Towards 3D Deployment of UAV Base Stations in Uneven Terrain

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Abstract—Unmanned Aerial Vehicles (UAVs), also known as drones, have become a new paradigm to provide emergency wireless communication infrastructure when conventional base stations are damaged or unavailable. In this paper, we propose new schemes to enable the 3D deployment of drones, which can provide network coverage and connectivity services for users located in uneven terrain. We formalize two models, including optimal coverage model and optimal connectivity model, which belong to \textit{NP}-hard. To be specific, we first consider both the quality of service (QoS) requirements of users and the capacity of drones. We then formalize the problem and design a heuristic scheme, called Particle Swarm Optimization (PSO) algorithm to achieve a cost-effective solution. We also address the optimal connectivity problem in a scenario, in which a number of isolated local networks have been established by users through ad hoc communication and/or device-to-device (D2D) communication. We further develop the cost-effective heuristic algorithm to effectively minimize the total number of required drones. Via extensive performance evaluation, our experimental results demonstrate that the proposed schemes can achieve the effective deployment of drones for users in uneven terrain with respect to the number of required drones.

Index Terms—Unmanned Aerial Vehicles, Coverage and Connectivity, Network Performance Optimization, Mobile Networks

I. INTRODUCTION

With the advancement of wireless communication techniques, Unmanned Aerial Vehicles (UAVs), also known as drones, are playing an important role to support numerous applications, such as public safety disaster recovery, and monitoring and control of cyber-physical systems (smart grid, smart transportation, smart city, etc.) [1]–[7]. To support applications, UAVs can serve as drone Base Stations (BSs) in the air. Unlike conventional ground Base Stations (BSs), drone BSs can help provide wireless network service in cases where the ground base stations do not exist or have been damaged. Thus, determining how to dynamically deploy emergency mobile communication infrastructures with limited resource becomes critical.

Due to their aerial capabilities, drones can be rapidly deployed and dynamically relocated. Thus, the deployment of drones is a promising solution to resolve communication outages. A number of considerable efforts have been devoted to the deployment of drone-assisted network infrastructures [8]–[19]. Nonetheless, there are a number of avenues for improvement. For example, in some of these schemes, only the placement of one drone was considered [8], [9]. While the deployment of multiple drones has been considered, a number of existing schemes have assumed that the altitude of the drones is constant, such that the deployment problem in 3D space can be mapped into a deployment problem in 2D space. In addition, most of the existing studies assume that all users are located on a flat plane [10]–[13]. Thus, based on these assumptions, existing schemes for the deployment of drones resolve only a specific situation, and cannot be generalized to various scenarios.

More practically, in this paper we consider the situation where users are located on uneven terrain, in comparison with the existing works. Because the different altitudes of users result in a different angle of elevation between the users and drones, the path loss varies among users. To ensure that the deployment scheme is more applicable in real-world scenarios, it is important for the deployment schemes to consider users with different altitudes. In addition, users in different situations may have different performance requirements, and drones have limited network capacity. Thus, the deployment schemes should satisfy both the performance requirements of the users and capacity constraints of the drone.

The primary contributions of this paper are summarized below:

- We present novel schemes that conduct the 3-dimensional deployment of drones, which provide the coverage and connectivity for users. We formalize two models, including optimal coverage model and optimal connectivity model, which belong to \textit{NP}-hard. Particularly, with respect to the coverage with performance guarantee to users, we consider the situation in which users need to be covered by drones and obtain sufficient bandwidth, while the number of deployed drones and their capacities are considered. In addition, we formalize the problem and design a cost-effective heuristic algorithm, Particle Swarm Optimization (PSO) algorithm to compute the positions and altitudes of drones. With respect to connectivity, we consider a realistic scenario, in which the critical issue is to connect each user with the minimum number of
TABLE I

<table>
<thead>
<tr>
<th>Notations</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>$a, b$</td>
<td>Constant values of environments</td>
</tr>
<tr>
<td>$\eta_{\text{LoS}}$</td>
<td>Average additional loss to the free space propagation for LoS connection</td>
</tr>
<tr>
<td>$\eta_{\text{NLoS}}$</td>
<td>Average additional loss to the free space propagation for NLoS connection</td>
</tr>
<tr>
<td>$f_c$</td>
<td>The carrier frequency</td>
</tr>
<tr>
<td>$C_j$</td>
<td>The capacity of the drone $j$</td>
</tr>
<tr>
<td>$B_i$</td>
<td>The required bandwidth of user $i$</td>
</tr>
<tr>
<td>$d_{i,j}$</td>
<td>The distance between user (or drone) $i$ and $j$</td>
</tr>
<tr>
<td>$R_u$</td>
<td>The communication radius of each user</td>
</tr>
<tr>
<td>$R_d$</td>
<td>The communication radius of each drone</td>
</tr>
<tr>
<td>$N_u$</td>
<td>The number of all users</td>
</tr>
<tr>
<td>$N_d$</td>
<td>The number of all drones</td>
</tr>
<tr>
<td>$N_s$</td>
<td>The number of local networks established by the users</td>
</tr>
<tr>
<td>$U_u$</td>
<td>The set of all users</td>
</tr>
<tr>
<td>$U_d$</td>
<td>The set of all drones</td>
</tr>
<tr>
<td>$U_s^{(k)}$</td>
<td>The set of users which belong to the $k^{th}$ local network</td>
</tr>
<tr>
<td>$\text{PL}_{i,j}$</td>
<td>The path loss between the user $i$ and drone $j$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>The allowed maximum path loss</td>
</tr>
</tbody>
</table>

For this purpose, the users will form a number of isolated local networks and within each network, users are connected through ad-hoc and/or D2D communication. In this case, the drones can provide connectivity between different local networks that are originally isolated. To resolve drone capacity limitations, we design a cost-effective algorithm that can compute the minimal number of drones to provide the required connectivity of different local networks.

- Through the extensive experimentation, we evaluate the performance of our proposed schemes with respect to the quantity of drones which reflect the deployment cost. Our performance evaluation encompasses four scenarios, including suburban, urban, dense urban, and high-rise urban environments. Our experimental results show that there exist different levels of path loss between the various scenarios, and that path loss increases with the increasing altitude or distance between the users and drones. In addition, we demonstrate that our schemes can reduce the number of drones required to provide adequate network services.

The remainder of the paper is organized as follows: We introduce system model in Section II. We formalize the problems in Section III. We present our proposed schemes in Section IV. In Section V, we provide our experimental results and validate the effectiveness of our proposed schemes. In Section VI, we review relevant research literature. Finally, we conclude the paper in Section VII.

II. SYSTEM MODEL

To enable the deployment of drones in the uneven terrain, we consider an area where users are located in different altitudes, as shown in Fig. 1. It is worth noting that the increasing altitude of users will reduce the coverage radius of drones. To make the deployment scheme feasible in real-world practice, we must consider how to provide network services for users on uneven terrain. All notations in this paper is shown in Table I.

Considering that the drones are deployed at different altitudes from users, it is necessary to use a proper air-to-ground channel model that reflects such a condition. One representative model is the optimal Low-altitude Aerial Platforms (LAP) altitude model proposed in [8], which can provide the maximum radio coverage to users on the ground. Considering the effects of obstacles (buildings, trees, etc.), there exist two conditions: (i) Line-of-Sight (LoS) and (ii) Non-Line-of-Sight (NLoS), as shown in Fig. 2. The former indicates that the signals propagate in a straight line from a sender to receiver, while the latter denotes that the receivers can still receive coverage without LoS, via strong reflections and diffractions. Furthermore, we consider that the drone BSs have the same transmit power. Then, their coverage radius only depends on the path loss of the air-to-ground channel model.

According to the above air-to-ground channel model, the probability of LoS, denoted as $P(\text{LoS})$, is an important factor in modelling air-to-ground path loss [8]. This probability can be formulated as:

$$P(\text{LoS}) = \frac{1}{1 + a \exp(-b(\frac{180}{\pi} \theta - a))}.$$  \hspace{1cm} (1)

Here, $a$ and $b$ are constant values that depend on the environment (suburban, urban, dense urban, high-rise urban, etc.) and $\theta$ is the elevation angle, which is equal to $\arctan(\frac{\Delta h}{r})$, where $r$ is the horizontal distance between the drone and the user, and $\Delta h = h_d - h_u$ is the height difference between the drone’s height $h_d$ and user’s height $h_u$, respectively.

Then, if we ignore the random behaviors of the radio channel, the mean path loss model can be used [8]:

$$\text{PL} = 20 \log\left(\frac{4\pi f_c d}{c}\right) + P(\text{LoS})\eta_{\text{LoS}} + P(\text{NLoS})\eta_{\text{NLoS}},$$ \hspace{1cm} (2)

where $f_c$ is the carrier frequency, $c$ is the speed of light, and $d = \sqrt{\Delta h^2 + r^2}$ is the distance between the drone and the user. In addition, $P(\text{NLoS}) = 1 - P(\text{LoS})$, and $\eta_{\text{LoS}}$, and $\eta_{\text{NLoS}}$
are the average additional losses due to free space propagation, for LoS and NLoS connections, respectively, which depend on the environment.

III. PROBLEM FORMALIZATION

We now present the problem formalization. Recall that the objective of this study is to provide coverage and connectivity for users. In the following, we first present the problem formulation of optimal coverage, and then present the optimal connectivity problem.

A. Optimal Coverage Problem

With respect to coverage, one key issue is to ensure that the users can obtain sufficient network resources from the drones, as shown in Fig. 3. In this situation, the drones must provide coverage to connect with users directly, and satisfy the network performance requirements of corresponding users. To provide satisfactory QoS for these users, the drones must satisfy the following requirement:

\[ \sum_{i \in U_j} B_i \leq C_j. \]  

Here, \( U_j \) is the set of users that are connected with drone \( j \), \( B_i \) is the required bandwidth by user \( i \), and \( C_j \) is the capacity of drone \( j \).

Similarly, the drones will also establish a wireless network to help exchange data among each other. To ensure each drone can communicate with other drones, the connectivity between them must be satisfied as well. That is, no matter how the network of drones is divided, there exists at least one path between the two divided parts. Then, this constraint can be formalized as follows:

\[ \forall U'_d \subseteq U_d, \exists i \in U'_d, j \in U_d \setminus U'_d : d_{i,j} \leq R_d, \]  

where \( U_d \) is the set of all drones, \( U'_d \) represents any nonempty subset of \( U_d \), \( d_{i,j} \) is the distance between drone \( i \) and \( j \), and \( R_d \) is the communication radius of each drone.

Then, to maintain connectivity amongst all users, each user must be connected to at least one drone, namely,

\[ \forall i \in U_u, \exists j \in U_d, PL_{i,j} \leq \gamma, \]  

where \( U_u \) is the set of all users, \( U_d \) is the set of all drones, and \( \gamma \) is the required maximum level of path loss acceptable to users.

B. Optimal Connectivity Problem

With respect to connectivity, a key issue is that users must be connected with each other, as shown in Fig. 4. Thus, we can frame the issue as an optimal connectivity problem, which can be solved to provide connectivity for users while requiring the minimum number of drones. To address this issue, we assume that neighboring users can exchange data without the assistance of drones. That is to say, if the neighbor users are located close enough, they can communicate with their neighbors by establishing a local network using ad-hoc and/or D2D communications among them.

To ensure that each user can communicate with other users in the same local network, the connectivity among users must be satisfied (i.e., no matter how local networks are divided), there always exists at least one path between the two divided parts. The constraint can be formalized as follows:

\[ \forall U'_s \subseteq U_s, \exists i \in U'_s, j \in U_s \setminus U'_s : d_{i,j} \leq R_u, \]  

where \( U'_s \) is the set of users in the \( k \)th local networks, \( U_s \) represents any nonempty subset of \( U_s \), \( d_{i,j} \) is the distance between user \( i \) and \( j \), and \( R_u \) is the communication radius of each user. Similar to the former problem, the drones must also establish a wireless network between themselves to help share data among the drones. This constraint is shown in Equation (4).

Next, the connectivity between the drones and the established local networks should be satisfied. Thus, there must exist at least one user in each local network who can communicate with the drone directly. Similarly, the constraint can be represented below:

\[ \forall U_s, \exists i \in U_s, j \in U_d : PL_{i,j} \leq \gamma, \]  

where \( U_s \) is the set of users in the local network, \( U_d \) is the set of all drones, and \( \gamma \) is the maximum level of path loss allowed by users.

IV. OUR APPROACH

In this section, we propose two optimal models to solve the problems defined in Section III. In these two models, we propose a cost-effective PSO algorithm to find the optimal positions and altitudes of drones. In the following, we first present the design rationale and then present our solutions for optimal coverage and optimal connectivity problems.
A. Design Rationale

Recall that the drones can satisfy different levels of requirements from users and two optimization problems are presented in Section III. To address these issues, we propose two optimal models, each to solve the coverage and connectivity problems. The objective of the optimal coverage model is to maximize the QoS for users (i.e., satisfying the requirements of users under the limitation of drone capacity and/or a limited number of drones). In addition, we consider another model, which only focuses on reducing the number of required drones while ignoring the network performance requirements. Thus, the objective of the optimal connectivity model is to minimize the number of drones while maintaining the connectivity of users.

To be specific, in the former model, the limitation of drone capacity is considered when satisfying the QoS of users. Under the limitation of drone capacity, the required bandwidth of each user can be well satisfied. Then, in the latter model, neighboring users will form local networks to exchange data. With the help of the local networks, the number of required drone will be reduced. In summary, these two optimization problems can be solved, and the applications deployed to users can achieve satisfactory levels of performance.

If we assume all users as a universe $U_u$ and the users covered by the same drone BS as a subset of a universe $U_{u_d}$, the deployment arrangements of the drone BSs can be reflected by a family $S$ of subsets of $U_u$, then the objective of the above optimal coverage problem will become to find out a subfamily $C \subseteq S$ that uses the fewest subsets and ensures their union is $U_u$. This is the typical set covering optimization problem [20], which is a well-known $NP$-hard problem [21]. In addition, the above optimal connectivity problem can be considered as an optimal coverage problem among the selected edge users of the local networks. It means that the optimal connectivity model is also an $NP$-hard problem. Thus, the overhead of exhaustive algorithm for both of optimization problems will become unacceptable when the number of the users and drones increases and a cost-effective heuristic algorithm needs to be designed to solve the above two problems. Notice that the PSO algorithm, as a cost-effective heuristic algorithm, is designed for supporting both optimal models. The detailed processes are presented below.

B. Optimal Coverage Model

We now present the optimal coverage model, including constraints, algorithms, and analysis.

1) Constraints: Considering the QoS requirements of some users, the sum of the required bandwidths of users who are connected with a drone should not exceed the limitation of the capacity of the drone. Then, the minimum number of required drones can be derived based on the constraint of drone capacity. First, to ensure the QoS of users, each user should be connected to at least one drone, which can be represented as:

$$\forall i \in U_j : PL_{i,j} \leq \gamma,$$

where $i$ is the user in the set $U_j$, $U_j$ is the set of users that can be connected to drone $j$, $PL_{i,j}$ is the path loss between the user $i$ and drone $j$, and $\gamma$ is the maximum allowed path loss.

In addition, the sum of required bandwidth in user set $U_j$ cannot exceed the capacity of drone $j$. Then, the coverage problem can be represented as follows:

$$\begin{align*}
\min & \quad N_d \\
\text{s.t.} & \quad \forall i \in U_u, \exists j \in U_d: PL_{i,j} \leq \gamma \\
& \quad \forall j \in U_d: \sum_{i \in U_j} B_i \leq C_j \\
& \quad \forall U'_d \subseteq U_d, \exists i \in U'_d, j \in U_d \setminus U'_d: d_{i,j} \leq R_d
\end{align*}$$

Here, $N_d$ is the number of required drones, $PL_{i,j}$ is the path loss between user $i$ and drone $j$, $\gamma$ is the maximum allowed path loss, $U_u$ is the set of all users, $U_d$ is the set of all drones, $U_j$ is the set of users connected with drone $j$, $B_i$ is the required bandwidth by user $i$, $C_j$ is the capacity of drone $j$, $d_{i,j}$ is the distance between the user or drone $i$ and $j$, $U'_d$ represents any nonempty subset of $U_d$, and $R_d$ is the communication radius of each drone.

2) Exhaustive Algorithm: As the number of users and drones are limited, it is obvious that the drone deployment problem can be solved by an exhaustive algorithm. Nonetheless, an exhaustive algorithm will incur a significant computational overhead, and may even become impossible in practice, especially when there are many users in the target area.

To demonstrate the problem’s complexity, we present the 2D deployment problem as a simplified example. In a 2D deployment problem, all $N_u$ users are located on a flat plane, meaning that their altitudes are not considered. Furthermore, the coverage of $N_d$ drones can be treated as a series of circles, which have the same radius $R$. Thus, the objective of the 2D deployment problem will become how to cover a series of given points on the 2D plane with the least number of circles having the same size.

We now present an exhaustive algorithm to solve the above problem as follows. In the first step, all the point pairs whose distance is no greater than $2R$ will be identified, as these point pairs can be covered by one circle (drone). Otherwise, each point pair requires two circles to cover each point of the pair if their distance is greater than $2R$. Denote the number of
the complexity of the above exhaustive algorithm, the time complexity of the first step is \( O(N_d \cdot (N_d - 1)) \), and the time complexity of the second step is \( O(2^m) \). The range of \( m \) can be \([N_d - 1, N_d \cdot (N_d - 1)]\), depending on the locations of users on the 2D plane. Thus, as the number of users increases, the complexity of the exhaustive algorithm will increase even more rapidly and eventually become computationally unacceptable. As the UAV’s coverage problem involves a 3D plane, the complexity of the exhaustive algorithm will increase even more rapidly and eventually become computationally unacceptable as well.

3) PSO Algorithm: As we mentioned above, finding the locations of drones is a very complicated problem (NP-hard), especially when their altitudes are involved in a 3D plane. In order to solve this problem, some heuristic algorithms such as particle swarm and genetic algorithms can be applied. In this paper, we propose a solution with PSO algorithm [22]. First, the PSO algorithm initializes a population of random solutions and corresponding fitness values referring to quality of given metrics. Then, it will iteratively update candidate solutions to improve their individual best fitness value, as well as the global best fitness value of all candidate solutions. Both can affect the update process in the next round. In our algorithm, to compare the results of each candidate solution, the fitness value should be composed of two key components: the bandwidth requirements and the path loss of users.

First, when the positions and altitudes of drones are initialized, the connectivity between the users and the drones is much more important than the path loss between them. Thus, we consider a fitness value as a function of the satisfied bandwidth requirements of users, which is preliminarily defined as,

\[
F_1 = \sum_{j \in U_d} \sum_{i \in U_j} B_i, \quad (10)
\]

where \( U_d \) is the set of all drones, \( U_j \) is the set of users connected with drone \( j \), and \( B_i \) is the required bandwidth by user \( i \).

Thus, the fitness value \( F_1 \) will increase with the increasing number of connected users. To maximize the number of connected users, the set of users who are connected with drone \( j \) must satisfy the following constraints:

\[
\max \left\| U_j \right\| \quad \text{s.t.} \quad \sum_{i \in U_j} B_i \leq C_j, \quad \forall i \in U_j : \text{PL}_{i,j} \leq \gamma \quad (11)
\]

Here, \( U_j \) is the set of users connected with drone \( j \), \( B_i \) is the required bandwidth by user \( i \), and \( C_j \) is the capacity of drone \( j \).

Second, when all the users are connected, our approach will attempt to reduce the path loss between the users and drones. Thus, we consider another fitness value as follows:

\[
F_2 = -\sum_{i \in U_u} \min(\text{PL}_{i,\cdot}), \quad (12)
\]

where \( U_u \) is the set of all users, and \( \text{PL}_{i,\cdot} \) is the path loss between user \( i \) and any drone. Thus, the fitness value \( F_2 \) will increase when the total path loss of users decreases.

According to Equations (10) and (12), when all the users are connected to the drones, the fitness value \( F_1 \) will reach the maximum value, and the fitness value \( F_2 \) will always have a upper bound. The maximum value of \( F_1 \) and the minimum value of \( F_2 \) can be represented as follows:

\[
F_1_{\text{max}} = \sum_{i \in U_u} B_i, \quad (13)
\]

\[
F_2_{\text{min}} = -\gamma \cdot N_u. \quad (14)
\]

Then, the fitness value that measures the performance of the candidate solutions is the combination of the two, defined as:

\[
F = \begin{cases} 
\sum_{j \in U_d} \sum_{i \in U_j} B_i - \gamma \cdot N_u, & \bigcup_{j \in U_d} U_j \subseteq U_u \\
\sum_{i \in U_u} \min(\text{PL}_{i,\cdot}), & \bigcup_{j \in U_d} U_j = U_u 
\end{cases} \quad (15)
\]

Thus, the objective of finding the optimal deployment position for drones is determined by finding the candidate solution with the maximum fitness value.

**Algorithm 1** PSO algorithm for optimal connectivity problem

1. Initialize \( N_p \) random particles, each particle has size \( 3 \times N_d \). Set fitness \( F^{(k)} = F^{(k)}_{\text{local}}, F^{(k)}_{\text{global}} = \min\{F^{(k)}_{\text{local}}, k = 1, \ldots, N_p\} \)
2. while \( t < t_{\text{max}} \) do
3. for each \( k \in [1, N_p] \) do
4. Update \( P^{(k)}, V^{(k)}, F^{(k)} \);
5. if \( F^{(k)}_{\text{local}} < F^{(k)} \) then
6. \( F^{(k)}_{\text{local}} = P^{(k)}_{\text{local}} = F^{(k)} \);
7. if \( F^{(k)}_{\text{local}} < F^{(k)}_{\text{global}} \) then
8. \( F^{(k)}_{\text{global}} = F^{(k)}_{\text{local}}, F^{(k)}_{\text{global}} = F^{(k)}_{\text{local}} \);
9. if Redundancy is found then
10. \( N_d \) decreases by 1;
11. Update all parameters;
12. end if
13. end if
14. end if
15. end for
16. \( t = t + 1 \);
17. end while

Notice that, at the beginning of the PSO algorithm, \( N_p \) particles and their corresponding velocities are randomly initialized. Each particle is formed as a series of triples, which represent the coordinates of all drones. Then, the best fitness value for each particle is denoted as \( F^{(k)}_{\text{local}} \), and the best fitness value for all particles is denoted as \( F^{(k)}_{\text{global}} \), while the corresponding position and velocity are denoted as \( P^{(k)} \) and \( V^{(k)} \), respectively. In each iteration, the fitness value \( F^{(k)}_{\text{local}} \)
and $F_{\text{global}}$ will be updated, as well as the particles and velocity, which can be represented as follows:

$$V^{(k)}(t + 1) = w \cdot V^{(k)}(t) + c_1 \cdot (P_{\text{local}}(t) - P^{(k)}(t)) + c_2 \cdot (P_{\text{global}}(t) - P^{(k)}(t)),$$

$$P^{(k)}(t + 1) = P^{(k)}(t) + V^{(k)}(t + 1).$$

Details of the proposed algorithm are found in Algorithm 1. In this PSO algorithm, we attempt to find the 3D deployment of drones to provide the connectivity for users, and then try to reduce the path loss of users. When all users are connected, our scheme will also try to find whether there is any redundant drone, which does not affect the network service, meaning that the fitness value is the same whenever this drone exists or not. If a redundant drone is found, the index of this drone will be removed from all the particles $P^{(k)}$, velocity $V^{(k)}$, and other related parameters. After repeating these steps, the final results will use the minimum number of drones derived from the algorithm.

Notice that in Algorithm 1, there are two loop statements which control the loop executions of the program and traverse all the particles, respectively. Thus, the time complexity Algorithm 1 is $O(N_p \cdot t_{\text{max}})$, where $N_p$ is the number of particles and $t_{\text{max}}$ is the maximum number of iterations. We can observe that the complexity is positively correlated to the number of particles and iterations. To be specific, a larger number of particles increases the convergence rate of the PSO algorithm, and more iterations increase accuracy as well.

C. Optimal Connectivity Model

In the following, we present the optimal connectivity model, including constraints, proposed algorithm and analysis.

1) Constraints: Due to limited drone resources, both individually (e.g., battery capacity) and in total (e.g., number of drones), there are not always enough drones to provide the ideal communication service in some situations. Thus, the deployment problem will become how to implement connectivity among users with a limited number of drones. To solve this connectivity problem, local networks are introduced. Individual local networks connected via ad-hoc and/or D2D communication can be obtained under the following constraints:

$$\min_{N_d} \sum_{k=1}^{N_s} U^{(k)} = U_u$$

$$\forall U^{(k)} \subseteq U_u, \exists i \in U^{(k)}, j \in U_u \setminus U^{(k)} : d_{i,j} \leq R_u$$

Here, $N_s$ is the number of all users, $U_u$ is the set of all users, $U^{(k)}$ is the set of users in the $k$th local network and $U^{(k)}_i$ represents any nonempty subset of $U^{(k)}$. In addition, $d_{i,j}$ is the distance between the user $i$ and $j$, and $R_u$ is the communication radius of each user.

After the local networks are established, the purpose of deploying drones is to provide the network relay among the isolated local networks. First, we establish a graph, in which each vertex represents a local network and the weight on the edge between two local networks represents the minimum distance between these two local networks. Then, to minimize the total distance among all local networks, we can obtain a minimum spanning tree from the above graph, in order to reflect the optimal connectivity of these local networks. In this minimum spanning tree, each weighted edge points out two users located at the edge of different local networks. Denote the set of edge users as $U_e$. Thus, the optimal connectivity problem can be represented as follows:

$$\min_{N_d} \sum_{k=1}^{N_s} U^{(k)}$$

$$\forall U^{(k)} \subseteq U_u, \exists i \in U^{(k)}, j \in U_u \setminus U^{(k)} : d_{i,j} \leq R_u$$

$$\forall U^{(k)} \subseteq U_u, \exists i \in U^{(k)}, j \in U_u \setminus U^{(k)} : d_{i,j} \leq R_u$$

$$\forall U^{(k)} \subseteq U_u, \exists i \in U^{(k)}, j \in U_u \setminus U^{(k)} : d_{i,j} \leq R_u$$

Here, $N_d$ is the number of the required drones, and $U^{(k)}$ and $U^{(l)}$ are the sets of users in the $k$th and $l$th local networks, respectively. In addition, $d_{i,j}$ is the distance between the user and drone $i$ and $j$, $R_u$ is the communication radius of each user, $PL_{i,j}$ is the path loss between user $i$ and drone $j$, $\gamma$ is the maximum allowed path loss, $U_d$ is the set of drones, $U^{(k)}_i$ represents any nonempty subset of $U_d$, and $R_d$ is the communication radius of each drone.

2) Local Network Generation Algorithm: In order to obtain the minimal number of local networks (all user devices are connected within the local network through ad-hoc and/or D2D communication), we implement a process for the local network generation, which is shown in Algorithm 2. Via this algorithm, the users will join local networks with their neighboring users. Then, the users on the edge of each local network can be derived based on the aforementioned minimum spanning tree. The drones will be deployed to provide network relays among the local networks. This problem becomes a special coverage problem for the users on the edge of local network, in which the capacity of drones is unlimited. Notice that as stated in Section IV-A, the optimal connectivity model is also an $NP$-hard problem. Thus, the connectivity problem can be transformed into a special case of coverage problem, which we have provided the solution for in Section IV-B, above.

Algorithm 2 Algorithm for local network generation

1: for each $i \in U_u$ do
2: if $i$ does not belong to any local network then
3: Add $i$ to a new local network $U^{(j)}_i$;
4: end if
5: for each $j \in U_u$ do
6: if $j$ does not belong to any local network then
7: Add $j$ to a new local network $U^{(j)}_i$;
8: end if
9: if $d_{i,j} \leq R_u$ then
10: Merge local network $U^{(i)}_i$ and $U^{(j)}_i$;
11: end if
12: end for
13: end for

In Algorithm 2, there exists two loop statements in Line 1 and 5, which traverse all the users. Thus, the time complexity
of Algorithm 2 is $O(N_u^2)$, in which $N_u$ is the number of all users. We can see that a larger number of users will significantly increase the time complexity of the algorithm.

In addition, the figure shows that the minimum path loss in dense and high-rise urban areas will be much larger than in the suburban and urban areas, because of more obstacles such as buildings. Thus, we set the allowed maximum path loss in the above four environments are 90, 90, 100, 125 dB, respectively.

**Deployment of Drones.** To evaluate the deployment cost of our schemes, we measure the number of required drones to reflect the consumed device resources. In our coverage model, we assume that each drone base station can provide the bandwidth requirement for at most 5 users. Also, we define the initial number of drones to be 20 for the starting configuration of the PSO algorithm. As the algorithm progresses, the iterations update the candidate solutions, and the number of required drones will be reduced if any redundant drone is found. As shown in Fig. 6, we consider four environments in the same uneven terrain, where parameters is listed in Table II. These variables are directly linked to the ratio of built-up land area to the total land area and the mean number of buildings per unit area [8]. It is worthy noting that the drones are placed where the users gather around, in order to achieve a large coverage with a small number of drones.

Actually, the number of required drones are 11, 12, 11, and 11 in four different environments, while the altitude of drones ranges from 94.0 to 599.9 m. On the other hand, we propose an optimal connectivity model to obtain the connectivity. In our connectivity model, the number of required drones can reach to 6, 10, 4, and 3 in four different environments, while the altitude of drones ranges from 108.3 to 510.8 m, as shown in Fig. 7. There are less drones required in the dense urban and high-rise urban areas, because their allowed maximum path loss is set much higher than that in suburban or urban areas, as we mentioned above. Due to influence of the dense or huge obstacles, a compromise must be made in the path loss in order to achieve the approximate coverage radius, despite the fact that the quality of air-to-ground channel will decrease. Nonetheless, the performance provided by our schemes achieves a good trade-off between the channel quality and deployment cost of drones in the above four different environments.

### V. Performance Evaluation

In this section, we describe the performance evaluation of our approach with respect to effectiveness and deployment cost, measured in the number of drones required to be deployed. In the following, we first present the evaluation setup, and then detail the evaluation results.

**Simulation Setup:** To extensively evaluate the performance of our approach, we consider four typical simulation scenarios, including suburban, urban, dense urban, and high-rise urban environments, which are presented in [8]. The detailed parameters for the distinct areas are outlined in Table II. In each scenario, we assume that 50 users are randomly located in a $1000 \times 1000$ m$^2$. The altitude of this uneven terrain ranges from 0 to 200 m. Recall that we present an air-to-ground model and a PSO algorithm to assist in solving the optimal problems, the detailed simulation parameters in these models are shown in Table III. We consider the number of required drones as the metric in order to reflect deployment cost which needs to be minimized. All simulations were implemented in MATLAB.

**Simulation Results:** In the following, we provide our evaluation results. First, we present the relationship between the path loss of users and the altitude of the drones. Then, we present the deployment of drones in our coverage model and connectivity model, which reflects the decrease in the required number of drones.

**Path Loss versus Altitude.** As shown in Fig. 5, the path loss curves descend to their minimum value and then rise with the increasing altitude of drones, no matter horizontal distance $r$ is 100 m or 400 m. Thus, the minimum path loss and the corresponding altitude difference of drones indicate the best location of drones and quality of air-to-ground channel, no matter which environment they are in. When the altitude of the drones is lower than the optimal altitude, the path loss will rapidly increase because of obstacles blocking the way. When the altitude of the drones is higher than the optimal value, the path loss will also increase because of the longer distance.

### TABLE II

**The Parameters for Different Areas**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Suburban</th>
<th>Urban</th>
<th>Dense urban</th>
<th>High-rise urban</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$</td>
<td>4.88</td>
<td>9.61</td>
<td>12.08</td>
<td>27.23</td>
</tr>
<tr>
<td>$b$</td>
<td>0.43</td>
<td>0.16</td>
<td>0.11</td>
<td>0.08</td>
</tr>
<tr>
<td>$\eta_{LoS}$</td>
<td>0.1</td>
<td>1</td>
<td>1.6</td>
<td>2.3</td>
</tr>
<tr>
<td>$\eta_{NLoS}$</td>
<td>21</td>
<td>20</td>
<td>23</td>
<td>34</td>
</tr>
</tbody>
</table>

### TABLE III

**The Simulation Parameters**

<table>
<thead>
<tr>
<th>System Parameter</th>
<th>Value</th>
<th>PSO Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_c$</td>
<td>2 GHz</td>
<td>$w$</td>
<td>0.8</td>
</tr>
<tr>
<td>$C$</td>
<td>20 Mbps</td>
<td>$c_1$</td>
<td>2</td>
</tr>
<tr>
<td>$B$</td>
<td>1 Mbps</td>
<td>$c_2$</td>
<td>2</td>
</tr>
</tbody>
</table>

### VI. Related Work

Low-altitude UAVs usually fly at many thousands of meters in altitude, and perform various tasks without human intervention. Significant research efforts towards UAVs can be categorized by from perspectives, such as size, flying features (static/dynamic), and control methods (autonomous/human) [23]–[25]. For instance, UAVs vary in size and weight, serving diverse requests and different levels of tasks. Due to their unique characteristics (i.e., high mobility, accessibility, cost effectiveness), UAVs have been widely employed in both mission critical tasks and civilian uses, such as armed attacks, object delivery, and communications.

In terms of communication, the UAV is capable of carrying light-weight Base Stations to perform rapid establishment of temporary networks for communication enhancement or traffic offloading. Compared with other communication techniques,
such as satellite and Cell-On-Wheels (COWs) [26], the UAV is extremely advantageous due to fast response, mobility, cost efficiency, and the better chance of LoS communication [27]–[29]. The communication applications supported by UAVs are network coverage, information relaying, data dissemination/collection, and others. Network coverage indicates that the UAV acting as a Base Station in the aerial space, providing communication coverage for users on the ground. In addition, UAVs can leverage their high mobility to relay information between two far-away users or groups. Similarly, UAVs can increase speed and efficiency of data collection and dissemination.

Various applications rely on UAVs as key elements, and are in place to perform diverse tasks, including search and rescue, temporary network establishment, and others. Particularly, in search and rescue, a number of UAVs can be deployed in the target area, equipped with cameras and other sensors, and can perform search and rescue operations in a rapid and effective manner [30]–[32]. Another application is to enable communication in public safety scenarios (natural disaster and man-made disasters). The UAV equipped with a base station can be rapidly deployed to support communication among rescue teams and victims. By doing this, the network throughput, coverage, and capacity can be significantly improved [33], [34].

Distinct from existing research efforts, which assume that all users are located on a flat plane [10]–[13], in this paper we proposed novel schemes that could deploy drone BSs to provide network service for users, especially in uneven terrain. In addition, we take into account the ad-hoc and/or D2D communication among neighbor users, which reduce the number of required drone BSs through the established ad-hoc/D2D local networks. Furthermore, to solve our coverage or connectivity problems which can be mapped to a well-known NP-hard problem [21], we designed effective heuristic algorithms based on PSO algorithm. Via the extensive experimentation, our results show that our proposed schemes can effectively deploy drone BSs in uneven terrain with respect to the QoS of users and the number of required drones.

VII. FINAL REMARKS

In this paper, we have addressed the 3D deployment issue for unmanned aerial vehicles, which can help drones serving as base stations to provide network service for the users in uneven terrain, which can be used in numerous applications such as public safety disaster recovery. Particularly, we have formalized two models, including optimal coverage model and
optimal connectivity model, which belong to NP-hard. The optimal coverage model considers the QoS requirements of users and the limitations of the drones’ throughput capacities. This is addressed through the development of a PSO algorithm to satisfy the requirements of users who need sufficient and reliable resources from the drones. In addition, we consider the optimal connectivity model which only focuses on decreasing the number of required drones. The optimal connectivity model considers the assistance of local communication networks formed by users, such that the drones are needed only to act as relays, bridging various local networks. By doing this, the total number of drones can be reduced (i.e., a fewer number of drones can provide the required connectivity to connect users in a wide area). Via extensive performance evaluation, our experimental results show that the proposed schemes can enable the 3D deployment of drones for the users on the uneven terrain, and thus the number of drones can be minimized.

REFERENCES


