Simultaneous User Association and Placement in Multi-UAV Enabled Wireless Networks

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***Abstract*—In this paper, we are proposing a map-based approach for the optimal placement of multiple UAV-based flying wireless relays in a cellular network. The tackled problem is two-fold, involving a joint UAV-user association problem and 3D placement problem. While related problems were addressed before, the novelty of our approach lies in the fact it builds on a combination of probabilistic and deterministic line-of-sight (LoS) classifiers which exploits the availability of a 3D city map. While the original problem is very challenging in its dimension, we give a low-complexity approach to the placement problem by approximating the optimum UAV positions with a suitably weighted combination of user positions. Our simulations suggest a performance close to that obtained with high complexity exhaustive search for placement.**

***Index Terms*—UAV, drone, placement, wireless, relay, association, networks**

I. Introduction

The exploitation of drones, a.k.a unmanned aerial vehicle (UAV) for future wireless cellular communication networks has recently gained significant attention under so-called Drone-as-a-Terminal (DaaT) and Drone-as-a-Relay (DaaR) scenarios. In the DaaR context, the UAV is envisioned as a complement to classical fixed infrastructure by allowing ultra-flexible deployments, with use cases ranging from disaster recovery scenarios, servicing of temporary cultural or sporting events, and hot-spots coverage [11], [16]. Much of prior works dealing with UAV-aided networks has focused on gain analysis such as e.g. [15], placement and path planning problems e.g. [9], [13]. In its widest generality, the placement problem considers seeking a location (or a cyclic path) for a UAV-based relay so as to optimally serve one or more ground users given specific user locations and traffic density distributions.

Note that while the problem of placement a single flying relay was previously considered in e.g. [3], an additional challenge for the multiple UAV case lies in the fact that users must be associated to one of the UAVs before being relayed to the BS. The user-UAV association rule depends on the UAV location while the optimal position for the UAV itself depends on which users are to be served by each UAV, making placement and association two tightly coupled problems. This fact was recently highlighted in [13]. However there are several differences between [13] and this work in that (i) we are interested in the static placement problem while [13] is addressing a path planning problem under a fixed flight time constraint and more importantly (ii) we propose to exploit the availability of a 3D city map so as to provide deterministic rate guarantees based on accurate LoS prediction to the ground users, while purely statistical channel models considered in most previous works [2], [10], [11], [13] aim at giving probabilistic guarantees.

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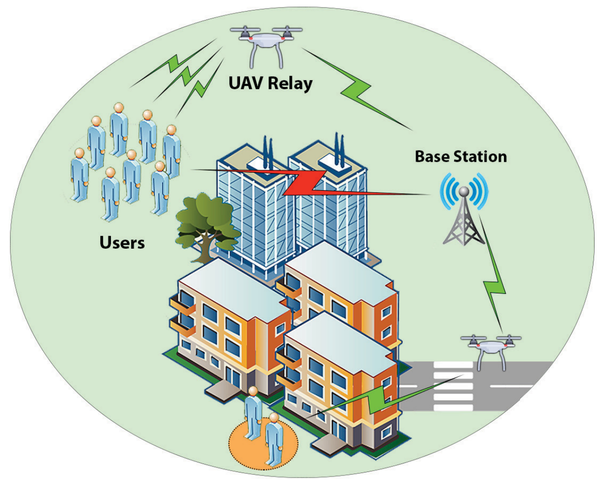

Fig. 1: An illustration of map-based simultaneous users association and placement of multiple UAV-based flying wireless relays.

II. System Model

This study considers an urban area consists of a set of N ground level outdoor users carrying radio transmitting equipments which are scattered randomly in the city and surrounded by a number of city buildings. Moreover, a set of M UAVs are flying over the city and functioning as communication relays between base station (BS) and users as is shown in Fig. 1. The 3D map of the city is assumed to be known (estimated) in advance which can be obtained using either photogrammetry or radio (including recently UAV-aided) based reconstruction approaches [6], [8]. This paper aims to develop a strategy for intelligent placement of the multiple UAVs so as to maximize a system communication performance metric. In our scenario, we choose to optimize the data rate offered to the worst off user, so as to enhance traffic while

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maintaining user fairness[1]. The ground users have GPS-tracked 2D positions denoted by $X_U^n = (x_U^n, y_U^n) \in R^2, n = 1 \ldots N$. In particular the path loss between the n-th user at the UAV locations $X_D^m = (x_D^m, y_D^m, z_D^m) \in R^3, m = 1, \cdots, M$ is denoted by γ^{nm}. Finally we assume orthogonal time/frequency slots are used to communicate with the M drones and also within the users associated to the same drones. Note that this assumption could be relaxed for the sake of spectral efficiency, however emphasis is placed on the placement problem in this paper rather than the well researched interference mitigation problem.

A. Channel Models

The air-to-ground mobile channel has been studied extensively in the recent years (see for instance [1], [12]). Classically the channel path loss between the user and the UAV in dB is modeled as

$$\gamma_s = \beta_s + 10\alpha_s \log_{10} d \ , s \in \{LoS, NLoS\} \tag{1}$$

Where α_s is the path loss exponent, d is the distance between the transmitter (ground user) and the receiver (UAV), β_s is the average channel path loss at a reference point. The subscript s emphasizes the strong dependence of the propagation parameters on the LoS or non-line-of-sight (NLoS) nature of the channel [14]. Hence for one given UAV position, we have two cases $s =$ "LoS" or $s =$ "NLoS" for each ground user taken separately. Note we assume that the base station always is LoS to the UAV. We also assume that the parameters $\{\alpha_s, \beta_s\}$ have been pre-estimated based on prior measurements [4].

B. 3D Map-based User Classification

For every possible UAV location, we seek to classify each of the N users in LoS or NLoS mode. For this, we propose to exploit the availability of 3D city map. Note that the 3D map can be obtained from external information sources or potentially obtained (or enhanced) from the RSSI measurements made with the drone itself [6]. From a trivial geometry argument we can predict LoS (un)availability on any given UAV-user link. Let's assume that the UAV is hovering at position X_D, then user U is considered in LoS to the UAV if the straight line passing through both the UAV and the user lies unobstructed from any building in between.

III. Multi-UAV Placement

A. System Performance Metric

We consider an up-link scenario where the M drones or UAVs form a flying networks of relays and where each user communicates through one of the available relays. Let us assume the n-th user is served by the m-th UAV and this link has LoS/NLoS status s. By virtue of orthogonal channel access, for simplification, the interference-free capacity of the drone to user link is approximated (upper bounded) by

$$C_{D-U}^{nm} = \log_2\left(1 + \frac{P_U}{\gamma_s^{nm}\sigma^2}\right) \tag{2}$$

[1]Other system performance metrics can also be considered such as maximum sum throughput etc..

where γ_s^{nm} is the predicted path loss between user n and UAV m under LoS class s. Similarly the capacity of m-th UAV-BS link is

$$C_{D-BS}^{m} = \log_2\left(1 + \frac{P_D}{\gamma_{BS}^{m}\sigma^2}\right) \tag{3}$$

where $P_U,\ P_D$ are the up-link transmit power of the user and UAV respectively and where the upper-bounding argument originates in the Jensen's inequality applied to the concave log function in the actual Shannon capacity expression [5]. The additive white Gaussian noise at the receivers is denoted by σ^2, and γ_{BS}^m stands for the path loss between m-th UAV and base station.

B. Joint Association and Placement

We now are interested in developing an algorithm for joint placement and UAV-user association which can operate on the basis of the available data only, that is (i) the propagation parameters $(\alpha_s, \beta_s\,;\, s \in \{LoS, NLoS\})$, (ii) the 3D city map, and (iii) the GPS coordinates of the BS and ground users. Finally, we are interested in numerically-friendly methods that avoid exhaustive search of positions in the full 3D flying volume.

The UAV placement and association algorithm is largely dependent on the nature of the quality of service (QoS) we wish to offer to users. In this paper, we take the example of a fairness-oriented QoS scenario whereby the network seeks to maximize the rate of the worst-off users. Hence in a system with backlogged traffic and assuming a simple decode-forward relay protocol, the drones' positions and users association are selected according to:

$$\max_{\mathcal{X}_D,\, Q} \left\{ \min_{n\in[1,N]} \left[\sum_{m=1}^{M} q_{nm} \min\left(C_{D-U}^{nm}, C_{D-BS}^{m}\right) \right] \right\} \tag{4}$$

Where $\mathcal{X}_D = \left\{X_D^m \in R^3, \forall m\right\}$ is the UAV location vector and $Q = \{q_{nm}, \forall n, m\}$ is the binary association solution where $q_{nm} = 1$ indicates that user n associates to the m-th drone (and only that one) and $q_{nm} = 0$ otherwise. Note that the inner "min" operator reflects the fact that in a standard decode-forward the capacity of the relay channel is limited by the segment with lowest capacity. Classically, problem (4) can be reformulated by relaxing the binary association constraint (see e.g. [13]).

$$\begin{aligned} \max_{\mathcal{X}_D,\, Q} \quad & \mu \qquad\qquad\qquad\qquad\qquad\qquad (5) \\ \text{s.t.} \quad & \textstyle\sum_{m=1}^{M} q_{nm} \log_2\left(1 + \frac{P_U}{\gamma_s^{nm}\sigma^2}\right) \geq \mu\,,\ \forall n \\ & \log_2\left(1 + \frac{P_D}{\gamma_{BS}^{m}\sigma^2}\right) \geq \mu\,, \forall m \\ & \textstyle\sum_{m=1}^{M} q_{nm} = 1,\ \forall n \\ & 0 \leq q_{nm} \leq 1,\ \forall n,\, m \end{aligned}$$

where μ can be interpreted as the worst channel capacity among all the network links. Problem (5) is hard to solve as

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it combines the association problem with the UAV placement problem. To simplify further , we can split up the problem (5) into two optimization sub-problems and classically iterate between them (i.e. associating users to UAV with a given position and updating the UAV positions given the preceding association solution).

C. User Association

Given a set of candidate positions $\mathcal{X}_D^*$ for the M drones, the association can be optimized in a standard fashion along the following lines:

$$\max_{Q} \quad \mu \tag{6}$$

$$\begin{aligned} \text{s.t.} \quad & \textstyle\sum_{m=1}^{M} q_{nm} \log_2\left(1+\frac{P_U}{\gamma_s^{nm}\sigma^2}\right) \geq \mu\,, \forall n \\ & \log_2\left(1+\frac{P_D}{\gamma_{BS}^{m}\sigma^2}\right) \geq \mu\,, \forall m \\ & \textstyle\sum_{m=1}^{M} q_{nm} = 1,\ \forall n \\ & 0 \leq q_{nm} \leq 1,\ \forall n,\, m \end{aligned}$$

Note that because there in no interference nor load balancing constraint in this scenario, the association problem is easily solved by associating any user to the UAV exhibiting the highest RSSI, hence:

$$q_{nm} = \begin{cases} 1 & m = \arg\min\limits_{k} \gamma_s^{nk} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

D. Multi-UAV Placement

In this section we consider the problem of Multi-UAV placement exploiting 3D maps for a given association solution. Up to our knowledge this problem was never addressed before. Note that the search for all drone positions decouples into M independent position searches thanks to the orthogonal multiple access across all users. While the optimal position for one drone involves a 3D search, we simplify it by decoupling the search for a UAV position in the 2D horizontal plane from the search from an optimized flying altitude, as follows:

1) Optimal Horizontal UAV Position : Let us assume a fixed flying altitude z_D^m for the m-th UAV. Due to the segmented nature of the channel model, i.e. the notion that LoS status can change completely when going around a street corner, the search for the optimum 2D UAV position is highly non-convex and a heuristic method is our best hope for a solution. In this paper, we propose a practical strategy placing the UAV as a suitably weighted center of gravity of all its associated users' positions. Specifically, we propose:

$$(x_D^{m*}(z_D^m), y_D^{m*}(z_D^m)) = \frac{\sum_{n=1}^{N}(1-l_n(z_D^m))\, q_{nm} X_U^n + X_{BS}^{'}}{\sum_{n=1}^{N}(1-l_n(z_D^m))\, q_{nm}}, \forall m \tag{8}$$

where $X_{BS}^{'} = (x_{BS}, y_{BS})$ is the projection of base station position onto the ground and $0 \leq l_n(z_D^m) \leq 1$ is a weight to be selected and where z_D^m expresses the dependence on the assumed UAV altitude (the altitude will be optimized as a second step). In accordance to the chosen system performance metric, a possible strategy is to favor the weakest user. Note that in the case of homogeneous propagation (such as all LoS-based propagation) the solution would be to minimize the distance between the UAV and the most distant associated user. In the segmented channel model case however, the weakest user is the one which is also most impaired from LoS obstructions. In order to capture this intuition and build on the available 3D map, we introduce $l_n(z_D^m)$ to be an altitude-dependent "LoS factor". This factor is defined by the ratio of LoS region area at altitude z_D^m over the total area of search. In practice, this factor is estimated using the 3D map by taking P (P large enough) random uniform UAV points at altitude z_D^m and counting how many of these are in LoS from the target user n. For instance, a user surrounded by tall and close-by structures would require the UAV to fly right on top of it to experience LoS and hence has a LoS factor of nearly 0, while a user located in the middle of a large flat park would have a factor l closer to 1. Note that in order to take the base station into account for placement, we also consider the base station as an user with the LoS factor equals to 1 by assuming same transmit power for drones and users.

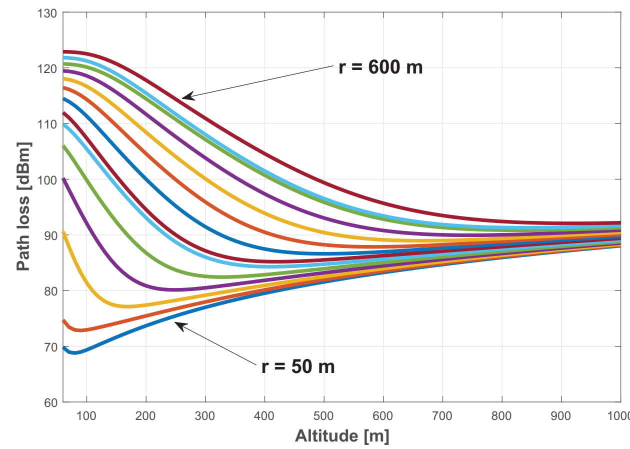
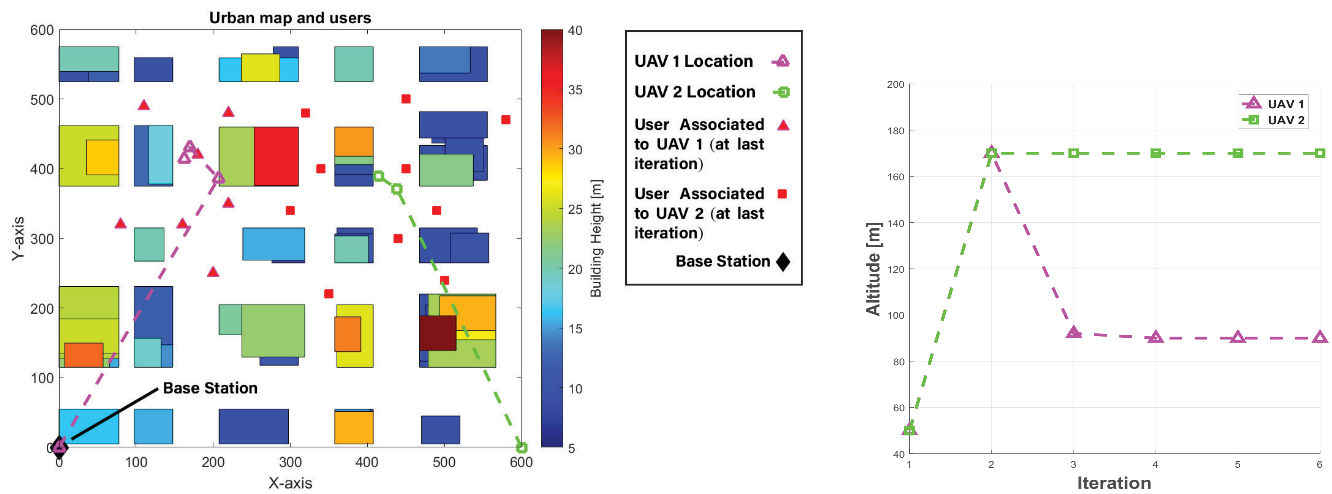


Fig. 2: Path loss pertaining to users with different distances (r) from drone versus drone altitude.

2) Optimal UAV Altitude: Now we proceed to optimize the UAV altitude for given horizontal UAV coordinates. While this problem is again challenging by nature of the segmented channel model, we relax the segmentation by resorting to a classical probabilistic model, where the LoS probability of n-th user with respect to m-th UAV can be for instance predicted from [2]:

$$P_{LoS}^{nm}(r, z_D) = \frac{1}{1 + a\, \exp\left(-b\left[\arctan\left(\frac{z_D}{r}\right) - a\right]\right)} \tag{9}$$

where r is the ground projected distance between the drone and the user, and a, b are called S-curve parameters and computed according to [2], and z_D denotes the respective drone altitude. Based on this, the *average* path loss for one UAV-user link can be obtained for a given drone altitude z_D^m



(a) (b)

Fig. 3: (a) Computed optimal UAVs' positions in each iteration over the city and associated users for the last iteration. The users assigned to the first UAV are shown by triangles and users associated to the second UAV are depicted in squares. (b) Evolution of respective UAVs' altitudes in each iteration.

by:

$$\Lambda^{nm}(r, z_D) = P_{LoS}^{nm}(r, z_D) \cdot \gamma_{LoS}^{nm} + (1 - P_{LoS}^{nm}(r, z_D)) \cdot \gamma_{NLoS}^{nm}, \forall n, m \quad (10)$$

Let's define r_{nm} as the ground distance between n-th user and m-th UAV. Then $i_m = \underset{n=1,\cdots,N}{\arg\max}\,(q_{nm} \cdot r_{nm})$ denotes the farthest associated user to the m-th UAV. We can show that the flying altitude can be optimized according to the proposition below:

Proposition 1. *The optimal UAV altitude (in the sense of probabilistic path loss) above ground location $(x_D^{m*}(z_D^m), y_D^{m*}(z_D^m))$ is given by:*

$$\max_{z_D^m} \quad \bar{\mu} \qquad (11)$$

$$\text{s.t.} \quad \log_2\left(1 + \frac{P_U}{\Lambda^{i_m m}(r_{i_m m}, z_D^m)\sigma^2}\right) \geq \bar{\mu}$$
$$\log_2\left(1 + \frac{P_D}{\gamma_{BS}^m \sigma^2}\right) \geq \bar{\mu}$$

Proof: (10) is an increasing function of r since the path loss of LoS channel is always less than that in a NLoS link. So, it indicates that the worst channel among all users pertains to the farthest user to the UAV. ■

Therefore problem (11) can now be used to find the optimal altitude. This optimization is facilitated from the fact that the expected path loss for the worst off user has a single unique local and global minimum as illustrated in Fig. 2.

E. Algorithm Design

The sub-optimal (yet low complexity) algorithm for solving (5) is based on a three way iteration between user association, drone altitude optimization and horizontal position optimization and is described concisely in Algorithm 1.

IV. Numerical Results

We consider a dense urban Manhattan-like 600 m by 600 m area consisting of a regular street grid and buildings with uniform random height in the range of $[5, 40]$ m . The base station is located in the origin with the height of 40 m. We consider $N = 17$ users to be served via two drones $(M = 2)$. The propagation parameters for the users are chosen as $\alpha_{LoS} = -2.27$, $\beta_{LoS} = -40$, $\alpha_{NLoS} = -3.64$, $\beta_{NLoS} = -30$ and for the UAV-BS link $\alpha_{LoS} = -2.1$, $\beta_{LoS} = -38$, generalized from typical fixed base station-based models as in WINNER II models [7]. The transmission powers are chosen as $P_U = 27$ dBm, $P_D = 27$ dBm, and the noise power is -70 dBm.

First, in Fig. 3a we illustrate the UAVs optimal positions which are computed in each of 6 iterations using our Algorithm. The first UAV (shown in triangles) initially starts flying from above the base station $X_{BS} = X_{D_0}^1 = (0, 0, 50)$ and the second UAV (squares) starts from location $X_{D_0}^2 =$

Algorithm 1 Map-based multi-UAV placement and user association

- Initialize the drones' positions at any arbitrary locations (far from each other).

I) User Association:

- Determine the optimal user association according to Section III-C.

II) Drone Placement:

- Find the weighted center of gravity of each UAV's associated users and locating the UAV there.
- Optimize the height by working out (11) for each UAV.

Go back to phase I and iterate until convergence.

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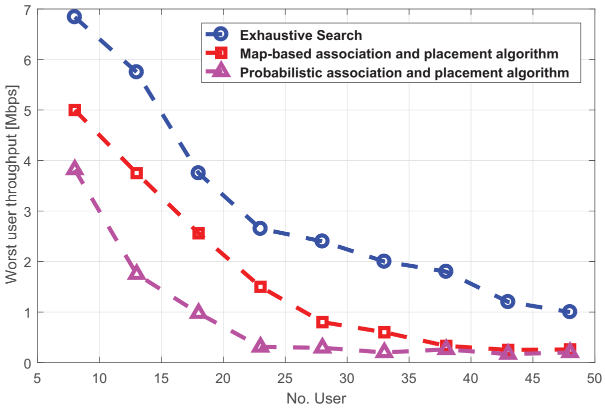

Fig. 4: Worst-off user throughput for three different algorithms.

$(600, 0, 50)$. The users assigned to the first UAV are shown by filled triangles and users associated to the second UAV are depicted in filled squares. Note that, the results of the user association are related to the last iteration (final UAV's optimal position). Also, the corresponding computed altitudes for each UAV versus iteration are shown in Fig. 3b.

In Fig. 4 the worst user throughput for three different algorithms is shown. Note in all case, the throughput of the worst use is getting worse as more users are injected in the network, conforming to intuition. We can see that the performance of the proposed map-based algorithm exhibits desired robustness is between the values obtained with high complexity exhaustive search and the probabilistic approach. Note that, in probabilistic approach, the (3D) optimal locations for drones and also user association are performed totally based on the average path loss (10).

V. Conclusion

This paper studies a simultaneous UAV-user association and 3D placement problem in multi-UAV enabled wireless networks. The proposed solution builds on combined estimation of the users LoS availability based on statistical model and city map-based information. We propose a low-complexity approach to approximate the optimum UAV positions based on a suitably weighted combination of users' positions.

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