UAV Base Station Deployment for Assisting Ground Wireless Networks

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Abstract—**The inherent flexibility and adaptability of deploying Unmanned Aerial Vehicle-mounted base stations (UAV-BSs) offer a unique opportunity for enhancing wireless communication capacity in a place of interest (PoI), such as a hotspot or disaster-struck area. This paper introduces an innovative algorithm that optimizes three key parameters: the number of deployed UAV-BSs, their 3D positions and user association. This optimization is focused on optimizing the weighted average spectrum efficiency within a PoI to ensure it exceeds a predefined threshold. The algorithm decomposes a main optimization problem, where different variables are coupled together, into a number of subproblems, which are solved iteratively in each round. Extensive simulations are conducted to demonstrate the convergence and effectiveness of the proposed algorithm as compared to the baseline scenario, where there is no UAV-BSs but only a single ground base station that is deployed at a PoI.**

Index Terms—**Aerial communications, UAV deployment, user association, spectrum efficiency.**

I. Introduction

Unmanned aerial vehicles (UAVs) are rapidly gaining prominence across a spectrum of applications, spanning military operations [1], surveillance and monitoring [2], disaster management, telecommunications [3], [4], and cargo delivery. Notably, UAVs are poised to be integral to the forthcoming 6G wireless networks, functioning as mobile base stations or aerial relays to deliver wireless connectivity [1], [5]. Their adaptability in deployment and mobility renders UAV-mounted base stations (UAV-BSs) invaluable for delivering on-demand wireless broadband during sporadic events or offering wireless coverage in remote or hard-to-reach terrains [6]. UAV-BSs present an intriguing landscape brimming with opportunities but also underscored by formidable challenges, including but not limited to optimal placement and trajectory planning of UAVs in 3D space [7], limited flight endurance time, energy constraints, and frequency and interference management [8]. Numerous studies have already explored solutions to derive the optimal single UAV-BS deployment that can better serve ground users. For instance, the work by [9] has yielded an efficient algorithm for 3D UAV-BS placement, aimed at maximizing spectral efficiency in serving ground users. Similarly, in [10], authors proposed a method for 3D UAV-BS placement with the objective of maximizing ground user coverage.

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Definitely, deploying a single UAV-BS is no longer enough to serve users that are distributed in a large area, such as an earthquake zone, and so deploying multiple UAV-BSs is essential. Recent research has ventured into the deployment of multi-UAV-BSs, considering various objectives. For instance, in [11], the aim is to deploy a specific number of UAV-BSs to maximize the number of ground users covered by these UAV-BSs while accommodating UAV flight time constraints. In a similar vein, the paper [12] focuses on the joint maximization of served terrestrial users and their scheduling. Notably, the determination of the optimal number of UAV-BSs required for deployment has been largely overlooked in these prior works. This oversight could lead to unnecessary UAV-BS deployments [13], incurring additional costs. However, a noteworthy exception is the work in [14], where an algorithm for UAV-BS placement seeks to minimize the number of required UAV relaying nodes (RNs) while ensuring reliable connectivity for a substantial number of ground terminal nodes. Nevertheless, this work does not address the systematic optimization of UAV-BS positions to maximize network capacity.

It is widely known that deploying multiple UAV-BSs presents a challenge, and researchers have explored various approaches to tackle this issue. However, what has been largely overlooked is the systematic and analytical process of optimizing all three variables together: the number of required UAV-BSs, their 3D positions and the corresponding user association. The tight coupling of user association, the number of deployed UAV-BSs, and the positions of deployed UAV-BSs makes this joint optimization problem difficult to solve. Many solutions only optimize, for example, the 3D positions of UAV-BSs and user association by assuming that the number of deployed UAV-BSs is given [11]. Our research fills this gap with a unique contribution. That is, we design an innovative algorithm that can jointly optimize the three variables such that the number of required UAV-BSs is minimized and the weighted average spectrum efficiency of a target area is maximized and higher than the predefined threshold. We achieve this by converting the original complex non-convex problem into a number of smaller subproblems that are solved by a novel iterative algorithm. In essence, our work presents an advanced iterative algorithm that has the potential to improve wireless communication systems, particularly in scenarios where multiple UAV-BSs are needed to be deployed.

The structure of the remainder of the paper is as follows.

Section II describes the system model and the problem formulation, geared toward optimizing both the quantity and locations of UAV-BSs to maximize spectral efficiency of the communication network. Section III offers solutions for each of the defined subproblems, addressing the optimization of user association, UAV-BS placement, and the determination of the number of UAV-BSs. Following this, we present an iterative algorithm that builds upon the insights gained from the subsections within Section III. Section IV presents our simulation results and findings, and Section V concludes the paper.

II. System Model

A place of interest (PoI), which could be a hotspot or a disaster-affected 2D area, is divided into a grid of uniformly sized cells. Denote $\mathcal{I}$ as the set of these cells indexed by i. In the PoI as shown in Fig.1, a fixed gNB is located with an index of $n=0$ alongside N_{BS} UAV-BSs deployed and indexed by $n \in S_{BS}$, where $S_{BS} = \{1, ..., N_{BS}\}$ and $N_{BS} = |S_{BS}|$. Denote h_n as the altitude of UAV-BS n where each UAV-BS are permitted to operate within the minimum and maximum altitude, denoted as h_{min} and h_{max}. Let $l_{n,i} = \sum_{i' \in \mathcal{I}} x_{n,i'} l_{ii'}$ be the landscape distance between UAV-BS n and location i where $l_{ii'}$ is the landscape distance between locations i and i', and $x_{n,i}$ is a binary variable indicating whether UAV-BS n is positioned over location i (i.e., $x_{n,i}=1$) or not (i.e., $x_{n,i}=0$). Thus, the distance between UAV-BS n and UEs at location i is

$$d_{n,i} = \sqrt{l_{n,i}^2 + h_n^2} = \sqrt{\sum_{i' \in \mathcal{I}} x_{n,i'} l_{ii'}^2 + h_n^2}. \tag{1}$$

A. Pathloss Model Between a UAV-BS and a Location

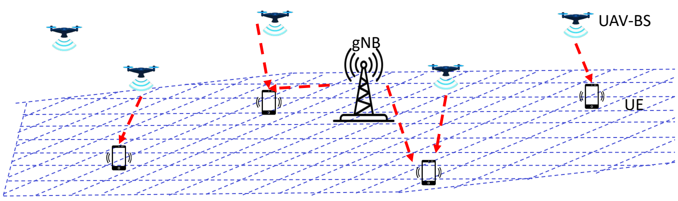


Fig. 1: UAV-BSs placing over an area with a gNB.

The wireless propagation channel between a UAV-BS and the UEs in location i can be divided into those with line-of-sight (LoS) connections and those with non-line-of-sight (NLoS) connections. In NLoS, UEs may still communicate with the UAV-BS but suffer from much stronger reflection and diffraction. The probability of having LoS between the n-th UAV-BS and the UEs in location i can be modelled as [15]:

$$\rho_{n,i} = \frac{1}{1+\alpha e^{-\beta(\theta_{n,i}-\alpha)}} = \frac{1}{1+\alpha e^{-\beta\left(\arctan\left(\frac{h_n}{l_{n,i}}\right)-\alpha\right)}}, \tag{2}$$

where $\theta_{n,i}$ is the elevation angle of UAV-BS n from location i, and α and β are the parameters determined by the environment of the PoI. Thus, the average pathloss (in dB) between the n-th UAV-BS and the UEs in location i can be estimated as [15]:

$$\eta_{n,i} = 20\log_{10}\left(\frac{4\pi f_c d_{n,i}}{c}\right) + \rho_{n,i}\xi_{los} + (1-\rho_{n,i})\xi_{nlos}. \tag{3}$$

Here, $20\log_{10}\left(\frac{4\pi f_c d_{n,i}}{c}\right)$ indicates the free space pathloss (where f_c is the carrier frequency) and $\rho_{n,i}\xi_{los}+(1-\rho_{n,i})\xi_{nlos}$ is the average additional pathloss (where ξ_{los} and ξ_{nlos} are the average additional pathloss for the LoS and NLoS scenarios, respectively) between UAV-BS n and the UEs in location i.

B. Spectrum Efficiency Model

The UEs in location i can be served by either the gNB or one of the N_{BS} UAV-BSs. However, the choice of UAV-BS may lead to different spectrum efficiency. Two models are used to estimate the spectrum from the gNB or any UAV-BS to a UE, and the UE will associate with a BS that has the highest spectrum efficiency.

Define $g_{n,i}$ as the channel gain from UAV-BS n to the UEs at location i. Assuming that pathloss primarily determines the channel gain between UAV-BS n and UEs at location i, we can estimate the channel gain $g_{n,i} = 10^{-\eta_{n,i}/10}$. Hence, the spectral efficiency of the link from UAV-BS n to any UE at location i is

$$\varphi_{n,i} = \log_2\left(1 + \frac{p_n 10^{-\eta_{n,i}/10}}{\sigma^2}\right), \tag{4}$$

where p_n is the transmit power of UAV-BS n and σ^2 denotes the noise power level. Similarly, the spectrum efficiency of transmitting data from the gNB to the UEs in location i can be written as

$$\varphi_{0,i} = \log_2\left(1 + \frac{p_0 10^{-\eta_{0,i}/10}}{\sigma^2}\right), \tag{5}$$

where p_0 is the transmit power of the gNB and $\eta_{0,i}$ is the pathloss from the gNB to the UEs in location i.

C. Problem Formulation

In UAV-assisted mobile access networks, UAV-BSs are strategically positioned within a PoI $\mathcal{I}$ to enhance the network capacity. Let $y_{n,i}$ denote the user association between the user located at location i and UAV-BS n. That is, $y_{n,i}=1$ implies UAV-BS n serves all the users at location i, and conversely, $y_{n,i} = 0$ implies the opposite indicating that location i is $y_{n,i} = 0$ for all $n \in S_{BS}$, that implies corresponding location i is served by the gNB. Moreover, the average spectrum efficiency, denoted as φ_{avg}, can be computed as $\varphi_{avg} = \sum_{i\in\mathcal{I}} w_i \big(\sum_{n\in S_{BS}} y_{n,i}\varphi_{n,i} + \big(1 - \sum_{n\in S_{BS}} y_{n,i}\big)\varphi_{0,i}\big)$. Here w_i is the weight of location i, which can be defined as, for example, UE density of location i so that the system is in favor of increasing the spectrum efficiency of a location with a higher UE density. Our objective is to optimize the number and 3D positions of deployed UAV-BSs as well as user association. The goal is to minimize the UAV-BS deployment while achieving the maximum weighted spectrum efficiency, denoted as φ^*_{avg} in the PoI, and ensuring it surpasses a predefined threshold. We can express the corresponding problem formulation as

$$\min_{N_{BS}} \quad N_{BS} \tag{6}$$

$$\text{s.t.} \quad \varphi^*_{avg} \geq \varphi_{avg,min} \tag{6a}$$

$$\text{where } \varphi^*_{avg} = \max_{\substack{x_{n,i}, y_{n,i}, h_n \\ \forall n \in S_{BS} \forall i \in \mathcal{I}}} \quad \varphi_{avg} \tag{7}$$

$$\text{s.t.} \sum_{i \in \mathcal{I}} x_{n,i} = 1 \qquad \forall n \in S_{BS}, \tag{7a}$$

$$\sum_{n \in S_{BS}} y_{n,i} \leq 1 \qquad \forall i \in \mathcal{I}, \tag{7b}$$

$$h_{min} \leq h_n \leq h_{max} \; \forall n \in S_{BS}, \tag{7c}$$

$$x_{n,i} \in \{0,1\} \; \forall n \in S_{BS} \; \forall i \in \mathcal{I}, \tag{7d}$$

$$y_{n,i} \in \{0,1\} \;\; \forall n \in S_{BS} \; \forall i \in \mathcal{I}. \tag{7e}$$

In our optimization framework, constraint (6a) guarantees that φ^*_{avg} remains above a predefined threshold, denoted as $\varphi_{avg,min}$. To enhance precision, constraint (7a) mandates that each UAV-BS be positioned at a single location. Further, constraint (7b) ensures that users in each location i are associated with only one BS node, be it a UAV-BS or the gNB. Additionally, constraint (7c) enforces that UAV-BSs operate within a specified altitude range, defined by h_{min} and h_{max}. The binary nature of variables $x_{n,i}$ and $y_{n,i}$ is indicated by constraints (7d) and (7e).

III. Proposed Optimization Methodology

The problem (6) is nontrivial as it is not a convex problem. Hence, we approach the optimization problem by first solving problem (7) for a given N_{BS} and then, based on that solution, proceed to solve problem (6). Note that the problem in (7) will be further decomposed into user association and UAV-BS placement problems, which will be solved by our proposed methods that are specified in Sections III-A and III-B, respectively. The problem in (6) will be solved by the proposed method specified in Section III-C.

A. Optimizing User Association

Assume that the number of UAV-BSs N_{BS} and the 3D positions of all the UAV-BSs (i.e., $x_{n,i}, h_n, \forall n \in S_{BS} \; \forall i \in \mathcal{I}$) are given, and then user association $y_{n,i}$ is the only variable in the problem, i.e.,

$$\max_{\substack{y_{n,i}, \forall i \in \mathcal{I} \\ \forall n \in S_{BS}}} \sum_{i \in \mathcal{I}} w_i \Big(\sum_{n \in S_{BS}} y_{n,i} \varphi_{n,i} + \big(1 - \sum_{n \in S_{BS}} y_{n,i}\big) \varphi_{0,i} \Big) \tag{8}$$

$$\text{s.t.} \qquad \text{Constraints (7b) and (7e).}$$

Denote n^*_i as the index of the BS (including the gNB and all the UAV-BSs that are deployed at the PoI), who can achieve the highest spectrum efficiency if location i is associated with it, i.e., $n^*_i = \arg\max_{n \in \{0, S_{BS}\}} \{\varphi_{0,i}, \varphi_{1,i}, ..., \varphi_{N_{BS},i}\}$. Then, the optimal solution of the problem outlined in (8) is

$$y_{n,i} = \begin{cases} 1, & n = n^*_i. \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

B. UAV-BS Placement

Assuming that the user association $y_{n,i}$ and the number of UAV-BSs N_{BS} are given, in this section, we will optimize the UAV-BS placement, i.e., $x_{n,i}, h_n, \forall n \in S_{BS} \; \forall i \in \mathcal{I}$. Hence, the problem formulation given in (6) can be simplified into

$$\max_{\substack{x_{n,i}, h_n \\ \forall n \in S_{BS} \\ \forall i \in \mathcal{I}}} \sum_{i \in \mathcal{I}} w_i \sum_{n \in S_{BS}} y_{n,i} \varphi_{n,i} \tag{10}$$

$$\text{s.t.} \qquad \text{Constraints (7a), (7c), and (7d).}$$

Assuming that $\mathcal{A}_n$ is the set of locations that have been associated with BS n, i.e., $\mathcal{A}_n = \left\{ i \in \mathcal{I} \,\middle|\, y_{i,n} = 1 \right\}$, the problem formulation given in (10) can be converted into

$$\max_{\substack{x_{n,i}, h_n \\ \forall i \in \mathcal{I}}} \sum_{i \in \mathcal{A}_n} w_i \varphi_{n,i} \tag{11}$$

$$\text{s.t.} \qquad \text{Constraints (7a), (7c), and (7d).}$$

Plugging (4) into the objective function in (11), we have

$$\begin{aligned} &\max_{\substack{x_{n,i}, h_n \\ \forall i \in \mathcal{I}}} \sum_{i \in \mathcal{A}_n} w_i \log_2 \left(1 + \frac{p_n 10^{-\eta_{n,i}/10}}{\sigma^2} \right) \\ \approx &\max_{\substack{x_{n,i}, h_n \\ \forall i \in \mathcal{I}}} \sum_{i \in \mathcal{A}_n} \log_2 \left(\frac{p_n 10^{-\eta_{n,i}/10}}{\sigma^2} \right)^{w_i} \\ = &\max_{\substack{x_{n,i}, h_n \\ \forall i \in \mathcal{I}}} \log_2 \left(10^{\sum_{i \in \mathcal{A}_n} -w_i \eta_{n,i}/10} \right) \\ = &\min_{\substack{x_{n,i}, h_n \\ \forall i \in \mathcal{I}}} \sum_{i \in \mathcal{A}_n} w_i \eta_{n,i}. \end{aligned} \tag{12}$$

Plugging (3) into (12), we have

$$\begin{aligned} \min_{\substack{x_{n,i'}, h_n \\ \forall i' \in \mathcal{I}}} \sum_{i \in \mathcal{A}_n} w_i \Bigg(& 20 \log_{10} \left(\frac{4 \pi f_c}{c} \sqrt{\sum_{i' \in \mathcal{I}} x_{n,i'} l^2_{ii'} + h^2_n} \right) \\ & + \rho_{n,i} (\xi_{los} - \xi_{nlos}) \Bigg). \end{aligned} \tag{13}$$

Define $\theta_{n,i}$ as the elevation angle between UAV-BS n and location i, i.e., $\cos\theta_{n,i} = \frac{\sum_{i' \in \mathcal{I}} x_{n,i'} l_{ii'}}{\sqrt{\sum_{i' \in \mathcal{I}} x_{n,i'} l^2_{ii'} + h^2_n}}$, the objective function, i.e., (13), can be converted into

$$\begin{aligned} &\min_{\substack{x_{n,i'}, h_n \\ \forall i' \in \mathcal{I}}} \sum_{i \in \mathcal{A}_n} w_i \Bigg(\rho_{n,i} (\xi_{los} - \xi_{nlos}) \\ &\qquad + 20 \log_{10} \left(\frac{\sum_{i' \in \mathcal{I}} x_{n,i'} l_{ii'}}{\cos\theta_{n,i}} \right) \Bigg) \\ = &\min_{\substack{x_{n,i'}, h_n \\ \forall i' \in \mathcal{I}}} \sum_{i \in \mathcal{A}_n} w_i \Bigg(\rho_{n,i} (\xi_{los} - \xi_{nlos}) - 20 \log_{10} \left(\cos\theta_{n,i} \right) \\ &\qquad + 20 \log_{10} \left(\sum_{i' \in \mathcal{I}} x_{n,i'} l_{ii'} \right) \Bigg). \end{aligned} \tag{14}$$

The terms $\rho_{n,i}(\xi_{los} - \xi_{nlos})$ and $-20 \log_{10} \left(\cos\theta_{n,i} \right)$ within the objective function exhibit variations with respect to $\theta_{n,i}$, which in turn relies on both $x_{n,i}$ and h_n. However, the term $20 \log_{10} \left(\sum_{i' \in \mathcal{I}} x_{n,i'} l_{ii'} \right)$ exclusively depends on $x_{n,i}$. Based on this observation, we can iteratively optimize the landscape location $x_{n,i}$ and altitude h_n of UAV-BS n. That is, given h_n, we can optimize $x_{n,i}$ by only minimizing the term $20\log_{10}\left(\sum_{i'\in\mathcal{I}} x_{n,i'}l_{ii'}\right)$ in the objection function, i.e., (14). Meanwhile, leveraging the optimized $x_{n,i}$, we refine h_n by only minimizing the term $\rho_{n,i}(\xi_{los}-\xi_{nlos}) - 20\log_{10}\left(\cos\theta_{n,i}\right)$. This iteration continues until the value of the objective function cannot be further improved. In the following, we will explain how to solve the UAV-BS landscape location optimization and altitude optimization problems.

1) UAV-BS Landscape Location Optimization: We formulate the optimization problem to determine the UAV-BS landscape location as follows:

$$\begin{aligned}\min_{\substack{x_{n,i'}\\ \forall i'\in\mathcal{I}}} \quad & \sum_{i\in\mathcal{A}_n} w_i\Bigg(20\log_{10}\Big(\sum_{i'\in\mathcal{I}} x_{n,i'}l_{ii'}\Big)\Bigg) \\ \text{s.t.} \quad & \text{Constraints (7a) and (7d).}\end{aligned} \tag{15}$$

In this optimization problem, the objective function can be simplified into

$$\begin{aligned}&\min_{x_{n,i'}} \sum_{i\in\mathcal{A}_n}\left(\log_{10}\Big(\sum_{i'\in\mathcal{I}} x_{n,i'}l_{ii'}\Big)^{w_i}\right) \\ =\ &\min_{x_{n,i'}} \prod_{i\in\mathcal{A}_n}\Big(\sum_{i'\in\mathcal{I}} x_{n,i'}l_{ii'}\Big)^{w_i} \\ =\ &\min_{x_{n,i'}} \sum_{i'\in\mathcal{I}} x_{n,i'}\Big(\prod_{i\in\mathcal{A}_n} l_{ii'}^{w_i}\Big).\end{aligned} \tag{16}$$

Given that, for all i, only one term of $x_{n,i}$ equals 1, the optimal solution to the problem in (16) can be rearranged as follows:

$$\forall i'\in\mathcal{I},\quad x_{n,i'} = \begin{cases}1 & i'=i^*,\\ 0 & \text{otherwise,}\end{cases} \tag{17}$$

where

$$i^* = \arg\min_{i'} \sum_{i\in\mathcal{A}_n}\log_{10}\Big(l_{ii'}\Big)^{w_i}. \tag{18}$$

2) UAV-BS Altitude Optimization: Given landscape location of UAV-BS n, in this section, we aim to optimize the altitude of UAV-BS n such that the average spectrum efficiency in $\mathcal{A}_n$ can be maximized. The optimization problem for variable h_n is formulated as follows:

$$\begin{aligned}\min_{h_n} \quad & \sum_{i\in\mathcal{A}_n} w_i\big(\rho_{n,i}(\xi_{los}-\xi_{nlos}) - 20\log_{10}\left(\cos\theta_{n,i}\right)\big) \\ \text{s.t.} \quad & \text{Constraint (7c).}\end{aligned} \tag{19}$$

The term $\rho_{n,i}(\xi_{\text{los}}-\xi_{\text{nlos}})$ exhibits a decreasing trend as h_n increases, while the term $-20\log_{10}\left(\cos\theta_{n,i}\right)$ shows an increasing trend with respect to h_n. Consequently, there exists an optimal value of h_n that minimizes the objective function. Denote the objective function of the optimization problem in (19) as $f(h_n)$. To determine the optimal solution for the problem formulation, we obtain the derivative of the $f(h_n)$ and then use the gradient descent algorithm to optimize h_n. Specifically, derive $\frac{\partial f(h_n)}{\partial\theta_{n,i}}$ and $\frac{\partial\rho_{n,i}}{\partial\theta_{n,i}}$ as

$$\frac{\partial f(h_n)}{\partial\theta_{n,i}} = w_i\left(\frac{\partial\rho_{n,i}}{\partial\theta_{n,i}}(\xi_{los}-\xi_{nlos}) + \frac{20}{\ln 10}\tan\theta_{n,i}\right) \tag{20}$$

and

$$\frac{\partial\rho_{n,i}}{\partial\theta_{n,i}} = \rho_{n,i}^2\alpha\beta e^{-\beta(\theta_{n,i}-\alpha)}. \tag{21}$$

Also, $\partial f(h_n)/\partial h_n$ can be calculated as

$$\frac{\partial f(h_n)}{\partial h_n} = \sum_{i\in\mathcal{A}_n} w_i\left(\frac{\partial\rho_{n,i}}{\partial\theta_{n,i}}(\xi_{los}-\xi_{nlos}) + \frac{20}{\ln 10}\tan\theta_{n,i}\right)\frac{\partial\theta_{n,i}}{\partial h_n} \tag{22}$$

where $\frac{\partial\theta_{n,i}}{\partial h_n} = \frac{\cos^2\theta_{n,i}}{\ell_{n,i}}$. Plugging (21) and (20) into (22), we have

$$\begin{aligned}\frac{\partial f(h_n)}{\partial h_n} = \sum_{i\in\mathcal{A}_n} w_i\Big(&\rho_{n,i}^2\alpha\beta e^{-\beta(\theta_{n,i}-\alpha)}(\xi_{los}-\xi_{nlos}) \\ &+\frac{20}{\ln 10}\tan\theta_{n,i}\Big)\frac{\cos^2\theta_{n,i}}{\ell_{n,i}}.\end{aligned} \tag{23}$$

The iterative update equation for the variable h_n according to the gradient descent algorithm can be written as

$$h_n^{new} = h_n^{old} - \delta\frac{\partial f(h_n)}{\partial h_n}\Big|_{h_n=h_n^{new}} \tag{24}$$

where the step size δ is

$$\delta = \frac{h_n^{new}-h_n^{old}}{\frac{\partial f(h_n)}{\partial h_n}\Big|_{h_n=h_n^{new}} - \frac{\partial f(h_n)}{\partial h_n}\Big|_{h_n=h_n^{old}}}. \tag{25}$$

To meet Constraint (7c), if $h_n^{new} < h_{min}$ or $h_n^{new} > h_{max}$, we map h_n^{new} into its feasible region based on

$$h_n^{new} = \begin{cases}h_{max}, & \text{if } h_n^{new} > h_{max}.\\ h_{min}, & \text{if } h_n^{new} < h_{min}.\end{cases} \tag{26}$$

Algorithm 1: Optimal Altitude

Input: $x_{n,i}$ and $\mathcal{A}_n$, $\forall i\in\mathcal{I}$.
Output: h_n.

```
Initialize h_n as h_n^new and step size δ.
Calculate f(h_n^new) and ∂f(h_n)/∂h_n |_{h_n=h_n^new} using (23).
while |f(h_n^new) − f(h_n^old)| ≥ ε_h do
    h_n^old = h_n^new; ∂f(h_n)/∂h_n |_{h_n=h_n^old} = ∂f(h_n)/∂h_n |_{h_n=h_n^new};
    Update h_n^new using (24);
    if h_n^new > h_max or h_n^new < h_min then
        Update h_n^new based on (26);
    Calculate f(h_n^new) and ∂f(h_n)/∂h_n |_{h_n=h_n^new} using (23);
    Update step size δ using (25);
h_n = h_n^new.
```

Algorithm 1 summarizes the mentioned gradient descent based altitude optimization to determine the optimal altitude for each UAV-BS in the network. To begin, the algorithm takes the variables $x_{n,i}$ and $\mathcal{A}_n$ for all $i\in\mathcal{I}$ as inputs, and initializes the altitude h_n as h_n^{new}, which is a random value between h_{min} and h_{max}, and initializes the step size parameter δ. The iterative optimization process begins with the calculation of the objective function $f(h_n^{new})$ and its derivative $\frac{\partial f(h_n)}{\partial h_n}$ at the initial altitude h_n^{new} using (19) and (23), respectively. This initial altitude is within the feasible altitude region for the

UAV-BS. Then, the algorithm conducts a while-loop to update the altitude h_n^{new}, while ensuring it remains within the feasible region. At each iteration, the algorithm calculates the $f(h_n^{new})$ and its derivative $\frac{\partial f(h_n)}{\partial h_n}$. The step size δ is also updated during each iteration using (25). The optimization iteratively adjusts the altitude until convergence, i.e., $|f(h_n^{new}) - f(h_n^{old})|$ falls below a predefined threshold ϵ_h, resulting in an altitude value that maximizes spectrum efficiency for $\mathcal{A}_n$. This altitude optimization is a critical part of optimizing the deployment of UAV-BSs for enhanced wireless communications.

Algorithm 2: UAV-BS Placement Optimization Algorithm

Input: N_{BS} and $\mathcal{I}$
Output: $x_{i,n}$, $y_{i,n}$, h_n, $\forall n \in S_{BS}$, $\forall i \in \mathcal{I}$.

Initialize the positions of N_{BS} UAV-BSs, i.e., $x_{n,i}$, h_n and x_n^{new} $\forall i \in \mathcal{I}$, $\forall n \in S_{BS}$;
Initialize $\mathcal{A}_n$ as $\mathcal{A}_n = \mathcal{I}$;
do
  $x_n^{old} = x_n^{new}$ $\forall n \in S_{BS}$;
  Update $x_{n,i}$ $\forall$ $n \in S_{BS}$,$\forall i \in \mathcal{I}$ using (17);
  Update $h_n = \forall n \in S_{BS}$ using Algorithm 1;
  Update $\varphi_{n,i}$ $\forall$ $i \in \mathcal{I}$ and $n \in S_{BS}$ based on (4) and (5);
  Update $y_{n,i}$ $\forall n \in S_{BS}$, $\forall i \in \mathcal{I}$, based on (9);
  Update $\mathcal{A}_n$ using $y_{n,i}$ $\forall i \in \mathcal{I}$, $\forall n \in S_{BS}$;
  Update x_n^{new} $\forall$ $n \in S_{BS}$, using $x_{n,i}$ and h_n $\forall i \in \mathcal{I}$, $\forall n \in S_{BS}$;
while $\frac{1}{N_{BS}} \sum_{n \in S_{BS}} \left\| x_n^{new} - x_n^{old} \right\| \leq \epsilon$;

3) Optimal Placement Algorithm for UAV-BSs: Based on the solutions in Sections III-A and III-B, we design an interactive algorithm to calculate the 3D positions of multiple UAV-BSs and user association such that the average spectrum efficacy of the PoI is maximized. Here, we assume that the number of UAV-BSs is given. As shown in Algorithm 2, in the initialization stage, the algorithm randomly places N_{BS} UAV-BSs in the PoI and assumes that the user association area of each UAV-BS is the same, i.e., $\mathcal{A}_n = \mathcal{I}$, $\forall n \in S_{BS}$.

Once the initialization is completed, the algorithm conducts a do-while loop, where the landscape locations, altitudes, and user association of the UAV-BS are sequentially updated in each iteration. First, the algorithm calculates $x_{n,i}$, $\forall i \in \mathcal{I}$ and $\forall n \in S_{BS}$, based on $\mathcal{A}_n$ that are calculated in the previous iteration by applying (17). Next, the algorithm updates the altitude h_n, $\forall n \in S_{BS}$, using Algorithm 1. Subsequently, the algorithm computes the spectral efficiency between all the locations and all the BSs based on their current positions by using (4) and (5). The algorithm then updates $y_{n,i}$, $\forall n \in S_{BS}$ based on (9), and finally updates $\mathcal{A}_n$. The while loop continues until all the UAV-BSs' positions that are calculated in the previous iteration are very similar to those in the current iteration, i.e., $\frac{1}{N_{BS}} \sum_{n \in S_{BS}} \left\| x_n^{new} - x_n^{old} \right\| \leq \epsilon$, where ϵ is the predefined threshold.

C. Optimization of number of UAV-BSs

Given the number of UAV-BSs, Algorithm 2 is capable of optimizing the 3D positions and user association of the UAV-BSs. However, it is still unclear how to determine the number of UAV-BSs while constraint (6a) can be met. In this subsection, we propose an algorithm aiming to minimize the number of UAV-BSs while maintaining spectral efficiency. Algorithm 3 summarizes the proposed algorithm, which basically is to increase the number of UAV-BSs by one in each iteration, and then calculate if the optimal weighted average spectrum efficiency of the area $\mathcal{I}$, i.e., φ_{avg}^*, greater than the predefined threshold $\varphi_{avg,min}$ after conducting Algorithm 2 to perform UAV-BS placement and user association. The iteration continues until $\varphi_{avg}^* > \varphi_{avg,min}$.

Algorithm 3: UAV-BS Optimization Algorithm: Quantity and Placement

Input: $\mathcal{I}, \varphi_{avg,min}$
Output: $N_{BS}, x_{i,n}$, $y_{i,n}$, h_n $\forall n \in S_{BS}$ $\forall i \in \mathcal{I}$

Initially assume $N_{BS} = 0$;
Calculate the average spectrum efficiency of $\mathcal{I}$ as φ_{avg}^*;
while $\varphi_{avg}^* < \varphi_{avg,min}$ **do**
  Set $N_{BS} = N_{BS} + 1$;
  Perform Algorithm 2 for N_{BS} number of UAV-BS to determine $x_{i,n}$, $y_{i,n}$, h_n $\forall n \in S_{BS}$ $\forall i \in \mathcal{I}$;
  Calculate average spectrum efficiency φ_{avg}^* of $\mathcal{I}$;

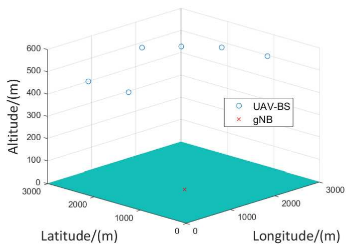
IV. Simulation Results

Considering the scenario that there is a PoI in terms of a hotspot area $\mathcal{I}$ with the size of 3 km × 3 km, which is further discretized into 300 × 300 locations. Each location has the identical dimensions of 10 m × 10 m. The gNB is positioned at the 2D coordinates of $(1000\text{m}, 1000\text{m})$, with an altitude of 20 m. Other simulation parameters can be found in Table I.

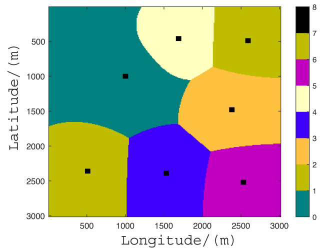
TABLE I: Simulation parameters

Parameter	Value	Parameter	Value
f_c	2 GHz	α	11.9
β	0.13	ξ_{los}	6 dB
ξ_{nlos}	26 dB	P_{gNB}	46 dBm
P_n	30 dBm	h_{min}	20 m
h_{max}	1000 m	h_{gNB}	30 m
$\mathcal{I}$	3 km $\times$ 3 km	gNB location	(1 km, 1 km)
$\varphi_{avg,min}$	2.5 bits/s/Hz	Cell size	10 m $\times$ 10 m

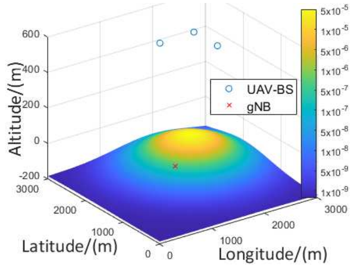
Fig. 2 presents the optimal spatial deployment of UAV-BSs and their associated user assignments, driven by the weight distribution. The variation in weight distribution is depicted using color maps in Figs. 2a and 2c, with UAV-BS and gNB projected locations marked within black squares on a 2D plane. In scenarios where the weight distribution, represented by w_i, is uniform, the proposed methodology strategically places UAV-BSs in regions with lower spectrum availability to maximize the φ_{avg}. Conversely, when the weight distribution follows a Gaussian pattern, UAV-BSs tend to be positioned nearer to areas with higher weight concentrations. This strategic placement results in accelerated progress towards the



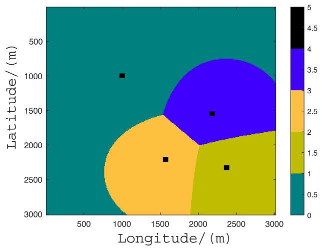
(a) Uniform weight distribution.



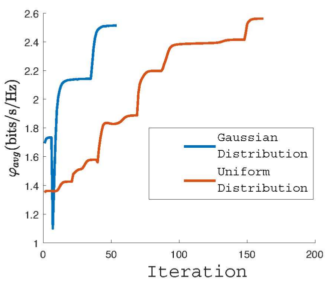
(b) User association based on the weight distribution in (a).



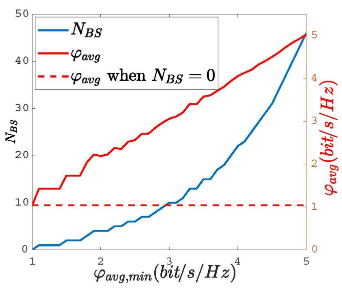
(c) Gaussian weight distribution, i.e., $w_i \sim\mathcal{N}([2000m, 2000m], 10^6 m^2 I_2)$.



(d) User association based on the weight distribution in (b).



(e) Average spectrum efficiency variation over iterations.



(f) Variation of N_{BS} and φ_{avg} with the $\varphi_{avg,min}$.

Fig. 2: Proposed algorithm optimization of UAV-BS location and user association with uniform and Gaussian distribution of w_i

desired φ_{avg} compared to the uniform weight distribution, as depicted in Fig. 2e. The iterative process involved in our proposed methodology for improving the average spectral efficiency is illustrated in Fig. 2e. The analysis takes into account the number of iterations executed within the while loop outlined in Algorithm 2. The sudden spikes of φ_{avg} with iterations in Fig 2e indicate an increase in the number of UAV-BS when the algorithm cannot satisfy the desired φ_{avg} with the current number of UAV-BS considered. From Fig 2e, we can observe that UAV-BSs are very suitable to be applied to the Gaussian weight distribution to achieve higher weighted spectrum efficiency by deploying the same or even fewer UAS-BSs as compared to uniform weight distribution.

Assume that the weights of locations follow a uniform distribution, and Fig. 2f shows how the number of deployed UAV-BSs N_{BS} and weighted average spectrum efficiency in the PoI φ_{avg} vary by increasing the threshold $\varphi_{avg,min}$. As a comparison, a baseline method, where there is no UAS-BS but only a gBS is deployed in the PoI, is applied (i.e., the dash red curve in Fig. 2f). The baseline method is considered as the lower bounds of the communication system to indicate the improvements obtained with the introduction of N_{BS} deployed UAV-BSs. From Fig. 2f, we can observe that N_{BS} increases exponentially as $\varphi_{avg,min}$ increases highlighting the direct relationship between the minimum performance assurance and the required deployment scale of UAV-BSs. Accordingly, φ_{avg} also linearly increases as $\varphi_{avg,min}$ increases owing to more UAS-BS deployment. However, as $\varphi_{avg,min}$ increases, the increment of φ_{avg} by deploying more UAS-BSs is reduced, i.e., the gap between solid red and blue curves is reduced after $\varphi_{avg,min} > 3$ bits/s/Hz, which means that deploy more UAS-BSs in the PoI is no longer cost-effective but only to ensure the minimum performance $\varphi_{avg,min}$ to be met.

V. Conclusion

The paper introduces a pivotal algorithm to ensure the minimum spectrum efficiency of a PoI while simultaneously minimizing the required quantity of UAV-BSs and optimizing their 3D deployments and user association. The simulation results convincingly demonstrate that the algorithm positions UAV-BSs strategically based on weight distributions, effectively maximizing average spectrum efficiency.

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