \sum_{i=1}^{p} C_{ij}$$
$$s.t. \;\; T_j \leq T_{max}, \tag{11}$$

where T_j is the network throughput of the UAV-BS j. The network throughput of each UAV-BS is equal to the sum of the network throughput of all UEs covered by it and they, which are not lower than the SINR threshold. If the network throughput of the UAV-BS is greater than its capacity T_{max}, then UE is lightly disconnected from the UAV-BS to make network throughput and UE coverage larger without exceeding their own capacity T_{max}. The network throughput *Total* in the disaster area is the sum of the network throughput of all UAV-BSs.

$$Total = \sum_{j=1}^{m} T_j, \tag{12}$$

The 3D coordinates of UAV-BS are used as the solution of the U-ABC algorithm, which aim to calculate the maximum network throughput.

$$\max_{x_j, y_j, h_j} \sum_{j=1}^{m} T_j, \tag{13}$$

The position P of the corresponding $m - 1$ UAV-BS can be obtained as follows:

$$P = \arg\max_{x_j, y_j, h_j} \sum_{j=1}^{m} T_j, \tag{14}$$

IV. SOLUTION

A. ABC ALGORITHM

ABC algorithm is a swarm intelligence optimization algorithm [36], [37], in which the bees' collecting process is simulated, and the bees are divided into employed, on-looker, and scout bees. These bees have two basic behavior, namely, search for honey sources and give up honey sources. All kinds of bees spread and share honey information through different honey collecting behavior. The number of honey sources is equal to half of the total number of bees. The number of employed and on-looker bees is half of the total number of bees. Employed bees tend to look for high-quality honey sources, whereas on-looker bees find a better honey source according to the quality of the honey source. If a honey source has not been replaced by a better honey source for a long time, then the corresponding on-looker bee will give up the honey source and become a scout bee. Thus, each honey source represents a solution to the optimization problem. The process of bees that search for honey sources is the model solving process. The use of three different kinds of bees has various effects. Employed bees are used to maintain good solutions, on-looker bees are used to improve convergence, and scout bees are used to enhance the ability to removing local optimums.

B. U-ABC ALGORITHM

U-ABC is used to solve the optimization problem defined in Formula (13). The U-ABC algorithm follows the same general framework as the original ABC algorithm. However, we redesign the fitness function and determine a better solution to improve the network throughput in the disaster area. $fitness(S_i)$ can be written as follows:

$$fitness(S_i) = \sum_{j=1}^{m} T_j, \tag{15}$$

Formula (15) is a new fitness function that represents the sum of the network throughput of m UAV-BS in solution S, where $i = \{1, 2, \ldots, U\}$. The solution with larger fitness value is more optimized.

1) INITIALIZATION PHASE

First, the U-ABC generates U initial solution sets S. Each initial solution S_i is defined as $S_i = \{s_i^1, s_i^2, \ldots, s_i^{3m}\}$, where $i = \{1, 2, \ldots, U\}$. $(s_i^j, s_i^{2j}, s_i^{3j})$ represents the position of the UAV-BS j^{th}, where $j \in \{1, 2, \ldots, m\}$, which contains the position of m UAV-BS. The formula for each UAV-BS position can be written as follows:

$$s_i^{dj} = (ub_d - lb_d) * rand - lb_d, \tag{16}$$

where $d = \{1, 2, 3\}$ is the dimension. *rand* is a random number between [0, 1]. *ub* and *lb* are the upper and lower limits of the solution space, respectively. The initial solution is brought into the objective function. Thus, the current optimal solution is calculated and recorded.

2) EMPLOYED BEE STAGE

Employed bees search for a better solution around the current solution. They search for a new candidate solution n_i^r near the current solution set and calculate its fitness value. The search formula can be written as follows:

$$n_i^r = s_i^r + \varphi_i^r * (s_i^r - s_k^r), \tag{17}$$

where $r \in (1, 2, \ldots, 3m)$ is the index of the randomly selected current solution. k is the index of the randomly selected candidate solution, and $k \neq i$. φ_i^r is a random number between $[-1, 1]$. If the fitness value of the candidate solution is greater than the current solution, then the candidate solution will replace the current solution.

3) ON-LOOKER BEE STAGE

The probability of the bee selecting the solution is proportional to the quality of the solution, thereby further optimizing the solution found by each employed bee. Each on-looker bee uses the roulette method to select a new solution. The greater the fitness value of the solution, the greater the probability of an on-looker bee selects the solution.

$$p_i = 0.9 * \frac{fitness(S_i)}{\max fitness(S)} + 0.1, \tag{18}$$

where $\max fitness(S)$ is the maximum fitness value of the solution set S. A random number $rand_i$ between [0, 1] is compared with p_i. If $rand_i < p_i$, then the observation bee selects an employed bee. Formula (17) is used to search for a new candidate solution near the current solution and to calculate its fitness value. If the fitness value of the candidate solution is greater than the current solution, then the current solution is replaced with the candidate solution.

4) SCOUT BEE STAGE

If a solution is not improved in a predetermined number of iterations, then the corresponding employed bee will give up the solution and turn into a scout bee using Formula (16) to re-find the new solution. The algorithm stops when the number of iterations reaches the predefined maximum number of iterations. Robustness increases with the number of runs.

Algorithm 1 U-ABC Algorithm

Require: number of UAVs m in a solution, number of solutions U, solution set S, maximum number of iterations *maxiteration*

Ensure: find out the optimal solution S_{best}

1: Select $m \times U$ UAV-BSs randomly to initialize U solutions;
2: Calculate these fitness values of U solutions with formula (15) and record the best solution S_{best};
3: $iteration = 0$
4: Use *EmployedBee()* to search for a better solution n_i;
5: Use *On-lookerBee()* to search for a better solution n_i with probability;
6: Use *ScoutBee()* to replace an unmodified solution that more than limit iteration with a new solution;
7: Calculate these fitness values of U solutions with formula (15) and record the best solution S_{best};
8: $iteration = iteration + 1$
9: Repeat step 4-step 9 until $iteration = maxiteration$;

In Algorithm 1, three functions, namely, *Employedbee()*, *On-lookerbee()* and *Scoutbee()*, are used. *Employedbee()* generates a new candidate solution near the current solution using Formula (17) and then calculates its fitness value. If the fitness value of the candidate solution is greater than the fitness value of the current solution, then the current solution will be replaced by the candidate solution. *On-lookerbee()* calculates the selection probability p_i using Formula (18) to decide whether to generate a new candidate solution near the current solution. The greater the fitness value of the current solution, the greater the probability of generating a new candidate solution. If a new candidate solution is generated, then its fitness value will be calculated. If the fitness value of the candidate solution is greater than the fitness value of the current solution, then the current solution will be replaced by the candidate solution. *Employedbee()* abandons a solution that cannot be improved when iterations reach their limit. Then, a new solution is generated to replace the abandoned solution using Formula (16).

TABLE 1. Experimental parameter settings.

Experiment Parameters	Numerical Values
Scene size	1000m×1000m×100m
UAV-BS flight altitude range	20-120m
UE height	1.7m
Signal frequency	3GHz
Number of UEs	100
Number of UAV-BSs	1-20
UAV-BS transmit power	90mW
Channel noise power	0.1mW
UAV-BS capacity	500Mbps
SINR threshold	3db
UE channel bandwidth	2.5MHz

V. PERFORMANCE EVALUATION

The performance of the algorithm is evaluated through performance evaluation. The experimental parameter settings are shown in Table 1. We compare UAV-BS deployment method based on U-ABC algorithm, genetic algorithm, Greedy-ABC algorithm, Particle Swarm Optimization (PSO) algorithm, DI-PSO algorithm and Particle Swarm Optimization-Grey Wolf Optimizer (PSO-GWO) algorithm. The impacts of UAV-BS flight altitude and interference on network throughput are also analyzed. The simulation results show that the proposed method improved the overall network throughput in the UAV-BS signal coverage area and achieved a high ground UE coverage rate under the condition of deploying a given number of UAV-BSs.

A. COMPARISON OF U-ABC ALGORITHM, GENETIC ALGORITHM, GREEDY-ABC ALGORITHM, PSO ALGORITHM, DI-PSO ALGORITHM AND PSO-GWO ALGORITHM

First, we briefly introduce these algorithms. Genetic algorithm is a computational model that simulates the natural evolution of Darwin's biological evolution theory and the biological evolution process of genetic mechanism. It is a method to search for optimal solutions by simulating natural evolutionary processes. Greedy-ABC algorithm is a hybrid algorithm combining greedy algorithm and U-ABC algorithm. The algorithm finds the local optimal solution by U-ABC algorithm in each step. PSO algorithm simulates birds in a flock by designing a massless particle. The optimal

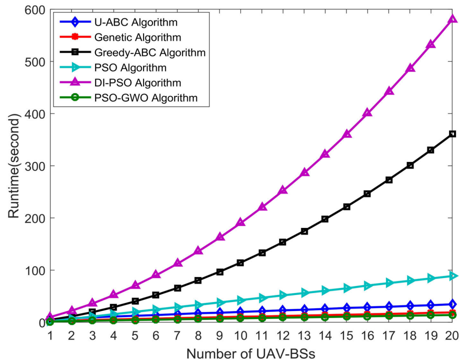


FIGURE 3. Comparison of running time of six algorithms.

solution for each particle to search separately is called the individual extremum, and the optimal individual extremum in the particle swarm is taken as the current global optimal solution. DI-PSO algorithm uses PSO algorithm independently on each UAV-BS. As each UAV-BS is deployed independently, the spatial ergodicity of the DI-PSO increases, which leads to a higher probability of finding a global optimum [31]. PSO-GWO algorithm is a hybrid optimization algorithm that combines the functions of PSO algorithm and GWO algorithm. In Figure 3, the running time of each execution of the UAV-BS deployment methods are compared on the basis of U-ABC algorithm, genetic algorithm, Greedy-ABC algorithm, PSO algorithm, DI-PSO algorithm and PSO-GWO algorithm. The running time of DI-PSO algorithm is significantly higher than five other algorithms, and the longest time has reached 580 seconds. Genetic algorithm and PSO-GWO algorithm are slightly faster than U-ABC algorithm.

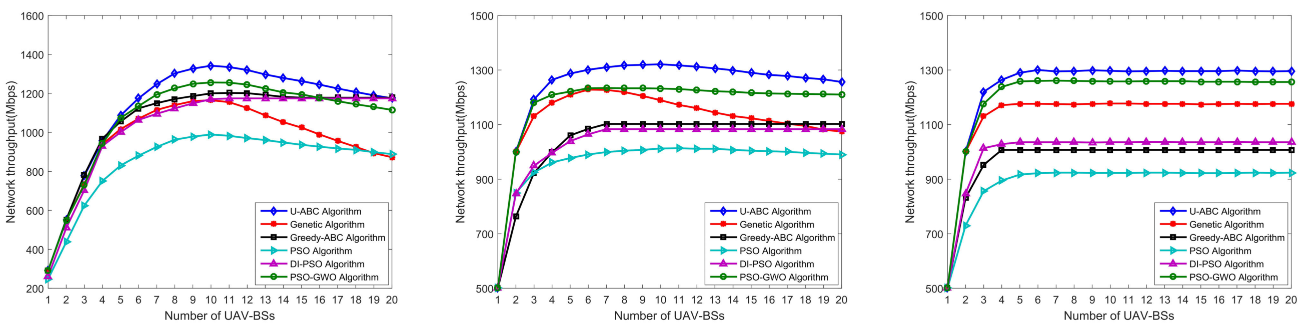
In Figure 4, the UAV-BS deployment methods are compared on the basis of U-ABC algorithm, genetic algorithm, Greedy-ABC algorithm, PSO algorithm, DI-PSO algorithm and PSO-GWO algorithm under three common distributions. In the random distribution, the interference signal increases with the number of UAV-BS. The network throughput that corresponds to U-ABC algorithm, genetic algorithm, PSO algorithm and PSO-GWO algorithm first increases and then decreases. The network throughput that corresponds to Greedy-ABC algorithm and DI-PSO algorithm first increases and maintains a steady trend. When the number of UAV-BS is 5 to 18, the U-ABC algorithm has an advantage. The maximum network throughput is obtained when the number of UAV-BS is 10. In the normal distribution, the network throughput of U-ABC algorithm is significantly higher than five other algorithms after the UAV-BS number becomes greater than 2. The number of UAV-BSs in U-ABC algorithm when the maximum network throughput is obtained is 10. In the exponential distribution, the network throughput of six algorithms is almost unchanged after the number of UAV-BS becomes greater than 6. The network throughput in U-ABC algorithm is approximately 50 to 400 Mbps higher than five other algorithms. Therefore, U-ABC algorithm is more advantageous than the five other algorithms in optimizing the network throughput.

B. IMPACT OF UAV-BS FLIGHT ALTITUDE ON NETWORK THROUGHPUT

In Figure 5, two UAV-BS deployment methods are compared under three UE distributions. The first uses the UAV-BS flight altitude as a variable of U-ABC algorithm, which is the proposed method. The second uses UAV-BS as a constant, and all UAV-BSs have the same flight altitude. The coverage of each UAV-BS in the first algorithm is not fixed. Thus, the UE can be covered better according to the distribution of the UE, thereby greatly improving the network throughput in the disaster area. In a random distribution, the network throughput of our method is higher than the second method. In the normal and exponential distributions, our method has minimal advantage due to the uneven distribution of UEs and the accumulation of UAV-BS in high-density areas, thereby causing the change in UAV-BS flight altitude to slightly affect network throughput. Therefore, UAV-BS flight altitude can be used as a variable of U-ABC algorithm to obtain greater network throughput.

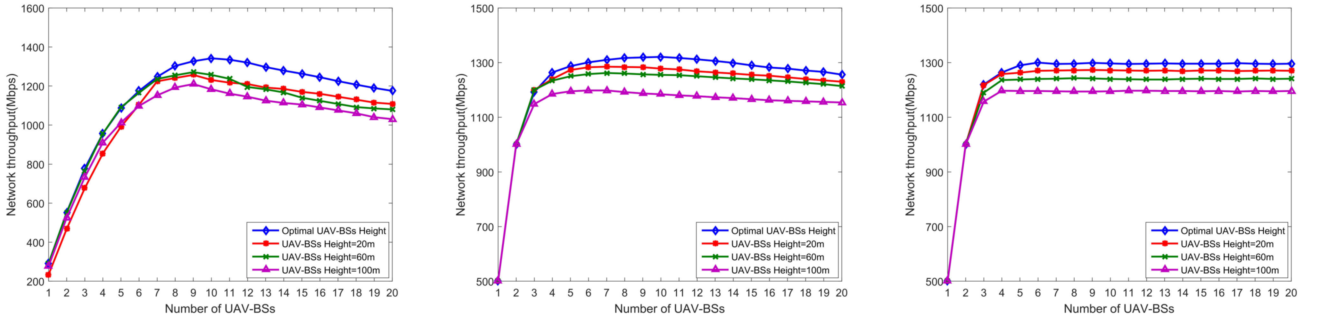
C. IMPACT OF UAV-BS INTERFERENCE ON NETWORK THROUGHPUT

In Figure 6, two methods are that U-ABC algorithm considering UAV-BS interference and U-ABC algorithm not



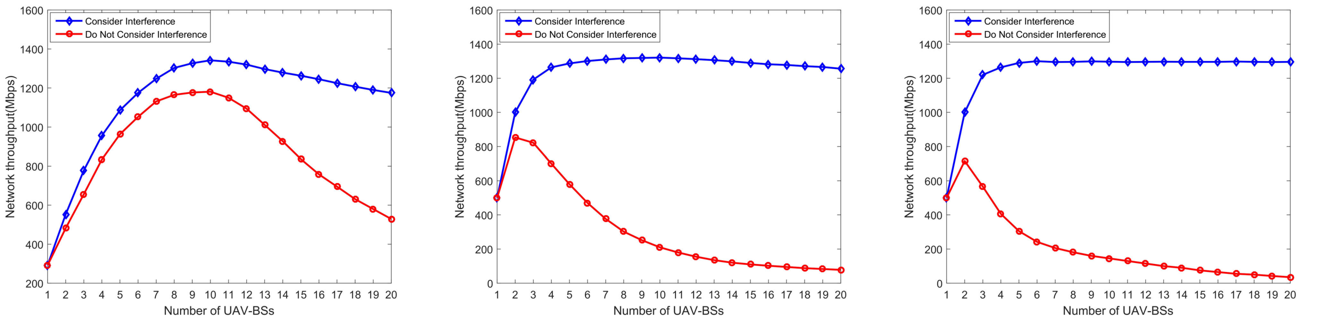
(a) Random Distribution (b) Normal Distribution (c) Exponential Distribution

FIGURE 4. Comparison of network throughput of six algorithms.



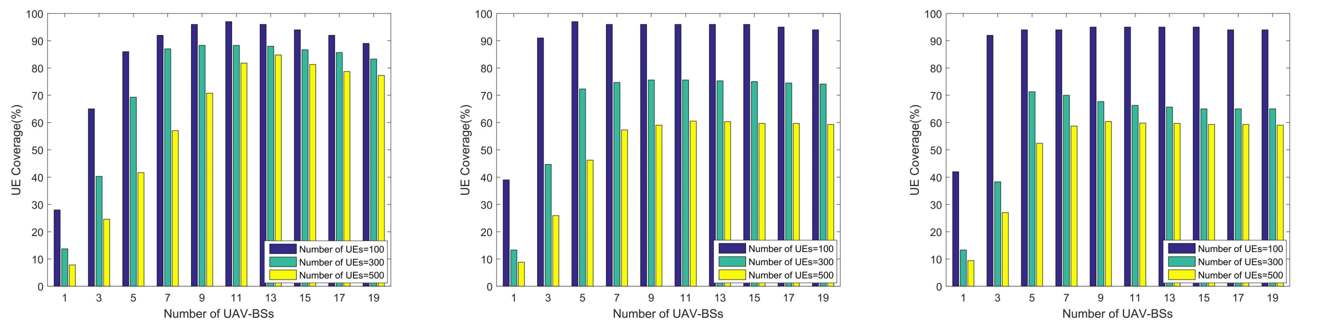
(a) Random Distribution (b) Normal Distribution (c) Exponential Distribution

FIGURE 5. Comparison of network throughput of UAV-BS at different flight altitudes.



(a) Random Distribution (b) Normal Distribution (c) Exponential Distribution

FIGURE 6. Comparison of network throughput about UAV-BS interference.



(a) Random Distribution (b) Normal Distribution (c) Exponential Distribution

FIGURE 7. Comparison of UE coverage ratios for different UEs.

considering UAV-BS interference under three UE distributions. In the random distribution, the network throughput of both methods increases first and then decreases. The overall throughput of considering the interference is higher than the case without considering the interference because the flight position is unreasonable without considering the interference. Under normal and exponential distributions, the method that does not consider interference is subject to the UAV-BS capacity constraint. The network throughput first increases briefly and then decreases to zero because the UAV-BS is concentrated in the high-density areas of the two distributions, and the interference signal received by the user is extremely strong. Therefore, the method that consider UAV-BS interference is more reasonable than the flight position of UAV-BS under the method of not considering UAV-BS interference.

D. IMPACT OF THE NUMBER OF UES ON COVERAGE

In Figure 7, the coverage of different numbers of UEs are compared under the three UE distributions. According to the test requirements of China Mobile Communications Group Company Limited, 3 db is the extreme difference threshold of SINR. Thus, we assume that when $SINR \geq 3db$, the UE is covered by the signal of the UAV-BS. When $SINR < 3db$, the UE is not covered by the signal of the UAV-BS. The greater the number of UAV-BS, the stronger the interference signal received by each UAV-BS because of the limitation of UAV-BS capacity and the influence of interference signals. Therefore, as the number of UEs increases, the UE coverage rate gradually decreases. The coverage of the three distributed UEs can reach more than 90% when the number of UEs is 100. Therefore, our method can cover most UEs under the three distributions when the number of UEs is approximately 100. Therefore, the fewer the UE, the higher the coverage.

VI. CONCLUSION AND FUTURE WORK

In the study of post-disaster UAV-BS deployment methods, a UAV-BS deployment method is proposed on the basis of U-ABC algorithm to improve the network throughput and the coverage of terrestrial UEs in the disaster area. First, a UAV-BS deployment model is established. Then, the model is applied to the U-ABC. The 3D coordinates of the UAV-BS are used as the solution of the U-ABC algorithm. Finally, we found the best UAV-BS flight position. The network throughput is improved while achieving high ground UE coverage. The results show that the proposed method has remarkable advantages compared with other methods. In future research, the UAV-BS energy consumption, as well as terrain, construction, and obstacles, can be considered.

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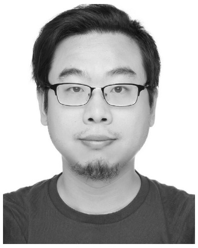

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