PSO-VFA: A Hybrid Intelligent Algorithm for Coverage Optimization of UAV-Mounted Base Stations

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Abstract

When the number of outdoor wireless users surges and fixed base stations (BSs) can hardly accommodate high-load communication traffic, unmanned aerial vehicles (UAVs) carrying BSs can provide wireless communication services, and the location deployment of the UAV-mounted BSs directly influences the reliability of network communications. For the target area scenario where the UAVs uniformly cover user nodes, we propose a hybrid intelligent coverage algorithm called PSO-VFA to optimize the coverage of a fixed number of UAV-BSs. The PSO-VFA algorithm consists of two phases employing different intelligent algorithms. First, we adopt a particle swarm optimization (PSO) method for a global search of the coverage areas. Then, for local search, a virtual-repulsive-force-based firefly algorithm (VFA) is proposed in this paper to maximize the user coverage. In the VFA algorithm, the users are treated as the objects attracting the UAVs, and the virtual repulsive force is used for UAV location adjustment. Simulation results show that the proposed PSO-VFA hybrid algorithm has faster convergence and significantly increases the communication coverage of UAV-mounted BSs compared with individual intelligent algorithms such as VFA, PSO, genetic algorithm (GA), and simulated annealing (SA).

Keywords: UAV-mounted base station, Deployment coverage, Intelligent algorithm, Firefly algorithm, Particle swarm optimization

1 Introduction

With the development of 5G/6G technologies and the increasing demand of wireless network applications, unmanned aerial vehicles (UAVs) carrying communication base stations (BSs) can quickly and flexibly deploy aerial BSs [1], thereby temporarily solving the network congestion caused by insufficient outdoor ground BSs. Compared with traditional fixed BSs and emergency communication vehicles, the UAV-mounted BS (UAV-BS) can better compensate for deficiencies in terms of time and space dimensions, such as the high cost and resource overhead. Therefore, it is an ideal choice to use the UAV-BSs as a means of outdoor emergency communications. Additionally, when UAVs are mounted with wireless BSs, the deployment scheme of UAVs must be rationally planned to support practical applications due to the significant impact of their specific deployment on the user experience, network performance, and operational costs [2].

The research on UAV communication coverage mainly falls into the categories of scanning coverage and deployment coverage [3]. By applying scanning coverage, the UAV-BS can only briefly communicate with ground nodes in the scenarios where real-time communication is not required, such as collecting ground sensor information through reasonable path planning. On the contrary, the application of deployment coverage is suitable for providing long-time communication to user nodes, thus raising the demand for the reasonable deployment of UAV locations.

Specifically, the deployment coverage algorithms are sorted into two categories: coarse-grained deployment and fine-grained deployment. Coarse-grained deployment focuses on regional coverage, and it is difficult to consider some factors, such as the UAV load capacity and user communication quality. On the contrary, the fine-grained deployment schemes can calculate a more appropriate UAV location according to the UAV and user information, mitigating the flaws of coarse-grained deployment. However, its operation costs more. It is essential for fine-grained deployment to minimize the time and space complexity while keeping an effective deployment. To address this issue, a hybrid intelligent scheme is proposed. It achieves optimal solutions while alleviating the problems caused by only using a single intelligent algorithm, e.g., the tendency to fall into local optimal solutions and slow convergence [4].

Recently, some solutions based on scanning coverage have been proposed. For scanning coverage, the approach proposed by D'Amato et al. optimizes the UAV trajectory and controls the power to maximize the throughput of the UAV network [5]. To deploy wireless sensors in a target area, Li et al. proposed a heuristic weighted target coverage algorithm to find an optimal path by considering the target weights and UAV performance constraints [6]. Wang et al. proposed a regularized fast path planning algorithm for uniformly distributed wireless sensor networks, which divides the path planning of the global region into squares and then combines the paths in the squares based on the line precedence principle [7]. In the absence of accurate user location information, Liu et al. adopted the Q-learning algorithm to optimize the UAV trajectories [8].

Research is also done on providing the maximum coverage area based on the deployment coverage. Azari et al. studied the outage probability of wireless networks, arriving at the relationship between the maximum coverage area of UAVs and the signal-to-noise ratio (SNR) [9]. This study proves that

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DOI: 10.53106/160792642022052303007

the UAV has an optimal vertical height that can be used to maximize its communication coverage range. To meet the different quality of service (QoS) requirements of users, Chen et al. adopted an improved multi-swarm genetic algorithm to optimize the deployment of UAV-BSs [10]. An improved cuckoo algorithm is introduced to achieve the focused optimization of hotspot area coverage and achieves a higher coverage rate compared with the standard cuckoo algorithm [3]. However, this algorithm only covers a coarse-grained hotspot area, without considering the coverage of individual users meticulously. Qu et al. designed a K-mean-based algorithm for UAV deployment according to the user bandwidth requirements [11]. This method can reduce the number of UAVs, but it does not take the optimal coverage of UAVs into account.

In summary, by optimizing the deployment of UAV locations, we can improve the reliability of UAV network communication, expand the communication coverage, and guarantee the QoS of UAV-BSs [12-13]. Nevertheless, the researches discussed above focus less on fine-grained deployment, in which the use of UAV information for deployment has not been fully considered.

Deployment optimization of UAV-BS is an NP-hard problem, and some intelligent algorithms can solve such problems through self-learning and cooperation [14-15]. With good searchability as well as self-adaptability, some intelligent algorithms are employed in many application areas of wireless networks, including UAV-BS deployment [16-17]. Inspired by the mutual attraction of fireflies in the firefly algorithm (FA), in this paper, we propose a hybrid intelligent algorithm for UAV-BS deployment, i.e., the particle swarm optimization-virtual repulsive force firefly algorithm (PSO-VFA), taking the wireless users as the object to attract UAVs.

The PSO-VFA is a combination of two intelligence algorithms: the particle swarm optimization (PSO) algorithm [17], and the virtual-repulsive-force-based firefly algorithm (VFA), which is also proposed in this paper. We improve the FA algorithm by introducing virtual repulsive forces among UAVs to reduce the overlapping coverage areas [18]. This algorithm can effectively use the user information within the perception range of UAVs to adjust their locations. In addition, the PSO algorithm is employed as the overall algorithm framework for searching and further optimizing UAV deployment coverage. It can effectively make up for the weak global search capacity of the VFA algorithm. Each particle represents the deployment scheme of a UAV node-set. The update of each location is a process to move every particle towards the global and individual historical optimal particles. The main objective of this paper is to achieve a fine-grained deployment of UAVs with reduced algorithm iterations and better user coverage.

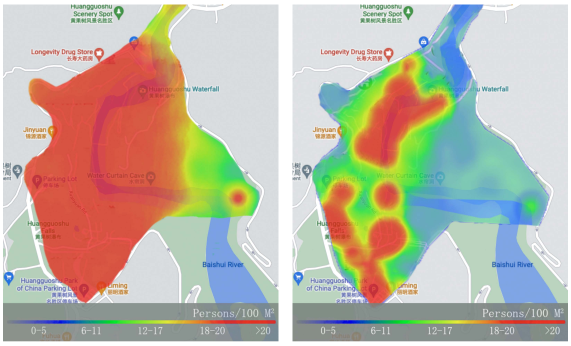
Different from the existing work such as given in [11-13], in this paper, we consider using a fixed number of UAV-BSs to serve ground users in different scenarios, so as to maximize the coverage of UAVs and speed up the convergence rate of algorithm. Additionally, the communication perception range of UAV is taken as the search radius in the VFA algorithm to support the UAV deployment strategy in different scenarios and achieve a better fine-grained deployment under the framework of PSO algorithm. The following are the main contributions to the research of this paper:

- We define and analyze the optimal perception radius and vertical height of the UAV in suburban and urban scenarios, which enables the UAV to fully utilize its own and user information for location adjustment while meeting the user communication requirements.
- We have proposed a firefly search algorithm based on virtual repulsive forces that is applied to the coverage optimization of UAV-BSs and provides the maximization of the user coverage.
- A hybrid intelligent algorithm is designed, in which the PSO algorithm is introduced as the overall algorithm framework, and the VFA algorithm performs coverage optimization to quickly converge to the global optimal solution.
- The performance of the proposed PSO-VFA algorithm is evaluated and compared with the PSO, VFA, genetic algorithm (GA), and simulated annealing (SA) algorithms for suburban environments with different numbers of UAVs.

2 System Model and Problem Formulation

2.1 Application Scenarios

It is necessary to deploy UAV-BSs on demand, considering the user locations and the size limitations of the UAV network. UAV deployment will face increases in outdoor users, such as the wireless users at hot scenic spots on Chinese holidays. Figure 1 presents the distributions of the tourists at a Chinese outdoor scenic spot in two different periods. Most of the tourists have Internet-capable mobile devices, therefore, they can be identified as wireless users. The darker the red area in the figure, the higher the tourist density in the area, and the more devices are connected to the mobile network outdoors. With the increase in outdoor users, more devices are connected to the mobile network outdoors. If the network is congested due to the traffic burst caused by the outdoor users' devices, the ground BSs may not be able to provide communication services for the users in time. On the contrary, if the target area with an uneven distribution of users has full coverage, this is a waste of network resources.



(a) Holiday (b) Non-holiday

Figure 1. Heat maps of the tourist volumes at the Huangguoshu Waterfall, a famous scenic spot in China
(The Chinese characters below the English characters in the pictures indicate the corresponding Chinese addresses of the English addresses. Data from Tencent Location Big Data, https://heat.qq.com/)

2.2 Coverage Problem and Model

Given that the UAVs are randomly assigned to different subareas of the target area during initial deployment, there might be two problems: more overlapping coverage areas and uncovered users. We consider using the FA algorithm to determine the positions of UAVs: more users can be covered and the overlapping coverage is reduced. However, one of the factors of UAV movement is the UAV's perception radius [19], and the UAV is attracted by the users within the perception radius. When the projected two-dimensional (2D) distance between a user and a UAV is less than the perception radius E_{max} and greater than the actual coverage radius R_m, the communication quality required by users cannot be met, because the UAV can only sense the user, not establish a connection.

After the UAV-BSs are deployed as shown in Figure 2, multiple UAVs hover in the air over the target area at an altitude of H to provide communication service for ground users. R is the maximum communication radius projected by the UAV to the ground, D is the maximum communication distance, and θ is the horizontal angle of the ground. Let $\mathcal{K}=\{1, 2, \ldots, K\}$ denote the set of users (note that the user's altitude is not taken into account). The position of user $k \in \mathcal{K}$, loc_k is (X_k,Y_k), and they are randomly distributed in the 2D target area O, where O=$\{(X_k,Y_k) \mid X_{min} \le X_k \le X_{max}, Y_{min} \le Y_k \le Y_{max}\}$. Let $\mathcal{M} = \{1, 2, \ldots, M\}$ denote the set of UAVs, and the position of UAV $m \in \mathcal{M}$ is $loc_m = (X_m, Y_m, H_m)$. The UAVs are deployed in the 3D target region O = $\{(X_k, Y_k, H_m) \mid X_{min} \le X_k \le X_{max}, Y_{min} \le Y_k \le Y_{max}, H_{min} \le H_k \le H_{max}\}$, where (X_{min}, X_{max}) and (Y_{min}, Y_{max}) are the constraints on the X- and Y-axes of the target region, respectively. (H_{min}, H_{max}) are the altitude constraints. The symbolic notation of the system model is given in Table 1.

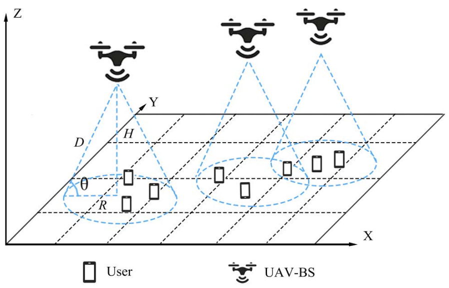


Figure 2. UAV-BS deployment

Table 1. Key variables and notations

Symbols	Description
$\mathcal{K}$	Set of users
$\mathcal{M}$	Set of UAVs
k	User k
m	UAV m
K	Number of user nodes
M	Number of UAV nodes
(X_k, Y_k)	User k coordinates on the X- and Y-axes
(X_k, Y_k, H_m)	UAV m coordinates on X-, Y-, and Z-axes
r_{mk}	Horizontal distance from the UAV m to the user k
d_{mk}	Projected 3D distance from the UAV m to the user k
a, b	Parameters corresponding to different environments
L_{A2G}	Average air-to-ground link loss
SNR_{mk}	Signal to the noise ratio between the UAV m and the user k
R_m	Actual coverage area of the UAV m

2.3 Air-to-Ground Channel Model

In wireless communications, the channel model is a very important factor. The vertical height of the UAV-BS deployment will affect the coverage and the reliability of communication links. According to the air-to-ground channel model proposed in [20], the advantage of UAV-BSs over fixed BSs is that the link between UAV and user has higher line-of-sight (LOS) propagation. At the same time, the communication link may be affected by the density and height of ground buildings, which results in non-line-of-sight (NLOS) propagation in the air-to-ground channel model.

The path loss of the LOS communication link L_{LOS} and NLOS communication link L_{NLOS} between a UAV m and user k are modeled by

$$L_{LOS} = 20\log\left(\frac{4\pi f_c d_{mk}}{c}\right) + \delta_{LOS} \tag{1}$$

$$L_{NLOS} = 20\log\left(\frac{4\pi f_c d_{mk}}{c}\right) + \delta_{NLOS} \tag{2}$$

where δ_{LOS} and δ_{NLOS} are the other free space losses under LOS and NLOS links, respectively. f_c, d_{mk}, and c are the carrier frequency, the projected 3D distance from the UAV to the user, and the speed of light, respectively. The probability of the existence of a LOS communication link L_{LOS} between the UAV m and user k are modeled by

$$P_{LOS} = \frac{1}{1 + a\exp(-b(\tau - a))} \tag{3}$$

$$\tau = \frac{180}{\pi}\arctan\left(\frac{H}{r_{mk}}\right) \tag{4}$$

where a and b are the environmental parameters, and H is the vertical distance of the UAV from the ground. The horizontal distance between the UAV m and the user k is calculated by

$$r_{mk} = \sqrt{(X_m - X_k)^2 + (Y_m - Y_k)^2} \tag{5}$$

Since the communication link is affected by environmental obstructions, we can calculate the average path loss of the link between the UAV m and the user k in this model according to (6):

$$L_{A2G} = L_{LOS} \times P_{LOS} + L_{NLOS} \times (1 - P_{LOS}) \tag{6}$$

Based on the air-to-ground channel model, we can define the communication perception range of UAVs. If the path loss between the UAV m and the user k is less than a threshold L_{th}, we assume that the user k can be sensed by the UAV m. However, the perception radius E_{max} cannot serve as the actual coverage of the service provided by the UAV. As discussed in [11, 21], the SNR of each user can be used to evaluate the communication quality of the channel without considering the interference between devices. It is calculated by (7), where P_{uav} is the UAV transmission power, and σ is the noise power:

$$SNR_{mk} = \frac{P_{\text{uav}}}{(H_m^2 + r_{mk}^2)\sigma} \quad \textbf{(7)}$$

2.4 Problem Definition

To simplify the UAV deployment problem, we map the UAV location deployment to a 2D plane, and assume that the vertical heights of all UAVs are the same during deployment. In order to maintain a good communication quality between the UAV-BS and the users, it is necessary to make the SNR greater than the threshold SNR_{th}. Using (7), the actual coverage R_m of the UAV m can be derived, and when the users are within the coverage area of the UAV m, they are considered to be covered by the UAV m. In (8), $UTG(m, k) = 1$; this means that the user k is covered by the UAV m, and $UTG(m, k) = 0$ otherwise.

$$UTG(m,k) = \begin{cases} 1, & r_{mk} \le R_m \\ 0, & r_{mk} > R_m \end{cases} \quad \textbf{(8)}$$

Then, we calculate the coverage rate COV of the UAV set $\mathcal{M}$ for all users in $\mathcal{K}$ through (9). The COV is an important factor to measure the pros and cons of a UAV deployment scheme, which needs to cover as many users as possible through appropriate path planning and location selection.

$$COV = \sum\nolimits_{m\in\mathcal{M}} \sum\nolimits_{k\in\mathcal{K}} UTG(m,k)/\ K \quad \textbf{(9)}$$

The optimization goal of our work is to use a certain number of UAVs to cover more users. The placement problem in the horizontal dimension is then formulated as where (10b) and (10c) are the constraints on the UAV location and user location, and (10d) indicates that each user is provided with communication service by at most one UAV.

$$\max \quad COV \quad \textbf{(10a)}$$

$$\text{Constraint: } loc_m \in \text{G}, \ \forall m \in \mathcal{M} \quad \textbf{(10b)}$$

$$loc_k \in \text{O}, \ \forall k \in \mathcal{K} \quad \textbf{(10c)}$$

$$\sum\nolimits_{k\in\mathcal{K}} UTG(m,k) \le 1, \ \forall k \in \mathcal{K} \quad \textbf{(10d)}$$

3 Proposed Algorithm

In this section, the proposed PSO-VFA algorithm is described in detail.

3.1 Firefly Algorithm Description

The FA algorithm is a bio-inspired optimization algorithm proposed by Yang in [22], and its main idea is based on the mutual attraction behavior of fireflies. In other words, fireflies move to other brighter fireflies in their line of sight for optimization purposes [23]. The attractiveness β_{ij} between fireflies i and j is calculated by (11):

$$\beta_{ij} = \beta_0 e^{-\lambda\gamma_{ij}^2} \quad \textbf{(11)}$$

where β_0 is the attractiveness at $\gamma = 0$, and γ is the distance between two fireflies. The parameter γ_{ij} is the distance between fireflies i and j, and λ is the light absorption coefficient. The position updating equation of a firefly is

$$x_i(t+1) = x_i(t) + \beta_{ij}(x_j(t) - x_i(t)) + \alpha\varepsilon \quad \textbf{(12)}$$

$x_i(t+1)$ denotes the position of firefly i in the $(t+1)$th iteration, $\alpha \in [0, 1]$ is the step factor, and $\varepsilon \in [-0.5, 0.5]$ is the random factor.

3.2 Virtual-Repulsive-Force-based Firefly Algorithm

To solve the problem of precise user coverage in fine-grained deployment, in this subsection, we propose an improved firefly algorithm based on a virtual repulsive force, i.e., VFA.

Virtual forces include repulsive forces and attractive forces. In the classical FA algorithm, fireflies are regarded as hermaphrodites, and any firefly may be attracted by other fireflies. To effectively deploy the UAV-BSs to user-intensive areas, we take the UAVs and users as fireflies of different genders. User-intensive areas have high attractions to UAVs, while there is no attraction between UAVs. Within the perception radius, the UAV selects the movement direction according to the fluorescent strengths of user nodes, and makes full use of the information of the user nodes to adjust its movement. β_{mk}, the attraction of the user k attraction to the UAV m, can be defined as follows:

$$\gamma_{mk} = \frac{r_{mk} - E_{min}}{E_{max} - E_{min}} \quad \textbf{(13)}$$

$$\beta_{mk} = B_k e^{-\lambda\gamma_{mk}^2} \quad \textbf{(14)}$$

where B_k represents the user's bandwidth requirement, and γ_{mk} is the normalized value of the distance between the UAV m and the user k. E_{max} and E_{min} are the maximum and minimum search ranges of the UAV, respectively. In a user-intensive area with high attraction, multiple UAVs may approach in the same direction and are close to each other. Therefore, it is necessary to adjust the positions of the UAV nodes to further expand the UAV service range and reduce the overlap area.

In addition, we introduce the virtual repulsion force for the position adjustment. For any two UAV nodes i and j, the horizontal distance between them is

$$\text{d}_{ij} = \sqrt{(X_{mi} - X_{kj})^2 + (Y_{mi} - Y_{kj})^2} \quad \textbf{(15)}$$

and the distance threshold is d_{th}. When $\text{d}_{ij} \ge \text{d}_{\text{th}}$, there is no virtual repulsion between the UAVs i and j. On the contrary, the virtual repulsion force between UAVs i and j, F_{ij}, is generated by the following:

$$F_{ij} = \begin{cases} Q(\text{d}_{ij} - \text{d}_{\text{th}}), & \text{d}_{ij} < \text{d}_{\text{th}} \\ 0, & \text{d}_{ij} \ge \text{d}_{\text{th}} \end{cases} \quad \textbf{(16)}$$

where Q is the repulsion force coefficient. Then, the virtual repulsion forces of UAV i on the X-axis and Y-axis imposed by other UAV nodes are calculated as follows:

$$\begin{cases} F_{\mathrm{x}} = \sum_{i=1, i\neq j}^{M} (F_{ij} \cdot f_x) \\ F_{\mathrm{y}} = \sum_{i=1, i\neq j}^{M} (F_{ij} \cdot f_y) \end{cases} \tag{17}$$

where f_x and f_y are the directions in which the UAV receives repulsive forces on the X-axis and Y-axis, respectively. Finally, combined with (14) and (17), the updated position of the UAV achieved by each iteration in the improved firefly search algorithm is as follows:

$$\begin{cases} X_m(t+1) = X_m(t) + \beta_{mk}(X_m(t) - X_k(t)) + \alpha\varepsilon + F_{\mathrm{x}} \\ Y_m(t+1) = Y_m(t) + \beta_{mk}(Y_m(t) - Y_k(t)) + \alpha\varepsilon + F_{\mathrm{y}} \end{cases} \tag{18}$$

3.3 PSO Algorithm Applied to the UAV Coverage Search

The PSO algorithm is an efficient parallel random search algorithm, where each particle represents a possible solution, and all particles form a population of particles. In order to find the optimal solution, the particle determines its moving speed and direction in solution space based on its historical information and group information. In the standard PSO algorithm [24], the formula for calculating the function of the ith particle in the d dimensional domain is

$$\begin{cases} V_{id}(t+1) = \omega \cdot V_{id}(t) + c1 \cdot r1 \cdot (p_{id}(t) - x_{id}(t)) \\ \qquad + c2 \cdot r2 \cdot (p_{gd}(t) - x_{id}(t)) \\ x_{id}(t+1) = x_{id}(t) + V_{id}(t+1) \end{cases} \tag{19}$$

In this paper, each particle corresponds to a deployment solution for UAVs. The population consists of N particles, and $S=\{x_1^{(t)}, x_2^{(t)}, \ldots, x_N^{(t)}\}$ denotes the position vector of all particles after the tth iteration. The position of the ith particle in the search space is $x_i^{(t)}=\{loc_{i1}^{(t)}, loc_{i2}^{(t)}, \ldots, loc_{iM}^{(t)}\}$ for the tth iteration. A particle contains all UAV nodes for this deployment solution in a 2D planar location (X_m, Y_m), $\forall m \in \mathcal{M}$. Different particles hold different location information for the UAV nodes and corresponding different user coverage rates.

As shown in Figure 3, the particle continuously updates its speed and position to the globally optimized values, and each update presents a position adjustment of all UAV nodes in each particle. UAV coverage optimization is a process in which a single particle continuously moves to the individual historical optimal particle and the globally optimal particle. However, only relying on the update of these two particles may lead to poor local search ability, because it does not take full advantage of the information of the UAVs and users, thereby limiting the convergence rate of the algorithm.

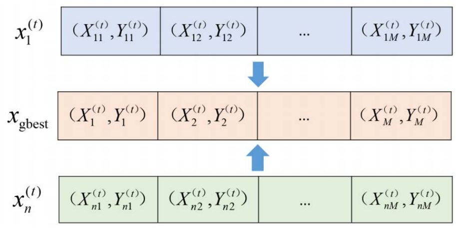


Figure 3. An instance of the process of a particle position update approaching to the globally optimal particle

3.4 PSO-VFA Algorithm

Compared with most of the other evolutionary algorithms, the PSO algorithm is a parallel search algorithm with historical memory for function. However, the PSO algorithm has some faults, such as its slow convergence rate in the later stages and its tendency to fall into local optimization, while the FA algorithm has strong local searchability [23]. Therefore, we combine the two algorithms and propose the PSO-VFA algorithm, which takes the process of the PSO algorithm as the algorithm framework. Each particle moves to the globally optimal particle and the historical individual optimal particle. After each iterative update of the position, the VFA algorithm is employed for local searching, which can make each particle adjust its position appropriately by using the information of user nodes. The PSO-VFA algorithm not only has the global parallel searchability of the PSO algorithm, it can also maintain the strong local search ability of the FA algorithm. It is described in Algorithm 1, where $Swarm\{x\}$ and $V\{x\}$ represent the position of x particles and the update velocity of x particles, respectively.

Algorithm 1. PSO-VFA

```
Input:
  M: number of UAV, T: number of iterations
  N: number of particles
  Vmax: maximum speed of particles
  Vmin: minimum speed of particles
  ω: inertia weight, c1 and c2: acceleration factors
Output:  loc_m, COV
Random initialization of all particles Swarm and velocity V
Calculate all particle objective function value COV, save gbest
  and pbest
for i=1, 2, …, T do
   for x=1, 2, …, N do
      Calculate particle update velocity:
         V{x}⟵ ω · V{x} + c1· rand() · (pbest{x}−
         Swarm{x}) + c2 · rand() ·(gbest − Swarm{x})
      Process particle velocity:
         Vmin ≤ V{x} ≤ Vmax
      Update particle position:
         Swarm{x}⟵ Swarm{x} + V{x}
      Use the VFA algorithm to adjust UAV position
      Calculate objective function value COV
      Update gbest and pbest :
         if COV > fun(gbest)
            gbest ⟵ Swarm{x}
         end if
         if COV > fun ( pbest{x} )
            pbest{x}⟵ Swarm{x}
         end if
   end for
end for
   loc_m ⟵ gbest (m)
return  loc_m ,  COV
```

4 Performance Evaluation and Analysis

4.1 Simulation Settings

In this paper, simulations are conducted on a computer with an Intel Core i5-9600KF processor (3.7 GHz) and 16 GB RAM. The proposed algorithm is coded in MATLAB and run on Windows10 1903. The target area is mapped to a 1000 m × 1000 m rectangular plane. The coordinates of the user and UAV nodes are generated using the *rand*() function of MATLAB. The number of ground user nodes is *K*. The number of more suitable UAV nodes *M* is calculated based on the UB-K-Means algorithm [11], and the distance threshold d_{th} is $\sqrt{3}R_m$ [19]. The specific experimental parameters are listed in Table 2. The algorithm parameters are set as follows: ω=0.5, $c1$=1.5, $c2$=1.5, $\alpha\in$[0, 10], and $\varepsilon\in$[-0.5, 0.5].

Table 2. Simulation parameters

Param.	Description	Value
A	Region area	1000 m × 1000 m
K	Number of user nodes	120
M	Number of UAV nodes	8
D_x	Max. moving step of UAV on X-axis	20 m
D_y	Max. moving step of UAV on Y-axis	20 m
d_{th}	Distance threshold between UAVs	$\sqrt{3}R_m$
L_{th}	Path loss threshold	85 db
N	Number of particles	20
T	Number of iterations	100
H_1	Vertical height of the UAV in the Suburban	73 m
H_2	Vertical height of the UAV in the Urban	142 m
R_m	UAV communication coverage radius	180 m

Additionally, we should choose the maximum perception radius, the optimal vertical height, and the optimal perception radius of the UAV. In this work, we set the parameters of the simulation scenes as given in [20], and they are shown in Table 3. Second, we find the optimal vertical height and optimal perception radius of the UAV. In Figure 4, the blue and red curves depict the change in the UAV's perceived radius with vertical height in the Suburban and Urban environments, respectively.

According to these curves, we can see that the optimal perception radius of the UAV in the Suburban environment is 264 m, and that of the Urban environment is 205 m. That is to say, the search radiuses in the VFA algorithm will be different due to the different perception radiuses in the two scenarios.

Table 3. Environmental parameters

Simulation Environment	a	b	δ_{LOS}	δ_{NLOS}
Suburban	4.88	0.43	0.1	20
Urban	9.61	0.16	1	20

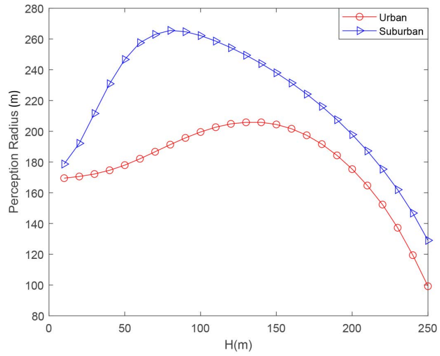
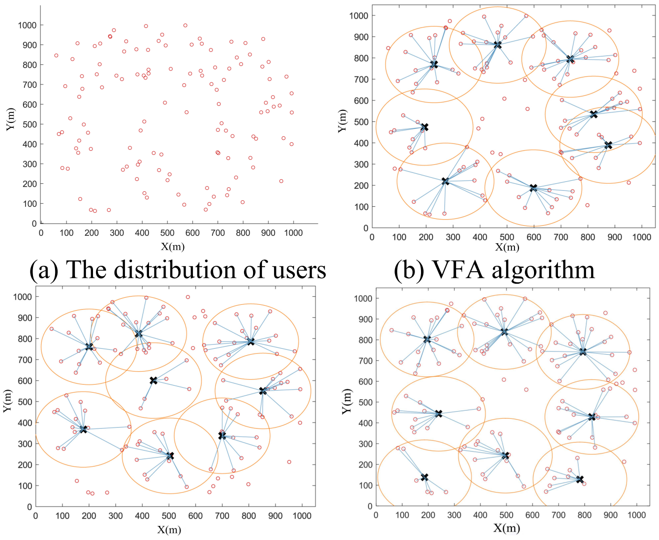


Figure 4. Perception radiuses in different altitudes

4.2 Results and Analysis

In this section, we verify and evaluate the effectiveness of our proposed algorithms in terms of the coverage rate in the Suburban and Urban environments.

The simulation scenario of the Suburban environment is presented in Figure 5(a), in which the users are randomly distributed, and the UAVs are deployed to their optimal vertical height to maximize the perception radius. Figure 5(b) to Figure 5(d) show the deployment locations of UAVs optimized by the VFA, PSO, and PSO-VFA algorithms, respectively. The orange circles represent the actual communication coverage of UAVs, and the blue lines are the wireless connections between UAVs and users. The VFA algorithm covers fewer overlapping areas than the PSO algorithm, and the UAV individuals tend to be distributed in more user-intensive areas than those in the PSO algorithm.

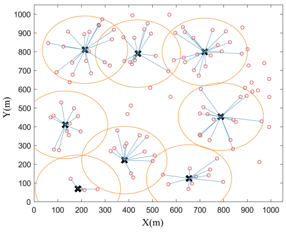


(a) The distribution of users (b) VFA algorithm

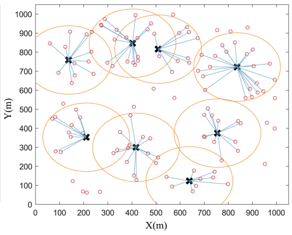
(c) PSO algorithm (d) PSO-VFA algorithm

Figure 5. UAV deployments with different algorithms in the target area of suburban

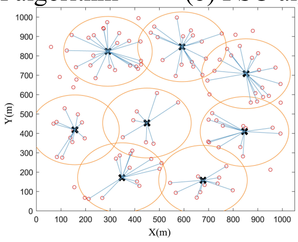
The perception radiuses of the Urban and Suburban scenarios are different, which is manifested in the different search radiuses in the VFA algorithm. Figure 6 shows the UAV deployment in the target area of the Urban environment. Compared with the VFA and PSO algorithms, the final deployment position of the UAVs based on the PSO-VFA algorithm makes the maximum number of user nodes covered by the UAVs. In particular, due to the combination of the advantages of the PSO and improved FA algorithms, the overlapping area between UAVs is the smallest for the PSO-VFA algorithm.



(a) VFA algorithm



(b) PSO algorithm

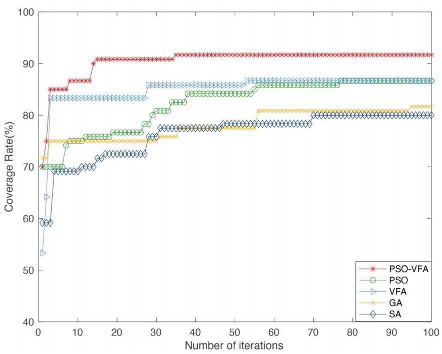


(c) PSO-VFA algorithm

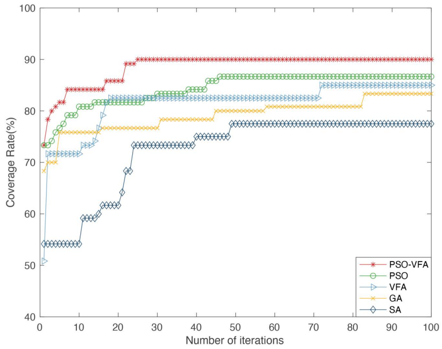
Figure 6. UAV deployments with different algorithms in the target area of Urban

We assume that the scenario of the Urban environment is the same as Figure 5(a). The coverage evolution curves of the three algorithms are shown in Figure 7. In the Suburban environment, the coverage reaches 91.7% after 100 iterations in the PSO-VFA case, while the coverage for both the VFA and PSO algorithms is 86.7%. In addition, the coverages of GA and SA reach 81.7% and 80.0%, respectively. The convergence rate of the VFA algorithm is faster than that of the PSO algorithm, while the PSO case has more feasible solutions than the FA case at the initial deployment, and its coverage is higher at initialization. Moreover, the initial coverage of the PSO-VFA algorithm is the same as that of the PSO algorithm, because the initial particles are the same.

In the Urban environment, as shown in Figure 7(b), the coverages of the PSO-VFA, VFA, PSO, GA, and SA algorithms are 90%, 85%, 86.7%, 83.3%, and 77.5%, respectively. Compared with the Suburban environment, the searchability of VFA is weakened, and the convergence rate of the PSO-VFA algorithm is slowed down due to the reduction of the UAV perception radius. It turns out that the search radius affects the search performance of the VFA algorithm, and a higher search radius can speed up the convergence. The results given in Figure 7 indicate that the coverage rate of the PSO-VFA algorithm is higher than that of the other two, and the convergence rate is faster. Additionally, the number of iterations required to reach an exact coverage rate is also the smallest for PSO-VFA.



(a) Suburban



(b) Urban

Figure 7. Coverage evolution curves of PSO-VFA, PSO, VFA, GA, and SA under different environments

In terms of algorithm complexity, the VFA algorithm has the lowest complexity, followed by the PSO algorithm. The time complexity of VFA is O($T*M*K$), because its optimization search is only carried out on the basis of a set of solutions. The PSO algorithm is second, and its time complexity is O($T*S*M$). The proposed hybrid algorithm, PSO-VFA, integrates the VFA algorithm and the basis of the PSO algorithm to adjust the position of the UAVs in more detail, so its time complexity is O($T*S*M*K$). While the algorithm complexity of the PSO-VFA algorithm is higher than that of the two other algorithms, it has little impact on the normal system overhead.

Figure 8 shows the average coverage of 120 users deployed after 100 iterations with different algorithms in a suburban environment, while increasing the number of UAVs. In terms of coverage index, it shows that the proposed PSO-VFA algorithm is significantly better than the SA algorithm. When the number of UAVs is more than 5, the PSO-VFA algorithm is more significant than the other four algorithms. When the number of UAVs reaches 11, the PSO-VFA algorithm achieves full user coverage.

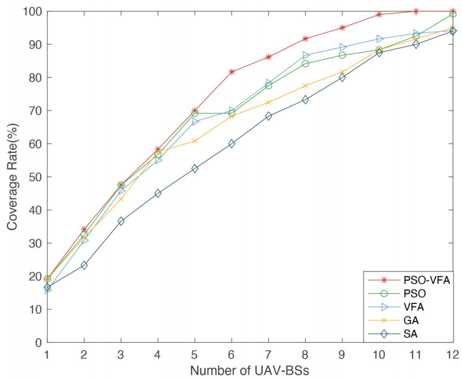


Figure 8. Coverage rate in different number of UAVs

5 Conclusion

Aiming at target application environments where UAVs cover evenly distributed user nodes, we first deduced the best perception radius and vertical height of the UAV based on two different scenarios. Then, we improved the standard FA algorithm and proposed the VFA algorithm, taking the perception radius as the search range of the UAV. On this basis, introducing the PSO algorithm as a framework, the two intelligent algorithms are combined to make up for the weak global search ability of the VFA algorithm and the slow convergence rate of the PSO algorithm in the later stage, which can easily fall into local optimization. The simulation results indicate that the proposed PSO-VFA algorithm, integrating the features of the PSO and VFA algorithms, can achieve a better optimization effect and is effective in the coverage optimization of the UAV nodes.

In this work, we focus on the optimization of the fine-grained deployment of UAVs, and we will consider the UAV's energy consumption more in the future. Because the power of the battery carried by the UAV is limited in actual applications, it is necessary to balance the energy consumption between UAVs so as to prolong the service time of the entire network. Therefore, the next step is to consider how to prolong the flight time of UAVs and ensure the reliability of the network on the basis of optimizing the deployment coverage.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China (NSFC) under grant 61902437, the Hubei Provincial Natural Science Funds of China under grant 2020CFB629, and the Fundamental Research Funds for the Central Universities, South-Central MinZu University under grant CZY22016.

References

[1] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, M. Debbah, A tutorial on UAVs for wireless networks: Applications, challenges, and open problems, *IEEE communications surveys & tutorials*, Vol. 21, No. 3, pp. 2334-2360, Third quarter, 2019.

[2] T. Peng, X. Li, X. Li, R. Qian, Joint trajectory and resource allocation design for throughput optimization in UANET, *Journal of Internet Technology*, Vol. 21, No. 6, pp. 1795-1808, November, 2020.

[3] T. Xiang, H. Wang, G. Yang, X. Meng, Research on distributed UAV network coverage optimization algorithm, *Journal of Air Force Engineering University (Natural Science Edition)*, Vol. 20, No. 4, pp. 59-65, January, 2019.

[4] Z. Li, L. Yang, D. Wang, W. Zheng, Parameter estimation of software reliability model and prediction based on hybrid wolf pack algorithm and particle swarm optimization, *IEEE Access*, Vol. 8, pp. 29354-29369, February, 2020.

[5] E. D'Amato, M. Mattei, I. Notaro, Bi-level flight path planning of UAV formations with collision avoidance, *Journal of Intelligent & Robotic Systems*, Vol. 93, No. 1, pp. 193–211, February, 2019.

[6] J. Li, Y. Xiong, J. She, M. Wu, A path planning method for sweep coverage with multiple UAVs, *IEEE Internet of Things Journal*, Vol. 7, No. 9, pp. 8967-8978, September, 2020.

[7] C. Wang, F. Ma, J. Yan, D. De, S. K. Das, Efficient aerial data collection with UAV in large-scale wireless sensor networks, *International Journal of Distributed Sensor Networks*, Vol. 11, No. 11, pp. 1-19, November, 2015.

[8] Z. Liu, Y. Shi, Y. Zeng, Y. Gong, Radar emitter signal detection with convolutional neural network, *2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT)*, Jinan, China, 2019, pp. 48-51.

[9] M. M. Azari, F. Rosas, K.-C. Chen, S. Pollin, Optimal UAV positioning for terrestrial-aerial communication in presence of fading, *2016 IEEE Global Communications Conference (GLOBECOM)*, Washington, DC, USA, 2016, pp. 1-7.

[10] Y. Chen, N. Li, C. Wang, W. Xie, J. Xv, A 3D placement of unmanned aerial vehicle base station based on multi-population genetic algorithm for maximizing users with different QoS requirements, *2018 IEEE 18th International Conference on Communication Technology (ICCT)*, Chongqing, China, 2018, pp. 967-972.

[11] H. Qu, W. Zhang, J. Zhao, Z. Luan, C. Chang, Rapid deployment of UAVs based on bandwidth resources in emergency scenarios, *2020 Information Communication Technologies Conference (ICTC)*, Nanjing, China, 2020, pp. 86-90.

[12] L. Yin, N. Zhang, C. Tang, On-demand UAV base station deployment for wireless service of crowded tourism areas, *Personal and Ubiquitous Computing*, pp. 1-13, February, 2021.

[13] X. Zhang, L. Duan, Fast deployment of UAV networks for optimal wireless coverage, *IEEE Transactions on Mobile Computing*, Vol. 18, No. 3, pp. 588-601, March, 2019.

[14] X. Liu, Y. Liu, Y. Chen, Reinforcement learning in multiple-UAV networks: deployment and movement design, *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 8, pp. 8036-8049, August, 2019.

[15] G. Chen, L. Wang, M. Alam, M. Elhoseny, Intelligent group prediction algorithm of GPS trajectory based on vehicle communication, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 22, No. 7, pp. 3987-3996, July, 2021.

[16] X. Lu, W. Cheng, Q. He, J. Yang, X. Xie, Coverage optimization based on improved firefly algorithm for mobile wireless sensor networks, *2018 IEEE 4th International Conference on Computer and Communications (ICCC)*, Chengdu, China, 2018, pp. 899-903.

[17] Y. Zhang, L. Zhang, C. Liu, 3-D deployment optimization of UAVs based on particle swarm algorithm, *2019 IEEE 19th International Conference on Communication Technology (ICCT)*, Xi'an, China, 2019, pp. 954-957.

[18] H. Wang, H. Zhao, W. Wu, J. Xiong, D. Ma, J. Wei, Deployment algorithms of flying base stations: 5G and beyond with UAVs, *IEEE Internet of Things Journal*, Vol. 6, No. 6, pp. 10009-10027, December, 2019.

[19] T. Zhao, H. Wang, Q. Ma, The coverage method of unmanned aerial vehicle mounted base station sensor network based on relative distance, *International Journal of Distributed Sensor Networks*, Vol. 16, No. 5, doi:10.1177/1550147720920220, May, 2020.

[20] A. Al-Hourani, S. Kandeepan, S. Lardner, Optimal LAP altitude for maximum coverage, *IEEE Wireless Communications Letters*, Vol. 3, No. 6, pp. 569-572, December, 2014.

[21] C. Zhang, L. Zhang, L. Zhu, T. Zhang, Z. Xiao, X. Xia, 3D deployment of multiple UAV-mounted base stations for UAV communications, *IEEE Transactions on*

Communications, Vol. 69, No. 4, pp. 2473-2488, April, 2021.
[22] X.-S Yang, *Nature-Inspired Metaheuristic Algorithms*, Luniver Press, 2008.
[23] L. Zhou, L. Ding, M. Ma, W. Tang, An accurate partially attracted firefly algorithm, *Computing*, Vol. 101, No. 5, pp. 477-493, May, 2019.
[24] S.-K. S. Fan, C.-H. Jen, An enhanced partial search to particle swarm optimization for unconstrained optimization, *Mathematics*, Vol. 7, No. 4, Article No. 357, April, 2019.

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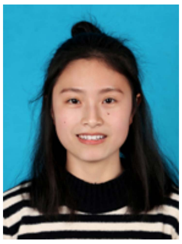

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