3-D Placement of UAVs Based on SIR-Measured PSO Algorithm

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***Abstract*—This work studies the deployment of unmanned aerial vehicles (UAVs) as emergency access points to provide wireless services to users in a green field. Specifically, three fundamental design issues are explored under practical 3D air-to-ground (ATG) channel models, namely the minimum number of UAVs, their optimal deployment locations and the optimal transmit power allocation. To decouple these design goals, a particle swarm optimization (PSO)-based scheme in conjunction with the balanced Signal to Interference plus Noise Ratio (SINR) transmit power allocation is proposed. Exploiting the closed-form expressions of the SINR-balanced optimal power allocation and the resulting SINR, the proposed PSO-based scheme optimizes the UAV location generation by generation. Furthermore, a K-means clustering-based initialization scheme is developed to improve the performance of the proposed PSO-based scheme. Finally, a power fine-tuning scheme is devised to further reduce the total transmit power. Extensive simulation is performed to confirm the good performance of the proposed scheme.**

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have been well regarded as ground-breaking technology to revolutionize the future wireless network architectures. Thanks to their high mobility, UAVs can be deployed as mobile access points or relay nodes in response to real-time data traffic changes. Furthermore, in sharp contrast to the conventional base stations (BS), the deployment of UAVs is subject to stringent constraints on the limited flight time and energy. As a result, UAV networks can provide substantially more comprehensive network coverage with more flexible network planning and engineering. In particular, UAV networks have been proposed to provide emergency network service recovery when the conventional communication infrastructure is damaged by natural disasters such as earthquake and typhoon. However, considerable research efforts are still required to materialize the benefits promised by UAVs in practice.

First of all, it is critical to optimize the UAV deployment location to enable the UAV to provide maximum coverage and high throughput. In [1], a three-dimensional (3D) air-to-ground (ATG) channel model was established before the optimal altitude was derived as a function of the maximum allowed pathloss and the environment parameters. Based on the ATG channel model, [2] developed a scheme to determine the 3D locations of UAVs for both coverage area and lifetime maximization using the circle packing theory. However, the scheme proposed in [2] requires non-overlapping coverage and subsequently, interference-free environment, which may be impractical for realistic UAV deployment. Recently, some particle swarm optimization (PSO)-based algorithms were proposed to address the UAV deployment problem. For instance, [3] considered the scenario for single UAV by minimizing the total pathloss to all users without taking into account the inter-user interference.

Besides the deployment issues discussed above, the energy consumption of UAVs is also a challenging problem for UAV networks. Since UAVs are battery powered, UAVs are under very stringent transmit power constraints. In [4], the UAVs were designed to adjust their flight altitude to minimize the energy consumption by detecting the ground events with their built-in cameras. Furthermore, [5] mathematically modeled the resource allocation problem for UAVs serving as mobile access points traveling at high altitude. However, [4], [5] did not consider the inter-cell interference among UAVs. Meanwhile, [6] proposed a framework to optimize the deployment and mobility of multiple UAVs for energy-efficient uplink data collection from ground users. To minimize the total transmit power from all users, [6] proposed an efficient approach to jointly and dynamically find the UAV locations, the association of devices to UAVs and the optimal uplink transmit power for given Signal to Interference plus Noise Ratio (SINR) constraints. However, [6] requires orthogonal channels for interference management by exploiting the frequency division multiple access (FDMA). For more general interference-limited environments, further investigation is required.

In this paper, we consider the deployment of multicopter UAVs in a green field without conventional BS's, assuming that the user position information is perfectly known. Each UAV is to be deployed at a fixed 3D location, acting as a flying emergency BS or an access point. In contrast to most works in the literature, we consider all UAVs are connected in a non-orthogonal channel network, which means that all UAVs interfere with each other. We study the problem of minimizing the number of UAVs to be deployed while optimizing their deployment locations and their transmission power, subject to a minimum SINR value for all users. This problem is very challenging due to the fact that these three design goals, *i.e.* the minimum number of UAVs, their optimal deployment

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locations and their optimal transmit power, are highly coupled. For instance, unless the number and locations of UAVs are determined, it is difficult to optimize their transmit power and subsequently, compute the resulting SINR for each user. Furthermore, deploying more UAVs can potentially better serve the same number of users at the cost of more severe interference. Finally, the highly sophisticated ATG channel model also imposes additional complexity into the problem.

The main contributions of this papers are summarized as follows:

- We propose to decouple the above optimization by developing a PSO-based scheme to jointly optimize the UAV locations and their transmit power for a given number of UAVs. A K-means clustering-based initialization scheme is proposed to intelligently select the UAV initial positions. Simulation results show that the PSO-based scheme endowed with the K-means clustering-based initialization is very effective in finding better solutions.
- We explicitly consider SINR as the performance measure in evaluating the performance of each UAV location in the algorithms, unlike the existing PSO-based algorithms that used pathloss as the performance measure to direct the UAV location update [3]. This SINR design can enable the proposed PSO-based scheme to directly compute the closed-form solutions to the optimal transmit power allocation and the resulting optimal SINR. Thus, the proposed PSO-based scheme can jointly optimize the UAV location, transmit power allocation and the resulting optimal SINR in a very computationally efficient manner.
- While the solutions derived above maximize the resulting minimum SINR over all users within the allowed transmit power budget, the resulting minimum SINR is usually higher than the targeted minimum SINR. To better preserve UAV battery power, a suboptimal power fine-tuning algorithm is developed to reduce the total transmit power by lowering the resulting minimum SINR to the targeted minimum SINR.

Notation: Vectors and matrices are denoted by boldface letters. $\boldsymbol{A}^T$ stands for the transpose of matrix $\boldsymbol{A}$ while $\|\boldsymbol{a}\|$ the Euclidean norm of vector $\boldsymbol{a}$. Furthermore, $\boldsymbol{A}_{i,j}$ denotes the i-th row, the j-th column element of $\boldsymbol{A}$. Finally, a superscript of $(\cdot)^{\text{dB}}$ indicates that the enclosed quantity is in decibel (dB) while quantities without the superscript are real values.

II. System Model and Problem Formulation

We consider deploying K UAVs to serve N single-antenna users on the ground in a green field as shown in Fig. 1. The 3D location of the k-th UAV is denoted by $\boldsymbol{\ell}_k = \{x_k^u, y_k^u, h_k^u\}$ for $k \in \mathcal{K} = \{1, 2, \cdots, K\}$. Furthermore, we assume all users are on a horizontal ground with the location of the n-th user being $\boldsymbol{r}_n = \{x_n^r, y_n^r\}$, for $n \in \mathcal{N} = \{1, 2, \cdots, N\}$. Thus the horizontal distance between the k-th UAV and the n-th receiver is given by

$$R_{k,n} = \sqrt{(x_k^u - x_n^r)^2 + (y_k^u - y_n^r)^2}. \quad (1)$$

In this work, we adopt the Low Altitude Platforms (LAPs) developed in [1] as the pathloss channel model. LAPs are par-

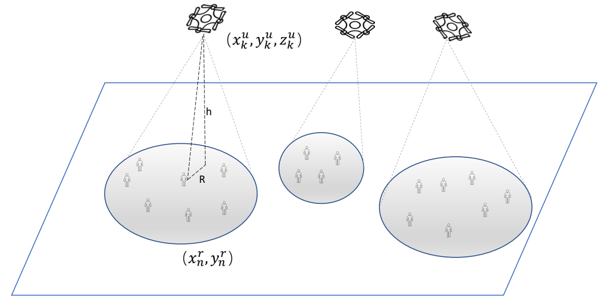

Fig. 1: Illustration of the deployment scenario.

ticularly attractive for the multicopter UAV-based applications considered in this work as the channel models are established for an altitude below the stratosphere. The small-scale fading effects are not considered in the sequel as coverage is of the main concern of this work.

Given the assumptions above, the ATG pathloss between the k-th UAV and the n-th user can be written in dB as [1]

$$\mathcal{L}_{k,n}^{\text{dB}} = \frac{A}{1 + ae^{-b\left[\tan^{-1}\left(\frac{h_k^u}{R_{k,n}}\right) - a\right]}} + 10\log\left((h_k^u)^2 + R_{k,n}^2\right) + B, \quad (2)$$

where

$$A = \eta_{\text{LoS}} - \eta_{\text{NLoS}}, \quad (3)$$
$$B = 20\log f + 20\log(4\pi/c) + \eta_{\text{NLoS}}, \quad (4)$$

with $a, b, \eta_{\text{LoS}}, \eta_{\text{NLoS}}$ being the environment parameters. Furthermore, f is the transmitted radio frequency and c is the velocity of light.

Assuming that each user attaches to only one UAV, we model the user-UAV association with the following function:

$$\mathcal{A}(n) = k, \quad (5)$$

with $n \in \mathcal{N}$ and $k \in \mathcal{K}$.

Let $\boldsymbol{p}$ be the power allocation strategy $\boldsymbol{p} = [p_1, p_2, \cdots, p_N]^T$ with p_n being the transmit power allocated to the n-th user for $n \in \mathcal{N}$. Then, the SINR of the n-th user is given as follows:

$$\Gamma_n = \frac{p_n \cdot \mathcal{L}_{\mathcal{A}(n),n}^{-1}}{I_n + \Psi_n}, \quad (6)$$

where $\mathcal{L}_{k,n} = 10^{\frac{\mathcal{L}_{k,n}^{\text{dB}}}{10}}$. Furthermore, I_n is the total interference that the n-th user receives from all UAVs and given by

$$I_n = \sum_{\substack{m=1 \\ m \neq n}}^{N} \alpha_{\mathcal{A}(m),n} \cdot \frac{p_m}{\mathcal{L}_{\mathcal{A}(m),n}}, \quad (7)$$

with $\alpha_{\mathcal{A}(m),n}$ being the damping factor between the $\mathcal{A}(m)$-th UAV and the n-th user arisen from the non-orthogonality between each sequences [7]. In addition, Ψ_n is the thermal noise power of the n-th user.

Finally, we denote by S_T the maximum number of users that each UAV can support. To model these constraints on the user-UAV association, a user-UAV association matrix $\mathbf{A}$ of dimension $K \times N$ can be defined as:

$$A_{k,n} = \begin{cases} 1 & \text{if } \mathcal{A}(n) = k, \\ 0 & \text{otherwise}, \end{cases} \tag{8}$$

for $k \in \mathcal{K}$ and $n \in \mathcal{N}$.

Thus, the UAV deployment problem of minimizing the number of deployed UAVs by optimizing the UAV locations, their transmit power and the user-UAV association, subject to the SINR requirement for each user can be written as

$$\begin{aligned} &\underset{\boldsymbol{A},\boldsymbol{p},\{\boldsymbol{\ell}_k\}}{\text{minimize}} \quad K && (9) \\ &\text{Subject to} : \min_{n\in\mathcal{N}} \Gamma_n \geq \Gamma_0, && (C_1) \\ &\qquad \sum_n A_{k,n} \cdot p_n \leq P_{k,\max}, \quad \forall k \in \mathcal{K} && (C_2) \\ &\qquad \boldsymbol{\ell}_k \in \mathcal{D}, \quad \forall k \in \mathcal{K} && (C_3) \\ &\qquad \sum_n A_{k,n} \leq S_T, \quad \forall k \in \mathcal{K} && (C_4) \\ &\qquad \sum_k A_{k,n} = 1, \quad \forall n \in \mathcal{N} && (C_5) \end{aligned}$$

where $P_{k,\max}$ is the maximum total power of the k-th UAV. Furthermore, Γ_0 and $\mathcal{D}$ are the minimum required SINR and the set of feasible UAV locations, respectively.

Clearly, the problem in Eq. (9) is non-convex over high-dimensional space. As a result, its optimal solutions are analytically intractable. In the following, we propose a computationally efficient scheme as shown in Fig. 2 to compute a sub-optimal solution to Eq. (9).

III. PSO-based Deployment Scheme

To decouple the three design goals, namely the minimum number of UAVs, their optimal deployment locations and the corresponding optimal transmission power, we propose to first devise a scheme to jointly optimize the UAV locations and transmit power for a given number of UAVs. This is motivated by the following observation: If such a joint UAV location and transmit power optimization scheme is established, the scheme starts with $K = 1$ UAV; Repeat the joint location-power optimization algorithm by increasing the number of UAVs by one when any one of the resulting SINR's doesn't meet the requirement Γ_0^{dB} according to $C1$ in Eq.(9); This process will be repeated until all users' SINR's meet Γ_0^{dB} with the minimum number of UAVs deployed. In this section, we develop a PSO-based scheme to perform the joint optimization of UAV locations and the transmit power. In addition, the adoption of SINR performance measure will enable us to take advantage of an SINR-balanced power allocation algorithm whose solutions are given in closed-form [8]. Finally, to simplify the user-UAV association, we assume that each user is assigned to the UAV with whom the user has the smallest pathloss computed from the ATG model.

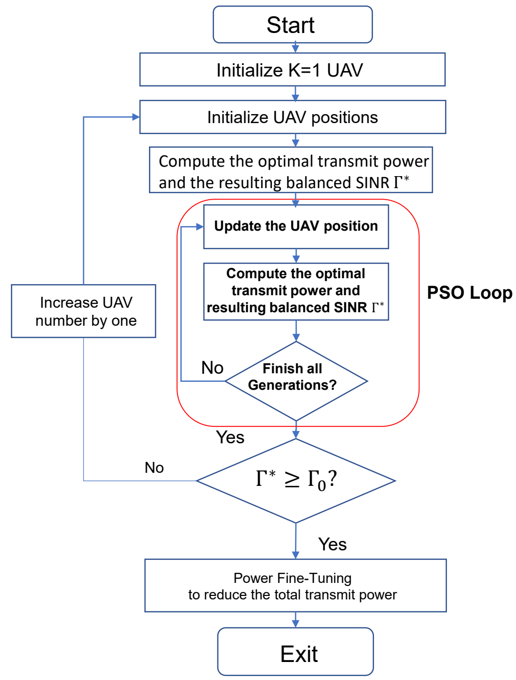

Fig. 2: Flowchart of the proposed PSO-based scheme.

A. PSO-based UAV Location Optimization

To cope with the high-dimensional searching space for the optimal UAV locations, we propose a PSO-based scheme. In sharp contrast to [3] in which the PSO algorithm is used to minimize the total pathloss from one single UAV to all users by optimizing the UAV location, we consider optimizing the locations of multiple UAVs to improve the users' SINR values. We denote by $\boldsymbol{\omega}$ the UAV location vector of K UAVs as

$$\boldsymbol{\omega} = \left[\boldsymbol{\ell}_1^T, \boldsymbol{\ell}_2^T, \cdots, \boldsymbol{\ell}_K^T\right]^T. \tag{10}$$

In the PSO framework, the proposed scheme starts from J initial location vectors denoted by $\boldsymbol{\omega}_j^{(0)}$, for $j = 1, 2, \cdots, J$, as the first generation of UAV locations. Then, the proposed scheme iteratively updates each of the J location vectors generation by generation along the direction leading to improved SINR. For each of the J location vectors in the i-th generation, the proposed scheme performs an SINR-balanced power control algorithm to optimize the transmit power allocated to each user before deriving the resulting balanced SINR for all users. Details of the transmit power control algorithm will be elaborated in Sec. III-C.

More specifically, let $\boldsymbol{\omega}^{(i)*}$ and $\boldsymbol{\omega}_g^*$ stand for the location vector corresponding to the best SINR in the i-th generation and over all generations, respectively. After obtaining the resulting SINR for each location vector $\boldsymbol{\omega}_j^{(i)}$ in the i-th generation, the proposed PSO algorithm then ranks all J location vectors, for $j = 1, 2, \cdots, J$, based upon their corresponding SINR values before updating $\boldsymbol{\omega}^{(i)*}$ and $\boldsymbol{\omega}_g^*$. Mathematically,

$\boldsymbol{\omega}$ is updated according to the following two steps:

$$\begin{aligned} V_j^{(i+1)} =& w V_j^{(i)} + c_1 \rho_j (\boldsymbol{\omega}^{(i)*} - \boldsymbol{\omega}^{(i)}) + c_2 \phi_j (\boldsymbol{\omega}_g^* - \boldsymbol{\omega}^{(i)}), \\ \boldsymbol{\omega}^{(i+1)} =& \boldsymbol{\omega}^{(i)} + V_j^{(i+1)}, \end{aligned} \tag{11}$$

where V_j is the velocity while w is the inertia weight. Furthermore, c_1 and c_2 are the personal and global learning coefficients, respectively. Finally, ρ_j and ϕ_j are random positive numbers.

B. K-means Clustering Initialization

One challenge that was usually overlooked in PSO-based algorithms was the initialization strategy as the initial generation is commonly randomly generated. However, such random initialization suffers from less satisfactory performance as shown in Sec. IV. To circumvent this drawback, we propose to use K-means clustering-based initialization to generate the horizontal locations of the initial generation. More specifically, the K-means clustering-based algorithm is employed to group the N users into K clusters by minimizing the following sum of squared error denoted by ϵ :

$$\epsilon = \sum_{k=1}^{K} \sum_{n=1}^{N} \delta_{k,n} \left\| \boldsymbol{r}_n - \boldsymbol{s}_k \right\|^2, \tag{12}$$

where $\boldsymbol{s}_k$ is the centroid of the k-th cluster on the ground and

$$\delta_{k,n} = \begin{cases} 1 & n \in \mathcal{C}_k, \\ 0 & \text{otherwise}, \end{cases} \tag{13}$$

with $\mathcal{C}_k$ being the user index set for all users grouped into the k-th cluster, for $k = 1, 2, \cdots, K$.

Recalling that $\{\boldsymbol{s}_k\}$ only contains (x, y), we will have to append a randomly generated height to each $\boldsymbol{s}_k$ to produce $\tilde{\boldsymbol{s}}_k$. Then, we initialize

$$\boldsymbol{\omega}_j^{(0)} = \left[\tilde{\boldsymbol{s}}_1^T, \tilde{\boldsymbol{s}}_2^T, \cdots, \tilde{\boldsymbol{s}}_K^T \right]^T. \tag{14}$$

Finally, after repeating the above K-means clustering process for J times, we obtain J sets of $\boldsymbol{\omega}_j^{(0)}$ as the first generation of the UAV locations for the proposed PSO-based scheme. In the sequel, the PSO-based scheme with the K-means clustering initialization is referred to as PSO-KMeans while that with random initialization as PSO-Rand.

C. SINR-balanced Power Allocation Algorithm

In this section, we elaborate on the transmit power allocation algorithm for a given set of UAV locations. Since this transmit power allocation algorithm is executed to update the UAV locations generation by generation in PSO, any computationally expensive algorithms will render impractical. Unfortunately, most existing transmit power allocation schemes designed to minimize the total transmit power require iterative computation, which makes these iterative schemes unsuitable for our application. In lieu of directly minimizing the total transmit power, we propose to focus on transmit power allocation leading to an identical SINR (also known as the balanced SINR) for all users, following a balanced SINR approach proposed in [8] . The advantage of such a power allocation scheme is that both the optimal power allocation and the resulting optimal SINR have closed-form expressions. More specifically, we can have the following expression after some straightforward algebraic manipulations of Eq. (6):

$$\frac{1}{\Gamma_n} \cdot p_n = \sum_{\substack{m=1 \\ m \neq n}}^{N} \alpha_{\mathcal{A}(m),n} \cdot \frac{\mathcal{L}_{\mathcal{A}(n),n}}{\mathcal{L}_{\mathcal{A}(m),n}} \cdot p_m + \Psi_n \cdot \mathcal{L}_{\mathcal{A}(n),n} \tag{15}$$

Let the matrix $\boldsymbol{G} \in \mathbb{C}^{N \times N}$ be defined as:

$$G_{n,m} = \begin{cases} \alpha_{\mathcal{A}(m),n} \cdot \frac{\mathcal{L}_{\mathcal{A}(n),n}}{\mathcal{L}_{\mathcal{A}(m),n}} & \text{if } n \neq m, \\ 0 & \text{otherwise}, \end{cases} \tag{16}$$

for $n, m \in \mathcal{N}$.

If we set the targeted SINR the same for all users, *i.e.* balanced SINR $\Gamma_n = \Gamma$ for $n \in \mathcal{N}$. Let $\boldsymbol{y} = [p_1, p_2, \cdots p_N, 1]^T$. Then for all users, Eq. (15) can be rewritten as

$$\frac{1}{\Gamma} \cdot \begin{bmatrix} p_1 & p_2 & \cdots & p_N & 0 \end{bmatrix}^T = \boldsymbol{B} \cdot \boldsymbol{y}, \tag{17}$$

where $\boldsymbol{h} = \left[\Psi_1 \mathcal{L}_{\mathcal{A}(1),1}, \Psi_2 \mathcal{L}_{\mathcal{A}(2),2}, \cdots \Psi_N \mathcal{L}_{\mathcal{A}(N),N} \right]^T$ and

$$\boldsymbol{B} = \begin{bmatrix} \boldsymbol{G} & \boldsymbol{h}_{N \times 1} \\ \boldsymbol{0}_{1 \times N} & 0 \end{bmatrix}. \tag{18}$$

Denoted by $(\boldsymbol{A})_k$ the k-th row of the assignment matrix $\boldsymbol{A}$, we define $\boldsymbol{C}^{(N+1) \times (N+1)}$ as

$$\boldsymbol{C} = \begin{bmatrix} \boldsymbol{I}_{N \times N} & \boldsymbol{0}_{N \times 1} \\ (\boldsymbol{A})_k & -P_{k,max} \end{bmatrix}. \tag{19}$$

Then, it is straightforward to derive from Eq. (17) that

$$\frac{1}{\Gamma} \cdot \boldsymbol{y} = \underbrace{\boldsymbol{C}^{-1} \cdot \boldsymbol{B}}_{\boldsymbol{D}} \cdot \boldsymbol{y}, \tag{20}$$

where

$$\boldsymbol{D} = \boldsymbol{C}^{-1} \cdot \boldsymbol{B} = \begin{bmatrix} \boldsymbol{G} & \boldsymbol{h}_{N \times 1} \\ \frac{(\boldsymbol{A})_k \cdot \boldsymbol{G}}{P_{k,max}} & \frac{(\boldsymbol{A})_k \cdot \boldsymbol{h}}{P_{k,max}} \end{bmatrix}. \tag{21}$$

Clearly, the optimal power allocation vector $\boldsymbol{y}^*$ is given by the eigenvector of $\boldsymbol{D}$ corresponding to the largest eigenvalue λ^* with the resulting SINR shown below [8]

$$\Gamma^* = \frac{1}{\lambda^*}.$$

In our proposed PSO-based scheme, Γ^* is then employed to direct the UAV location updates in each generation. If $\Gamma^* < \Gamma_0$ even after the maximum number of iterations has been reached, then the PSO-based scheme determines that the current number of UAVs is insufficient. Subsequently, the proposed scheme will be repeated with an additional UAV. Otherwise, the PSO-based scheme will be terminated and further power fine-tuning proposed in the next section is performed.

D. Power Fine-Tuning

It should be borne in mind that the battery on UAVs is rather limited. Therefore, it is highly desirable to preserve energy in all possible means to reserve the resources for emergence. One viable means is to reduce the transmit power of optimal power allocation solution $\boldsymbol{y}^*$ derived above without violating $\Gamma^* \geq \Gamma_0$ for given UAV and user locations. It should be emphasized that $\boldsymbol{y}^*$ is optimal in the sense that Γ^* is maximized within the allowed transmit power budget. In this section, we would like to find a suboptimal $\boldsymbol{y}$ that satisfies $\Gamma^* \geq \Gamma_0$ with the minimum total transmit power. The problem can be reformulated as

$$\begin{aligned} &\text{minimize} \quad \beta && (22)\\ &\text{Subject to} : \min_{n\in\mathcal{N}} \Gamma_n \geq \Gamma_0, && (C_1)\\ &\sum_n A_{k,n}\cdot p_n \leq \beta \cdot P_{k,max} \quad \forall k \in \mathcal{K}. && (C_2)\end{aligned}$$

The optimal value is restricted by the tightest power constraints: for the k-th UAV,

$$\sum_n A_{k,n}\cdot p_n = \beta \cdot P_{k,max}.$$

Using the Eq. (17)-(21), it can be shown that the new matrix $\boldsymbol{D}_1$ is given by

$$\boldsymbol{D}_1 = \begin{bmatrix} \boldsymbol{G} & \boldsymbol{h}_{N\times 1} \\ \frac{(\boldsymbol{A})_k \cdot \boldsymbol{G}}{\beta P_{k,max}} & \frac{(\boldsymbol{A})_k \cdot \boldsymbol{h}}{\beta P_{k,max}} \end{bmatrix}. \qquad (23)$$

As a result, the problem in Eq. (22) is simplified to find the largest eigenvalue of $\boldsymbol{D}_1$ by decreasing β.

IV. Simulation Result

In this section, extensive computer simulation is performed to confirm the performance of the proposed PSO-based scheme. In the simulation, N users are randomly distributed within a geographical area of $100 \times 100\ m^2$. The maximum transmit power of each UAV is set to $P_{\max} = 100$ mW, *i.e.* 20 dBm while we limit the UAV height to be within $[10, 100]$ meters. Furthermore, the ATG models corresponding to the urban environment are used in modeling the pathloss with $a = 9.60$, $b = 0.16$, $\eta_{LoS} = 1.0$ and $\eta_{NLoS} = 20$. Finally, the intra-cell and inter-cell damping factors α_0 and α_1 are set as 0.05 and 0.001, respectively. Unless specified otherwise, we set $\Gamma_0^{\text{dB}} = 0$ dB in the following experiments. Clearly, the proposed scheme is applicable to systems of any practical Γ_0^{dB} values.

Fig. 3 shows the resulting SINR value in dB achieved by the proposed PSO-based scheme in which we set the target SINR to be 0 dB. The four curves from left to right stand for the resulting SINR corresponding to $K = 1, 2, 3$ UAVs deployed, respectively. When the number of users is small, *i.e.* $N \leq 19$, a single UAV can cover all users with each user achieving a balanced SINR above 0 dB. However, the resulting balanced SINR decreases gradually to 0 dB as the number of users increases from 1 to 19. This is because that inter-user interference increases as more users share the spectrum while less transmit power is allocated to each user on average for

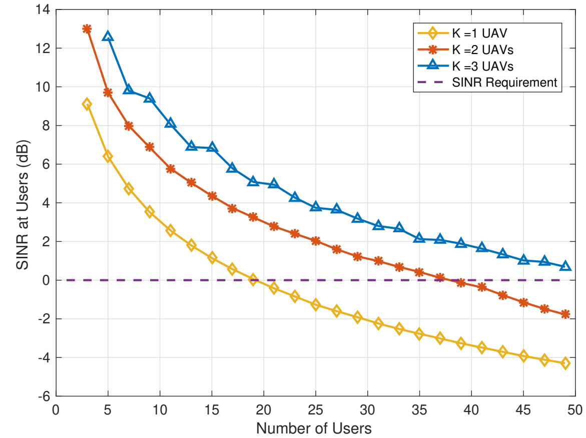

Fig. 3: SINR performance as a function of user and UAV numbers

fixed $P_{k,\max}$. When N increases beyond 19, two UAVs are required to provide the targeted balanced SINR of 0 dB to all users. Similarly, for $N \geq 37$, three UAVs are required as suggested by the rightmost blue curve.

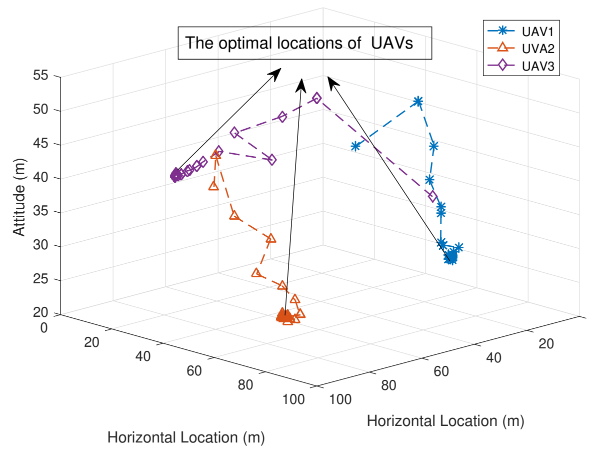

Fig. 4: PSO updates of UAV 3D locations for $K = 3$.

We then inspect the 3D UAV location updated by the proposed PSO-based scheme generation by generation. Inspection of Fig. 4 reveals that the UAV location converges towards their stationary positions for $K = 3$.

Next, we compare the performance of PSO-Rand and PSO-KMeans with $K = 3$. Fig. 5 shows the average SINR achieved by PSO-KMeans and PSO-Rand over 200 simulation runs. First, the curve labelled as ”KMeans-Only” in Fig. 5 shows the performance using simply K-means clustering without the proposed PSO scheme. Clearly, both proposed schemes, PSO-Rand and PSO-KMeans, provide significantly SINR improvement over ” KMeans-Only”. Furthermore, Inspection of Fig. 5 suggests that PSO-KMeans outperforms PSO-Rand over all user numbers investigated, particularly when the number

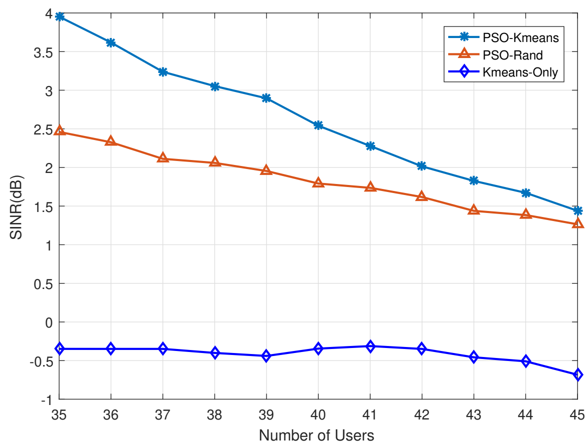

Fig. 5: SINR performance comparison as a function of users.

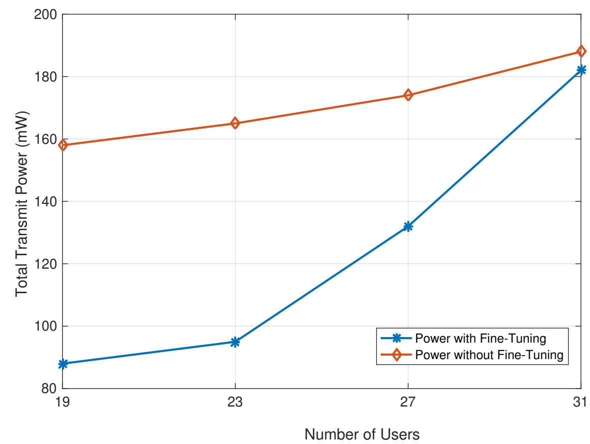

Fig. 7: Total transmit power as a function of users ($K = 2$).

of users is small. Fig. 5 has confirmed that the K-means clustering-based initialization can identify better initial points leading to higher SINR values.

Fig. 6 shows the SINR convergence behavior as a function of iterations/generations with $K = 3$ and $N = 40$. While PSO-KMeans outperforms PSO-Rand in terms of achieved SINR, Fig. 6 suggests that their convergence behavior is very similar.

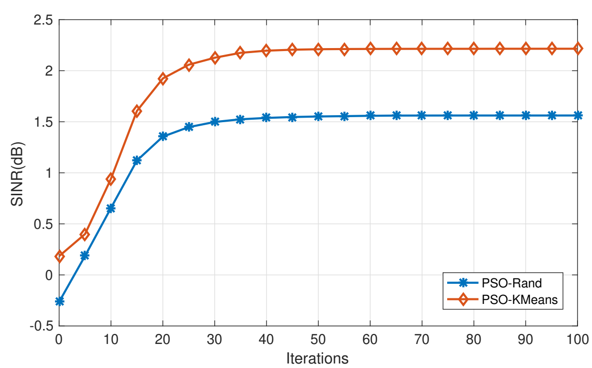

Fig. 6: Convergence behavior as a function of iterations.

Finally, we evaluate the performance of the power fine-tuning algorithm using $\Gamma_0^{\mathrm{dB}} = 0$ dB, $K = 2$ and $P_{\max} = 100$ mW for each UAV. Ψ_n is set to 10^{-10} mW. Fig. 7 shows the total power transmitted to all users, *i.e.* $\sum_{n=1}^{N} p_n$, as a function of users. The red line with diamond markers in Fig. 7 corresponds to the total power of $\boldsymbol{p}^*$ without the proposed power fine-tuning algorithm. In sharp contrast, the blue curve represents the total transmit power after the proposed power fine-tuning. Clearly, Fig. 7 shows that the power fine-tuning process has significantly improved power efficiency, particularly when N is small. This results can be also confirmed from Fig. 3 in which the SINR achieved by the PSO-KMeans is about $\Gamma^{*\mathrm{dB}} = 3$ dB for $K = 2$ and $N = 19$. Thus, it is possible to further optimize the transmit power while maintaining all users' SINR above $\Gamma_0^{\mathrm{dB}} = 0$ dB.

V. Conclusion

In this paper, a PSO-based deployment scheme has been proposed for interference-limited UAV networks to optimize three fundamental deployment issues, namely the minimum number of UAVs, their optimal deployment locations and the optimal transmit power allocation to satisfy a given SINR requirement. In each PSO generation, an SINR-balanced power allocation algorithm computes the closed-form solutions of the optimal power allocation and the resulting optimal SINR. As a result, the proposed PSO-based scheme can efficiently converge towards the optimal UAV locations. Furthermore, a K-means clustering-based initialization algorithm has been proposed for the PSO-based scheme to improve the performance. In addition, a power fine-tuning scheme has been developed to further reduce the total transmit power. Extensive simulation results have confirmed impressive performance of the proposed PSO-based scheme.

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