Efficient 3D Placement of UAVs with QoS Assurance in Ad Hoc Wireless Networks

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Efficient 3D placement of UAVs with QoS assurance in ad hoc wireless networks

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***Abstract*—In this work, we consider a wireless communication system consisting of multiple rotary-wing unmanned aerial vehicles (UAVs) used as areal base stations (ABSs) in order to provide downlink connectivity to the user terminals (UEs) on the ground. Towards investigating power efficient deployment strategies for such a system, the contribution of this article is twofold: we formalize the relevant multi-objective optimization problem, and secondly develop Particle Swarm Optimization (PSO) based techniques for optimization of the individual objectives, which are then exploited in an iterative manner. The relevant optimization objectives for reducing the total power consumed are the number of base stations (BSs) and their transmit powers. The optimization is performed while assuring minimum quality-of-service constraints (QoSs) such as *per-user coverage probability* and *per-user rate*. Through system level simulations, we show that the developed approach ensures great reductions for both the number of base stations as well as their individual transmit power, thus saving initial deployment cost as well as reducing operational costs induced due to energy consumption.**

***Index Terms*—unmanned aerial vehicles, green communications, 5G and beyond, energy aware network, ad hoc networks**

I. Introduction

Unmanned aerial vehicles (UAVs) (commonly known as drones) are becoming ubiquitous in various applications like safety surveillance, shipping and delivery applications, search and rescue operations, remote sensing and wireless communications. In wireless communications, thanks to their small size, mobility, and flexibility in positioning, they find key applications such as providing connectivity in remote areas or disaster-affected areas, or enhancing an already existing terrestrial cellular network [1]. UAVs can be deployed as aerial base stations (ABSs) in areas where it is not feasible to build ground cellular infrastructure or where service is required only for a short period of time. A key advantage of UAVs lies in the establishment of a fast and reliable line-of-sight (LoS) connection with the ground users and/or terrestrial network of ABSs by changing their position in 3D space in any required direction. After the massive loss of infrastructure in Puerto Rico due to Hurricane Maria in the year 2017, AT&T used drones fitted with LTE to provide cellular service to people on the island [2]. This further demonstrates the usefulness of UAVs in setting up ad hoc mobile connectivity. Despite the clear advantage they bring, there are many challenges involved in planning, designing and deploying them. Minimizing power consumption of the UAV based communication systems is a crucial research topic and attracted great attention recently [3][4][5][6].

The *total cost* of deployment of ABSs to provide downlink connectivity to the ground user terminals (UEs) has two cost components -

1) the fixed cost : which depends on the number of ABSs that need to be deployed;

2) the operational cost : major component of which is the *total* power consumption of the whole network, where the total power consumption of the network is further divided between the power needed by the UAVs to hover, and the power consumed in signal transmissions.

The two cost components are mutually coupled via the number of ABSs that are deployed. Thus, reducing the number of ABSs will help in reducing both the costs. However, in the long term, operational costs dwarf the fixed upfront costs, and are thus a bigger priority. Reducing the operational cost essentially boils down to reducing the total power consumed by the network, especially given the rising energy prices. Thus, the relevant optimization problem is to minimize this *total power consumption* with respect to the 3D placement of the UAVs while taking into account the quality-of-service (QoS) constraints such as *per-user coverage probability* and *per-user rate* for a fixed distribution of UEs on the ground.

The total power consumption is directly proportional to the number of ABSs as well as the average individual transmit power required by these ABSs. However, the multiple objectives of reducing both these quantities are complementary. Indeed, reducing the number of ABSs might lead to increased transmit power consumption, and conversely, reducing transmit power might lead to increase in required number of ABSs. In most of the existing works optimization of these two objectives is treated as two independent problems (fixing one while optimizing the other). For example in [7], the authors consider the problem of reducing the number of UAVs to be deployed while the transmit power of the ABSs is considered fixed. In [8], the authors consider the problem of minimizing total transmit power, but only the case with no interference among the UAVs has been addressed, and the number of ABSs is considered fixed.

In this paper, we argue that taking both the components into account in order to reduce the the *total power* consumed leads to better results compared to reducing only one of them. Optimizing the two components jointly is difficult due to the prohibitive complexity. Even optimizing a single component is non-trivial due to its non-convex nature. Therefore, we develop particle swarm optimization (PSO) based optimization algorithms for the individual objectives of minimizing the number of ABSs as well as their individual transmit powers. We then exploit these algorithms in an iterative manner to converge to locally optimal solutions. Through extensive simulations, we show the gain in performance achieved through the developed iterative process when compared to the cases when only one of the objectives was optimized. The algorithm therefore gives a cost efficient and energy efficient solution for 3D placement of ABSs in an ad hoc network without any need for cell planning.

The rest of this paper is organized as follows: In Section II we describe the system model and define various parameters that we examine. In Section III we formulate the main optimization problem. In Section IV we present the algorithms and explain how the PSO technique is adopted. In Section V we explain the simulation setup. In Section VI we present conclusions and give indicate future directions.

II. System description

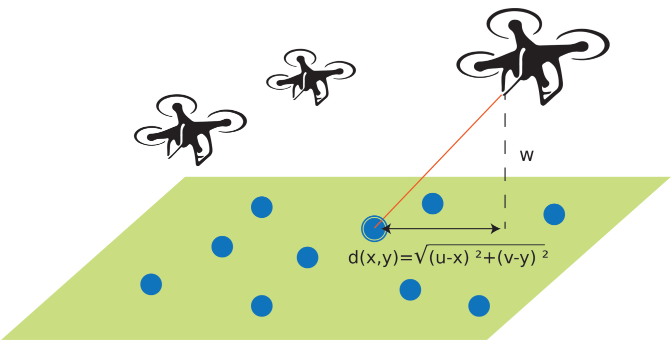

Fig. 1. UAVs deployed as aerial base stations and UEs distributed arbitrarily on the ground.

Consider a 2D plane in which n_u UEs are distributed at arbitrary fixed locations $\{(x_1, y_1), \ldots, (x_{n_u}, y_{n_u})\}$, on the ground. We begin by supposing that we need $n_b = [\frac{n_u}{k}]$ rotary-wing UAVs each carrying a ABS to provide downlink connectivity for the users. The value of the k needs to be fixed based on factors such as the maximum traffic load a ABS can handle on an average. We define P_{tot}, the total power consumed by the n_b UAVs as

$$P_{\text{tot}} = n_b(P_{\text{hov}} + P_t) \tag{1}$$

where P_{hov} is the power needed for a UAV to hover, and P_t is the individual transmitted power of all the ABSs. Our task now is to deploy these UAVs in 3D locations $\{(u_1, v_1, w_1), \ldots, (u_{n_b}, v_{n_b}, w_{n_b})\}$ such that target QoS constraints coverage probability and rate are assured to the users.

A. Air-to-ground channel model

For the jth ABS located at the coordinate (u_j, v_j, w_j), let $\Lambda_{ij} \in \{0, 1\}$ denote the event of LoS which takes the value 1 when there is LoS with the ith UE, and 0 otherwise. Then, the probability of LoS is given as [9]

$$P(\Lambda_{ij} = 1) = \frac{1}{1 + a\exp(-b[\frac{180}{\pi}\theta_{ij}^c - a])} \tag{2}$$

where, a and b are constants which depend on the environment (rural, urban, dense urban etc), $\theta_{ij}^c = \sin^{-1}(\frac{w_j}{d(x_i, y_i)})$ is the elevation angle, $d_j(x_i, y_i) = \sqrt{(u_j - x_i)^2 + (v_j - y_i)^2}$ is the distance on the ground. The path loss between the ABS and the UE in our model is given by

$$\begin{aligned} L_j(x_i, y_i)[\text{dB}] &= 20\log\left(\frac{4\pi f_c d(x_i, y_i)}{c}\right) \\ &\quad + \Lambda_{ij}\eta_{\text{LoS}} + (1 - \Lambda_{ij})\eta_{\text{NLoS}} \end{aligned} \tag{3}$$

where f_c is the carrier frequency, η_{LoS} and η_{NLoS} are the average additional loss to the free space propagation for LoS and no-line-of-sight (NLoS) connections respectively.

B. Connection policy

The connection policy that we adopt is that each UE gets connected to the ABS that offers the strongest signal-to-interference-plus-noise ratio (SINR), *provided* that it is greater than the coding-modulation target γ, which is required for successful reception. The SINR received by the ith UE located at (x_i, y_i) from the jth ABS located at (u_j, v_j, w_j) is given by

$$\text{SINR}_j(x_i, y_i) = \frac{P_t/L_j(x_i, y_i)}{N_0 + I_j(x_i, y_i)} \tag{4}$$

where $L_j(x_i, y_i)$ is as defined in Eq 3, N_0 is the noise, and $I_j(x_i, y_i) = \sum_{j'=1, j' \neq j}^{n_b} P_t/L_{j'}(x_i, y_i)$ is the interference caused due to all the UAVs other than the jth one. We now define the connectivity matrix as

$$\underset{\substack{0 \le i < n_u \\ 0 \le j < n_b}}{c_{ij}} = \begin{cases} 1 & \text{if } j = \min\limits_{0 \le j' < n_b} \{j' | \text{SINR}_{j'}(x_i, y_i) \ge \gamma\} \\ 0 & \qquad\qquad \text{otherwise.} \end{cases} \tag{5}$$

Following this definition, the entry c_{ij} is equal to 1 if and only if the ith user is connected to the jth ABS. Further, each row of the connectivity matrix contains at most one non-zero element because a user can only connect to one ABS at any given instance.

C. Qualities-of-service constraints (QoS)

1) Per-user coverage probability: The first QoS factor that we consider is the *per-user coverage probability* ($\bar{P}_{\text{cov}}$) which is the average value of coverage probability of all the users. We guarantee it to be greater than a target ξ as follows

$$\textit{Constraint 1: } \bar{P}_{\text{cov}} \ge \xi \tag{6}$$

where,

$$\bar{P}_{\text{cov}} = \frac{1}{n_u}\sum_{i=1}^{n_u} \mathbb{P}\left[\sum_{j=1}^{n_b} c_{ij} = 1\right], \tag{7}$$

and $\mathbb{P}[.]$ is the probability that the SINR received by the user at location (x_i, y_i) is greater than γ.

2) Per-user rate: The second QoS constraint that we consider is the *per-user rate* $\bar{R}$, and we constrain it to be greater than a target β.

$$\textit{Constraint 2: } \bar{R} \geq \beta \tag{8}$$

where,

$$\bar{R} = \frac{1}{n_u} \sum_{i=1}^{n_u} W_i \mathbb{E}\left[\log\left(1 + \sum_{j=1}^{n_b} c_{ij} \mathrm{SINR}_j(x_i, y_i)\right)\right] \tag{9}$$

where, $W_i = \frac{B}{M_j}$ is the bandwidth allocated to the ith user for a fixed total bandwidth B, and $M_j = \sum_i c_{ij}$ is the number of users that are connected to the jth ABS. Note that when a UE is not connected to any ABS, its received rate will be zero.

III. Problem formulation

As stated in Section I, we only consider minimizing the total power consumption (Eq 1) as it is the major component of the operational costs. Reduction of fixed costs is a by-product of this optimization, due to reduced number of ABSs.

We formulate the optimization problem of minimizing the total power consumption P_{tot} while constraints in Eq 6 and Eq 8 are satisfied:

$$\begin{aligned} \underset{u_j, v_j, w_j}{\text{minimize}} \quad & P_{\text{tot}} = n_b(P_{hov} + P_t)\,; \text{ where } j \in \{1, 2, .., n_b\} \\ \text{subject to} \quad & \bar{P}_{\text{cov}} \geq \xi \text{ and } \bar{R} \geq \beta. \end{aligned} \tag{10}$$

Our goal is to find the optimal 3D position coordinates (u_j, v_j, w_j) which minimize the total power required to satisfy the QoS constraints. This problem is non-convex in nature and standard convex optimization techniques are not applicable here.

As one can clearly see, the only controllable quantities in the objective function of Eq 10 are the number of base stations n_b, and their individual transmit power is P_t. Minimizing these quantities are two contrasting tasks as reducing the number of base stations might lead to increased average power consumption. Therefore, the optimization problem Eq 10 is a multi-objective optimization problem with the following objectives:

(objective-1) Minimization of transmit power - Considering n_b to be fixed, find the UAV positions (u_j, v_j, w_j) which minimize the transmit power P_t^*.

(objective-2) Minimization of no. of UAVs - Considering, instead, that P_t is fixed, find the UAV positions (u_j, v_j, w_j) which minimize n_b^*, the number of UAVs required.

Ideally, one would like to jointly optimize the two objectives. However, the computational complexity of this joint optimization is prohibitive. We therefore propose instead to use efficient PSO based algorithms for each objective and perform them in an iterative manner. A priori, it is not clear which of these objectives has a greater impact on the total power consumed P_{tot}. For example, if the power required for hovering was much higher than the individual transit power, $P_{\text{hov}}/P_t >> 1$, then reducing the number of base stations would have a higher priority. Therefore, we perform both the optimizations in an iterative manner till we converge to minimal values for both n_b and P_t, denoted henceforth as $(n_b P_t)^\star$. Keeping this in view we will develop PSO based algorithms for these two approaches in Section IV.

IV. Analysis

Solving the optimization problem in Eq 10 analytically is challenging due to the mutual dependence of (u_j, v_j, w_j) and M_j, and due to the fact that u_j, v_j, w_j are continuous variables that can take infinite possible values in 3D. Therefore, we solve the problem numerically using PSO based algorithms. Therein, a set of candidate solutions are iteratively improved upon with regards to a given cost function until a desired accuracy is reached. In our case, each candidate solution (a particle) represents the position coordinates of all UAVs in 3D space. In the analysis that follows, we describe the algorithms developed to numerically solve the optimization problem for both the individual objectives discussed in Section III.

A. Minimization of transmit power

We start with an initial population $\mathcal{S}^{(0)}$ containing P randomly generated particles $\{W_0(0), \ldots W_P(0)\}$ each of dimension $3 \times n_b$. We then iteratively evolve each particle according to the equation

$$W_p(\tau + 1) = W_p(\tau) + V_p(\tau + 1) \tag{11}$$

where, $V_p(\tau + 1)$ is the velocity term. This velocity term also changes every iteration based on: $W_p(\tau)$, the previous position of the pth particle; $V_p(\tau)$, its previous velocity; W_p^{local}, the positions associated with least cost for pth particle up to iteration τ; and W^{global}, the positions associated with the best particle up to iteration τ, in the following way:

$$\begin{aligned} V^{(p)}(\tau + 1) \;&=\; mV^{(p)}(\tau) \\ &+\; c_1 r_1 (W_{(p)}^{local} - W_{(p)}(\tau)) \\ &+\; c_2 r_2 (W^{global} - W_{(p)}(\tau)) \end{aligned} \tag{12}$$

where, m is the inertial weight governing the speed of convergence of PSO, c_1, c_2 are the personal and global learning coefficients respectively, and r_1, r_2 are two positive numbers drawn randomly at every iteration.

We define the cost function for Algorithm 1:

$$U(W^p) = \min\{P_t > 0 | \bar{P}_{\text{cov}} \geq \xi \text{ and } \bar{R} \geq \beta\}. \tag{13}$$

to be the least possible transmit power that satisfies the QoS constraints for a particle W^p. We then use this and find the optimal configuration of the UAVs for a given arbitrary distribution of the users. At the end of all the iterations, we record the best particle W^{global}, which is the set of 3D positions of all the UAVs at which QoS requirements have been satisfied with least amount of transmit power P_t^*.

Algorithm 1 PSO for optimization of transmit power

function PSO
  $\tau \leftarrow 0$
  Generate an initial population $\mathcal{S}^{(0)}$ composed of P random particles $\{W_1(0), W_2(0), \dots W_P(0)\}$ each of dimension $3 \times n_b$.
  $U_p^{\text{local}} \leftarrow U_p(0)$, $\forall p \in [1, P]$
  $U^{\text{global}} \leftarrow \min\{U_1(0), U_2(0), \dots, U_P(0)\}$
  $W_p^{\text{local}} \leftarrow W_p(0)$, $\forall p \in [1, P]$
  $W^{\text{global}} \leftarrow W_p(0)$ for p such that $U_p(0) = U^{\text{global}}$
  $\tau \leftarrow 1$
  while τ < MaxIters **do**
    $V_p(1) \leftarrow 0, \forall p \in [1, P]$
    for all p in {1,2,...,P} **do**
      Compute $V_p(\tau), W_p(\tau), U_p(\tau)$
      if $U_p(\tau) < U_p^{\text{local}}$ **then**
        $W_p^{\text{local}} \leftarrow W_p(\tau)$, $U_p^{\text{local}} \leftarrow U_p(\tau)$
        if $U_p^{\text{local}} < U^{\text{global}}$ **then**
          $W^{\text{global}} \leftarrow W_p(\tau)$, $U^{\text{global}} \leftarrow U_p(\tau)$
        end if
      end if
    end for
    $\tau \leftarrow \tau + 1$
  end while
  return (W^{global}, U^{global})
end function

B. Minimization of no. of UAVs

To minimize the number of ABSs, we employ the modified version Algorithm IV-B to contain two cost functions corresponding to the two QoS constraints defined in Eq 6 and Eq 8. We first find ABS positions that optimize the coverage probability, and then optimize the average rate while assuring that the coverage probability never falls below the target ξ. Once, we have the positions for all the ABSs, which offer good coverage probability as well as average rate, we start reducing the number of ABSs. To this effect, starting with the optimal configuration, we eliminate the redundant ABSs by going through them iteratively, and removing the ones that do not affect the two constraints. This approach is similar to the ones used in [10],[7]. During this optimization, the value of P_t is considered to be fixed. For P_t values that are too low, the algorithm may not show any improvement in terms finding the optimum configuration.

V. Simulation results

We analyze the performance of our iterative procedure through extensive simulations. To this end, we execute the algorithms described in Section IV with numerical values for parameters given in Table V (unless specified otherwise). We examine the scenario in which UEs are spread according to a 2D Gaussian distribution about the point $(0, 0)$ with a standard deviation of 2 km. For the UAVs we initialize the position coordinates (u, v, w) drawn uniformly with $u, v \in [-5 \text{ km}, 5 \text{ km}]$, and $w \in [100 \text{ m}, 600 \text{ m}]$.

Algorithm 2 PSO for minimization of no. of ABSs

function PSO
  $\tau \leftarrow 0$
  Generate an initial population $\mathcal{S}^{(0)}$ composed of P random particles $\{W_1(0), W_2(0), \dots W_P(0)\}$ each of dimension $3 \times n_b$.
  $U \leftarrow \bar{P}_{\text{cov}}$
  $U_p^{\text{local}} \leftarrow U_p(0)$, $\forall p \in [1, P]$
  $U^{\text{global}} \leftarrow \max\{U_1(0), U_2(0), \dots, U_P(0)\}$
  $W_p^{\text{local}} \leftarrow W_p(0)$, $\forall p \in [1, P]$
  $W^{\text{global}} \leftarrow W_p(0)$ for p such that $U_p(0) = U^{\text{global}}$
  $\tau \leftarrow 1$
  while True **do**
    $V_p(1) \leftarrow 0, \forall p \in [1, P]$
    for all p in {1,2,...,P} **do**
      Compute $V_p(\tau), W_p(\tau), U_p(\tau)$
      if $U_p(\tau) > U_p^{\text{local}}$ **then**
        $W_p^{\text{local}} \leftarrow W_p(\tau)$, $U_p^{\text{local}} \leftarrow U_p(\tau)$
        if $U_p^{\text{local}} > U^{\text{global}}$ **then**
          $W^{\text{global}} \leftarrow W_p(\tau)$, $U^{\text{global}} \leftarrow U_p(\tau)$
        end if
      end if
    end for
    if $U = \bar{P}_{\text{cov}}$ and $U \geq \xi$ **then**
      $U \leftarrow \bar{R}$
    end if
    if $U = \bar{R}$ and $U \geq \beta$ **then**
      return (W^{global}, U^{global})
    end if
    $\tau \leftarrow \tau + 1$
  end while
end function

Environmental parameters (Eq 2) and (Eq 3) (urban)	$a = 9.61, b = 0.16$ $c = 3 \times 10^8$, $\eta_{\text{LoS}} = 1$, $\eta_{\text{NLoS}} = 20$
System parameters (Eq 4)	$N_0 = -90$dBm, $\gamma = -7$dB $f_c = 2$ GHz, $B = 20$ MHz
Simulation Parameters (Eq 10) and (Eq 12)	$\xi = 0.95$, $\beta = 1$ Mbps $c_1 = 1.3962$, $c_2 = 1.3962$, $m = 0.3298$

In Fig. 4, we show the variation of *per-user coverage probability* and *per-user rate* with respect to individual transmit power of the ABSs. Different curves correspond to different values of carrier frequency f_c. We note that the constraints in Eq 10 for $\xi = 0.95$ and $\beta = 1 \times 10^6$ Hz are simultaneously satisfied only when P_t is *at least* greater than 2.5 W. Hence in the simulations done for the calculations of total power consumed by the system (Fig. 6), we assume the $P_t = 2.5W$ for the cases that do not minimize the transmit power P_t.

The effectiveness of our iterative method of performing the multi-objective optimization can be seen in Fig. 2. We see that massive improvements can be made in terms of number of ABSs as well as their individual transmit power. Starting from

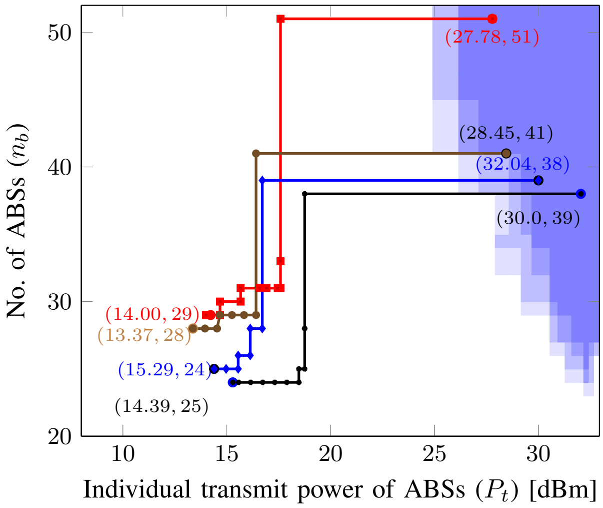

Fig. 2. The shaded region in P_t and n_b space is where both the QoS constraints are satisfied for random ABS locations (averaged over several UE distributions). To demonstrate the effectiveness of our algorithm, we pick up random points from this region as starting values and find the optimal configurations of ABSs where the constraints are satisfies for lower n_b and P_t values. Note that all these final values converge to the bottom left quadrant.

a point (P_t, n_b) in the region where both the constraints are satisfied for many possible UE distributions, we can optimize considerably in both directions.

This can be more clearly seen in Fig. 3, where we illustrate the initial and final ABS positions for the two different optimizations, as well as the result when both are optimized iteratively. We can see that for 1000 UEs, by minimizing only P_t we achieve the QoS at total transmit power of $35 \times 0.039 = 1.365$ W, whereas minimizing only objective-2 this is only made possible for total transmit power of $27 \times 2.5 = 67.5$ W. By minimizing both objectives iteratively, we manage to reduce the total transmit power to $24 \times 0.033 = 0.792$ W.

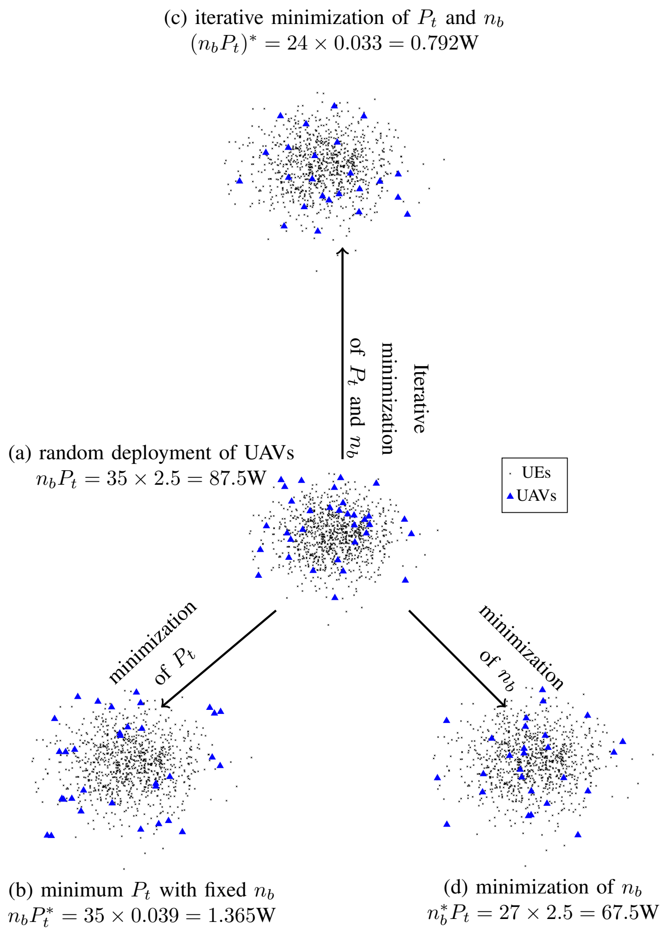

Fig. 3. (a) Initial random deployment of UAVs. (b) and (c) The resulting system configurations after individual aPSO optimizations. (d) System configurations after iterative application of the two algorithms. We can see that the iterative approach leads to a much better values for $(n_b P_t)^\star$.

In Fig. 5, we compare the P_t^* against the number of users per base station, k. We notice that P_t^* increases with k as expected, and is higher for larger values of carrier frequency f_c. The plot is obtained by averaging over several different initializations. Note, however, that the $P_t^\star$ is much smaller than the P_t required to satisfy the two QoSs (as in Fig 4).

A. Significance in reduction of total power expenditure

Taking power required to hover P_{hov} into account we can estimate the total power expenditure of the system. To this effect we consider the model $P_{\text{hov}} = \sqrt{(2Mg)^3/16\rho A}$ as in [11], for $M = m_d + m_{pl}$ where m_d is mass of the drone and m_{pl} is mass of the payload, $g = 9.8\text{m s}^{-1}$ is acceleration due to gravity, $\rho = 1.2\ \text{Kgm}^{-3}$ is density of air, $A = 0.362\text{m}^2$ is the rotor area. Also, we assume a linear relation $m_{pl} \propto 10\log(1000 * P_t)$. Notably, typical mass of a base station emitting 2.5W would be around 1.2Kg [12], and a drone able to carry such a payload is Phantom [13] which is 1.5kg in weight (including batteries). In Fig. 6, we use these relations and find the total power expenditure

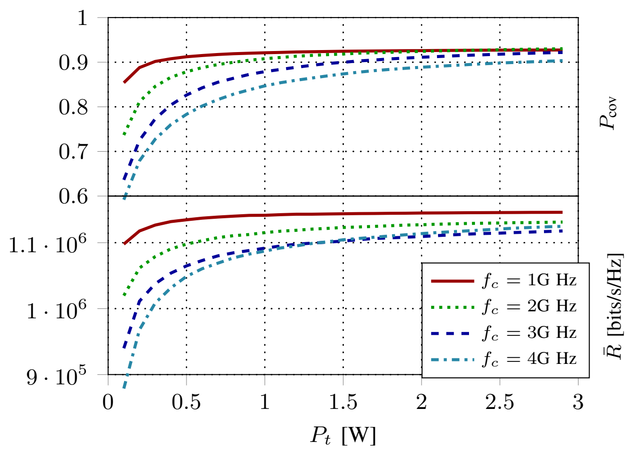

Fig. 4. Variation of *per user coverage probability* and *per user rate* with individual transmit power (1000 user terminals, 35 UAV base stations and averaged over several random configurations). Target values for both the constraints are satisfied when $P_t \geq 2.5$W.

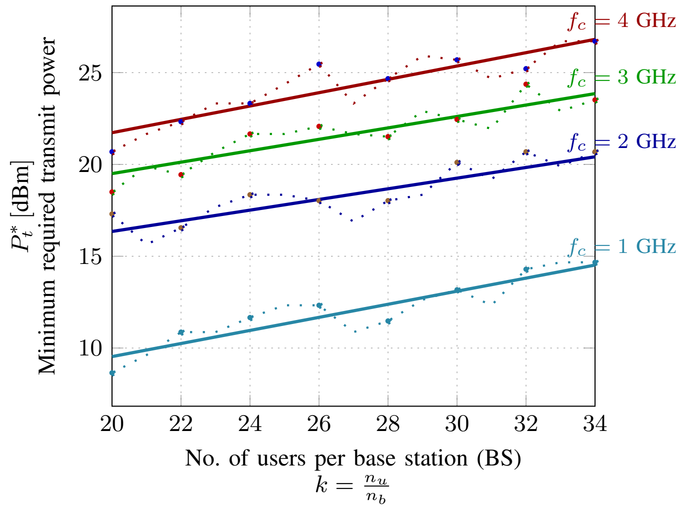

Fig. 5. *Optimal transmit power* of the UAVs for a range of values for k, for different carrier frequencies.

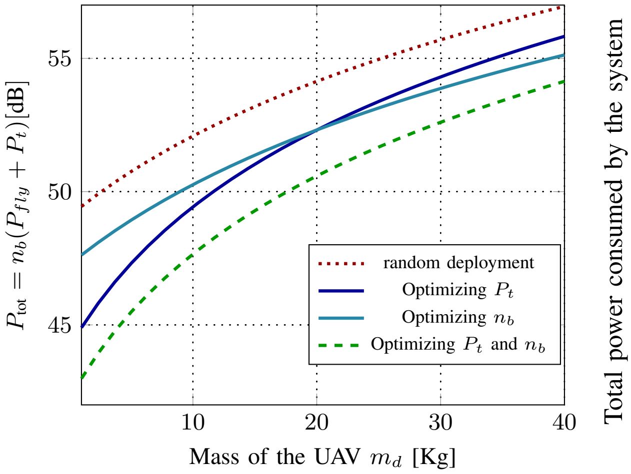

Fig. 6. Variation of total power consumed by the system with the mass of the drones. We see that for lighter drones ($<$ 20Kg), the total power consumption of the system is significantly reduced by minimizing P_t, whereas when the drones are heavier we see that minimizing n_b saves more energy. However in either case the iterative approach gives a relatively more efficient solution.

of the system, $n_b(P_{\text{hov}} + P_t)$, before and after optimization for different masses of drones. For these typical values, the gains achieved by optimizing P_t is considerable, even when compared with optimizing n_b. It should also be noted that higher UAV mass m_d is only needed when the base station emits at higher power, in which case, the benefits of first approach would be even more pronounced.

VI. Conclusion

In this work, we studied the power minimization problem in a wireless communication system where unmanned aerial vehicles (UAVs) are used as aerial base stations (ABSs) providing downlink connectivity to the ground users. We define the problem of optimizing the *total power* consumed by the system while ensuring target values of *per-user coverage probability* and *per-user rate* with respect to the 3D locations of the ABSs. We note that the *total power* expenditure is dependent on the number of ABSs as well as their transmit power. We develop algorithms to minimize each of these and analyse the reduction in *total power* through simulations. We notice that an iterative approach where these algorithms are applied on to the system repeatedly leads to a much more energy efficient solution to the optimization problem. In our future works, we plan to explore the theoretical aspects of this problem. Also, we would like to study optimal locations of charging points and optimization of trajectories of ABSs to and from these charging points.

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