# A Distributed Mechanism for Joint 3D Placement and User Association in UAV-Assisted Networks

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***Abstract*—In this paper, we study the joint 3D placement of unmanned aerial vehicles (UAVs) and users association under bandwidth limitation and quality of service constraints. In order to allow to UAVs to dynamically change their 3D locations in a distributed fashion while maximizing the network's sum-rate, we break the underlying optimization into 3 subproblems where we separately solve the 2D UAVs positioning, the altitude optimization, and the UAVs-users association. First, given fixed 3D positions of UAVs, we propose a fully distributed matching based association that alleviates the bottlenecks of the bandwidth and guarantees the required quality of service. Next, to address the 2D positions of UAVs, we adopt a modified version of K-means algorithm, with a distributed implementation, where UAVs dynamically change their 2D positions in order to reach the barycenter of the served users cluster. In order to optimize the UAVs altitudes, we study a naturally defined game-theoretic version of the problem and show that under fixed UAVs 2D coordinates, a predefined association scheme, and limited-interferences, the UAVs altitudes game is a non-cooperative potential game where the players (UAVs) can maximize the limited-interference sum-rate by only optimizing a local utility function. Our simulation results show that, using the proposed approach, the network's sum rate of the studied scenario is improved by $200\%$ as compared with the trivial case where the classical version of K-means is adopted and users are assigned, at each iteration, to the closest UAV.**

## I. Introduction

As cities grow and become more developed, they rely on more technology to offer a wide range of sophisticated services and improve citizens quality of life. One of these key technologies, that is playing and will continue to play a vital role in today's and future smart cities, is the unmanned aerial vehicles (UAVs) technology, also known as *drones* [1].

In this paper, we study the joint optimization of 3D positioning of UAVs and the users-UAVs association. Although a number of recent works have provided various approaches to approximately solve such an optimization problem, the majority of these works typically set up centralized algorithms to reach the best network performance. We believe that the dynamic nature of the surrounding environment and the growing size of today's networks make it extremely difficult to implement centralized schemes to achieve optimal/near-optimal solutions. Therefore, the main thrust of this paper is to design a distributed algorithm that can be implemented on UAVs in order to achieve reliable and efficient solutions by only using local information.

### A. Related Work

A large body of recent work is available in the literature that addresses resource allocation for UAV networks. In [2], authors study small-cells-UAVs association under backhaul capacity, bandwidth constraint, and maximum number of links limitation. They present a distributed greedy approach of low complexity to improve the users sum-rate. Although not mentioned in [2], their greedy approach is only a $\frac{1}{2}$-approximation algorithm and, thus, cannot always guarantee a good sum-rate performance. In [3], the authors investigate the mean packet transmission delay minimization for uplink communications in a multi-layer UAVs relay network. A gradient descent approach based on Bisection method is proposed to find the optimal power and spectrum allocation. Unlike the previous works where the 3D placement of UAVs is not considered, authors in [4] propose an algorithm to adjust the UAV path in order to maximize a lower bound of the users sum-rate over the uplink channel. Their optimization problem is solved using a line search for both time- and space-division multiple access. Authors in [5] study the problem of UAVs placement in order to minimize the deployment delay. The authors propose an algorithm of low complexity to maximize the coverage of a target area using heterogeneous UAVs of different coverage radii and flying speeds. The aforementioned works either consider a single UAV setup or multiple UAVs in interference-free environment. In general, optimizing the UAV placement, in isolation, is equivalent to finding the optimal 3D location that provides a good probability of line-of-sight, but at the same time, does not result in an important path loss. In the presence of interferences, an additional constraint should be considered as UAVs locations are tightly related to interferences and any inappropriate positioning of the UAV may severely affect the network performance. Authors in [6] present a heuristic particle swarm optimization algorithm to find the 3D placement of UAVs in order to maximize, under interferences, the users sum-rate. In their problem formulation, the authors consider the presence of a macro base station with a large backhaul bandwidth to serve delay-sensitive users. Although the proposed algorithm provides appreciable performance, it suggests a centralized implementation which can involve a large number of signaling messages and require a high computational effort. A distributed algorithm to improve the coverage region of drones is especially considered in [7]. The authors assume that the positions of Internet of Things (IoT) devices are permanently changing and provide a feedback based distributed algorithm to maximize the coverage region of drones while keeping them associated in clusters. The proposed algorithm still requires a centralized information pertaining the coordinates of the clusters centers in order to reach a good network configuration.

### B. Contribution

In this paper, we are interested in an urban type environment where aerial base stations are deployed to support damaged/overloaded ground base stations. Our objective is to efficiently place the UAVs in the 3D plan and associate the users in order to reach an efficient value of the sum rate of the network. In order to solve the non-convex and NP-hard problem, we break the underlying optimization into 3 subproblems where we separately solve the 2D UAVs positioning, the altitude optimization, and the UAVs-users association. To summarize, our contributions can be described as follows.

1) In order to address the UAVs-users assignment, we propose a fully distributed matching scheme that alleviates the bottlenecks of the bandwidth and guarantees the required quality of service.
2) We update the UAVs 2D coordinates using a modified K-means approach that locally improves the sum rate of the served users. We show through simulation results that the proposed updating rule presents a better sum rate performance when compared with the classical K-means algorithm primarily used to minimize the sum of distances.
3) In order to optimize the UAVs altitudes, we study a naturally defined game-theoretic version of the problem and show that under fixed UAVs 2D coordinates, a predefined association scheme, and limited interferences, the UAVs altitudes game is a non-cooperative *potential game* where the players (UAVs) can maximize the limited-interference sum rate by only optimizing a local utility function.

### C. Structure and Notations

The rest of the paper is organized as follows. The next section describes the studied system model. Section III presents the general optimization problem. In Section IV, the proposed approach is described. Simulation results are described in Section V. Finally, concluding remarks and possible extensions of this work are provided.

Let $\mathbf{M}$ and $m_{ij}$ denote the matrix and its $(i,j)$-th entry respectively. The set denoted by $\mathcal{S}\times\mathcal{C}$ represents the Cartesian product of $\mathcal{S}$ and $\mathcal{C}$. $\mathbb{E}_g$ is the expectation regarding random variable $g$. Vectors are denoted using boldface letters $\mathbf{x}$ whereas scalars are denoted by $x$. $|\mathcal{C}|$ denotes the cardinality of the set $\mathcal{C}$. Throughout the paper, the words *UAVs* and aerial base stations (*ABSs*) are used interchangeably.

## II. System Model

### A. Base Stations Deployment

Consider an area $\mathcal{A}$ where the ground base stations (GBSs) form a homogeneous Poisson point process (HPPP), $\Phi_G$, of intensity $\lambda_G$. Assume that a number of GBSs is not operational or under-functioning due to a congestion (e.g. during a temporary mass event) or a malfunction (e.g. a post-disaster scenario) of the infrastructure. The overloaded/damaged base stations are modeled by an independent thinning of $\Phi_G$ with a probability $p$. In order to support the terrestrial network, a number of aerial base stations (ABSs) is deployed following a 3D HPPP, $\Phi_A$, with the same intensity as the overloaded/damaged base stations. According to Slivnyak's theorem [8], this intensity is equal to $p\lambda_G$. Let $\mathcal{B}^G$ and $\mathcal{B}^A$ be realizations of $\Phi_G$ and $\Phi_A$ respectively. We denote by $(\mathbf{x}^A,\mathbf{y}^A,\mathbf{h})$ the 3D positions matrix of all ABSs, with $(\mathbf{x}^A,\mathbf{y}^A)$ the 2D locations of ABSs and $\mathbf{h}$ their altitudes vector. Let $\mathcal{U}$ be the set of ground users that need to be served by the ABSs. Although not all the GBSs are overloaded/damaged, we assume, throughout the paper, that ground users are allowed to associate with ABSs only in order to avoid any additional load to the terrestrial network.

### B. Air-to-Ground Channel Model

In order to capture the distortion of the signal due to obstructions, we consider the widely adopted air-to-ground channel model where the communication links are either line-of-sight (LoS) or non-line-of-sight (NLoS) with some probability that depends on both the UAV's altitude and the elevation angle between the user and the ABS. Given a UAV $j$ with an altitude $h_j$ and a user $i$ with a distance $r_{ij}$ from the projected position of the UAV on the 2D plane, the probability of LoS is given by [9]

$$p_{ij}^{\mathrm{LoS}} = \frac{1}{1+\alpha\exp(\frac{180}{\pi}\arctan\frac{h_j}{r_{ij}}-\alpha)}, \tag{1}$$

where $\alpha$ and $\beta$ are environment dependent parameters. Accordingly, the path loss between UAV $j$ and user $i$, in decibel, can be written

$$L_{ij}^{\mathrm{dB}} = 20\log\left(\frac{4\pi f_c\sqrt{r_{ij}^2+h_j^2}}{c}\right) + p_{ij}^{\mathrm{LoS}}\zeta_{\mathrm{LoS}} + (1-p_{ij}^{\mathrm{LoS}})\zeta_{\mathrm{NLoS}} \tag{2}$$

where the first term formulates the free space path loss that depends on the carrier frequency $f_c$ and the speed of the light $c$. Parameters $\zeta_{\mathrm{LoS}}$ and $\zeta_{\mathrm{NLoS}}$ represent the additional losses due to LoS and NLoS links respectively. It is worth noting that to account for interferences from GBSs, we consider the same channel model where the GBSs altitudes are assumed negligible compared with distances from the users.

### C. Average Spectral Efficiency

We consider downlink communication and assume that each ground/aerial base station $j$ transmits with power $P_j$. Hence, when a frame is transmitted by an ABS $j$, it is received at user $i$ with the power $P_j g_{ij} L_{ij}$, where $g_{ij}$ accounts for the multipath fading that is considered to follow an exponential distribution with mean $\mu$. The quality of the wireless link is measured in terms of signal-to-interference-and-noise-ratio (SINR), $\gamma_{ij}$, defined as follows

$$\gamma_{ij} = \frac{P_j g_{ij} L_{ij}}{\sigma^2 + \sum\limits_{k\neq j, k\in\mathcal{B}^A\cup\mathcal{B}^G} P_k g_{ik} L_{ik}}, \tag{3}$$

where $L_{ij} = 10^{-\frac{L_{ij}^{\mathrm{dB}}}{10}}$ and $\sigma^2$ represents the power of an additive Gaussian noise. Accordingly, the average spectral efficiency received at a user $i$ from an ABS $j$, $\eta_{ij}$, can be defined using Shannon capacity bound as the following

$$\eta_{ij} = \mathbb{E}_{\mathbf{g}}\left[\log_2(1+\gamma_{ij})\right]. \tag{4}$$

Assume each ground user $i$ has a rate request of $R_i$. Then, in order to satisfy the user's request, UAV $j$ needs to adjust the allocated bandwidth $b_{ij}$ according to the quality of the link such that $R_i = b_{ij}\eta_{ij}$.

## III. Problem Formulation

Let $\mathbf{A} = (a_{ij})$ be the ABSs-users association matrix. Our objective is to maximize the aggregate rates requested by all the ground users by optimizing, jointly, the users-ABSs association (i.e. $\mathbf{A} = (a_{ij})$) and the 3D placement of ABSs (i.e. $(\mathbf{x}^A,\mathbf{y}^A,\mathbf{h})$) in a way that the bandwidth limitation for all ABSs is always respected and the constraint on the quality of service is not violated. Our constrained optimization problem is formulated as follows.

$$\underset{\mathbf{A}, (\mathbf{x}^A, \mathbf{y}^A, \mathbf{h})}{\text{maximize}} \quad \sum_{j\in\mathcal{B}^A}\sum_{i\in\mathcal{U}} a_{ij}R_i \tag{5a}$$

$$\text{subject to} \quad \sum_{i} a_{ij}b_{ij} \le B_j, \quad \forall j \in \mathcal{B}^A, \tag{5b}$$

$$\frac{a_{ij}}{\eta_{ij}} \le \frac{1}{\eta^{\min}}, \quad \forall (i,j) \in \mathcal{U}\times\mathcal{B}^A, \tag{5c}$$

$$x^{\min} \le x_j^A \le x^{\max} \quad \forall j \in \mathcal{B}^A, \tag{5d}$$

$$y^{\min} \le y_j^A \le y^{\max} \quad \forall j \in \mathcal{B}^A, \tag{5e}$$

$$h_j \in \mathcal{H} \quad \forall j \in \mathcal{B}^A, \tag{5f}$$

$$\sum_{j} a_{ij} \le 1, \quad \forall i \in \mathcal{U}, \tag{5g}$$

$$a_{ij} \in \{0,1\}, \quad \forall (i,j) \in \mathcal{U}\times\mathcal{B}^A \tag{5h}$$

Constraint (5b) ensures that the limitation on the bandwidth resource of each UAV is respected (each UAV $j$ has a bandwidth limit $B_j$). Constraint (5c) guarantees that the average spectral efficiency is no less than a predefined threshold $\eta^{\min}$. Constraint (5d) and (5e) show that it is necessary that the ABS 2D coordinates belong to the target area. Moreover, constraint (5f) ensures that the UAVs altitudes will belong to the allowed flying altitude values described in the set of discrete altitudes $\mathcal{H}$. Constraints (5g) and (5h) restrict the ground user to be associated, at most, with one ABS. In practice, problem (5) is mathematically challenging as it involves a non-convex objective function, and non-convex and non-linear constraints. Clearly, the underlying optimization problem is a mixed integer non-linear problem (MINLP) that is NP-hard. Finding an optimal solution to such a problem may involve searching over 3D coordinates for all ABSs and for every possible users-ABSs association. In the following, we propose a distributed approach based on a decomposition process to achieve an efficient global solution in only a few number of iterations.

## IV. Proposed Approach

### A. Efficient UAVs-users Matching

To deal with the target optimization, we first assume fixed 3D locations of UAVs and propose a suitable distributed mechanism for UAVs-users association. The proposed mechanism is achieved using Gale-Shapley matching [10] where the preferences of the UAVs, on one hand, and the users on the other hand, are both based on the quality of service (i.e. the average spectral efficiency). A description of the proposed algorithm is given in **Algorithm** 1.

First, each user selects the ABSs that satisfy constraint (5c), and sorts them in a decreasing order by comparing their spectral efficiencies. At this step, each user has its own list of preferred ABSs (line 2). Similarly, each ABS establishes its list of preferred users by comparing the requested bandwidths (line 3). Each user sends a request to connect to its most preferred ABSs (line 7). Each ABS accepts its most preferred users one by one until its bandwidth limit is reached and rejects the remaining users (lines 8 and 9). Each rejected user attempts to connect to its second most preferred ABS, if no more bandwidth is left on this ABS, the ABS can disconnect a less desired user and replace it by the new one (lines 11 and 12)). Otherwise, the user and ABS are mutually removed from their respective preference lists (line 14). The algorithm stops when all ABSs have reached their bandwidth limit or each user has been either connected, or rejected by all its preferred ABSs (line 15).

**Algorithm 1** Users-ABSs Matching

1: **Initialization**
2: For each user $i$, sort $\eta_{ij} = \frac{R_i}{b_{ij}}$ in a decreasing order such that $\eta_{ij} > \eta_{\min}$, and establish a list $\mathcal{L}_i$
3: For each ABS $j$, sort $b_{ij} = \frac{R_i}{\eta_{ij}}$ in an increasing order, and establish a list $\mathcal{L}_j$
4: $a_{ij} = 0$ for each user $i$ and ABS $j$
5: **repeat**
6: **for** $i \in \mathcal{U}$ **do**
7: $i$ requests to connect to $j = \text{argmax}_{k\in\mathcal{L}_i}\{\eta_{ik}\}$
8: **if** $i = \text{argmin}_{s\in\mathcal{L}_j}\{b_{sj}\}$ & $\sum_{c\in\mathcal{U}, c\neq i} a_{cj}b_{cj} + b_{ij} \le B_j$ **then**
9: $a_{ij} = 1$
10: **else** $\sum_{c\in\mathcal{U}, c\neq i} a_{cj}b_{cj} + b_{ij} > B_j$
11: **if** There exists a user $s$ s.t. $b_{ij} < b_{sj}$ & $a_{sj} = 1$ & $\sum_{c\in\mathcal{U}, c\neq i,s} a_{cj}b_{cj} - b_{sj} + b_{ij} < B_j$ **then**
12: $a_{ij} = 1$, $a_{sj} = 0$
13: **else**
14: $\mathcal{L}_i = \mathcal{L}_i \backslash \{i\}$ & $\mathcal{L}_j = \mathcal{L}_j \backslash \{j\}$
15: **until** Bandwidth limit is reached or each user has been either connected, or rejected by all its preferred ABSs.

### B. 2D Placement

At this stage of the paper, we will only deal with the 2D placement of UAVs. In particular, we assume that the ABSs-users association scheme is the one described in Subsection IV-A and that the altitudes for all ABSs are fixed at some random values. The UAVs altitudes are addressed separately in Subsection IV-C. Our objective is to move the UAVs towards their served ground users in the 2D plan, in sequential steps, so that the quality of the link for each group is improved, and eventually, more bandwidth is left to serve additional users.

**Algorithm 2** 2D Placement Optimization

**Initialization**
For each ABS $j$, $(x_j^A(0), y_j^A(0))$ are chosen randomly within the target area $\mathcal{A}$
For each ABS $j$, $\mathcal{C}_j = \varnothing$
**repeat**
**for** $j$ in $\mathcal{B}^A$ **do**
**for** $i$ in $\mathcal{U}$ **do**
Update $\eta_{ij}$, update $\mathbf{A}$ according to **Algorithm** 1
**if** $a_{ij} = 1$ **then**
$\mathcal{C}_j = \mathcal{C}_j \cup \{i\}$
$x_j^A \leftarrow \frac{\sum_{i\in\mathcal{C}_j} x_i}{|\mathcal{C}_j|}$, $y_j^A \leftarrow \frac{\sum_{i\in\mathcal{C}_j} y_i}{|\mathcal{C}_j|}$
**until** UAVs cannot improve their 2D locations or number of iterations has reached a predefined value.

To this end, we propose a modified version of $K$-means algorithm [11] (with $K = |\mathcal{B}^A|$) that operates in a distributed and sequential fashion. This modified version positions the UAVs at the barycenter of the *served* users instead of the barycenter of the *closest* users as it is the case for the classical $K$-means algorithm. The procedure of the UAVs 2D placement via the modified version of $K$-means is presented in **Algorithm** 2.

Given $K$ initial positions of ABSs $(\mathbf{x}^A(0), \mathbf{y}^A(0))$ (line 2), the algorithm groups the users with their serving ABSs determined using the association scheme described in **Algorithm** 1 (line 7). Accordingly, each UAV's 2D position is updated as a barycenter of its cluster $\mathcal{C}_j$ (lines 10). When the position of the UAV is updated, the users association is updated as well. This process is then repeated until none of the UAVs 2D locations are updated or the number of iterations reaches a predefined value (line 11)[1].

### C. Altitude Optimization

In this subsection, we optimize the UAVs altitude given fixed 2D coordinates of UAVs and a predefined association scheme, specifically, the one described in Subsection IV-A.

*1) Definitions:* Throughout this section, we adopt the following definitions.

- **Neighborhood**: two base stations are considered neighbors if there exists at least one user that is covered by both base stations when they are at some given altitudes. In mathematical words, the neighborhood of a base station $j$ can be defined as follows.

$$\mathcal{N}_j = \{k \in \mathcal{B}^A \cup \mathcal{B}^G, \exists i \in \mathcal{U} \text{ s.t. } \exists (h_j, h_k) \in \mathcal{H}^2, P_j L_{ij} > \tau \text{ and } P_k L_{ik} > \tau\}, \quad (6)$$

  where $\tau$ is the received signal threshold.
- **Local sum rate function**: is the function that computes the sum rate over a local neighborhood set. Accordingly, for each ABS $j$, the local sum rate is given by

$$U_j(\mathbf{h}) = \sum_{l \in \mathcal{N}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \mathbb{E}_g\Big(\log_2\Big(1 + \frac{P_l g_{il} L_{il}}{\sigma^2 + \sum_{\substack{k \in \mathcal{N}_l,\\ k \neq l}} P_k g_{ik} L_{ik}}\Big)\Big). \quad (7)$$

  Note that when $\tau = 0$ the local sum rate function coincides with the social welfare provided by the global objective function in equation (5a).
- **Nash equilibrium (NE)** [12]: A strategy profile $\mathbf{h}$ is a Nash equilibrium of a game $\mathcal{G}$ if for each player $j$, $\forall h_j \neq h_j^*$

$$U_j(h_j^*, \mathbf{h}_{-j}^*) \geq U_j(h_j, \mathbf{h}_{-j}^*), \quad (8)$$

  where $\mathbf{h}_{-j}$ refers to the altitudes vector of UAVs other than $j$.
- **Potential game** [13]: is a class of games where the NE is also a local optimum of the social welfare function also named a *potential function*. Let $\mathcal{X}$ be a set of strategy profiles of a game $\mathcal{G}$. $\mathcal{G}$ is a potential game if there is a potential function $F : \mathcal{X} \longrightarrow \mathbb{R}$ such that for each player $j$, $\forall (h_j, \mathbf{h}_{-j})$ and $(h'_j, \mathbf{h}_{-j}) \in \mathcal{X}$

$$F(h_j, \mathbf{h}_{-j}) - F(h'_j, \mathbf{h}_{-j}) = U_j(h_j, \mathbf{h}_{-j}) - U_j(h'_j, \mathbf{h}_{-j}). \quad (9)$$

*2) Altitudes Adjustment :* Let $F(\mathbf{h})$ be the sum rate of all users where only interferences from neighboring base stations are considered. This function is given by

$$F(\mathbf{h}) = \sum_{j \in \mathcal{B}^A} \sum_{i \in \mathcal{U}} a_{ij} b_{ij} \mathbb{E}_g\Big(\log_2\Big(1 + \frac{P_l g_{ij} L_{ij}}{\sigma^2 + \sum_{\substack{k \in \mathcal{N}_j,\\ k \neq j}} P_k g_{ik} L_{ik}}\Big)\Big). \quad (10)$$

[1]The convergence of such a process to a stable equilibrium is left as part of future work

**Proposition 1.** *Let $\mathcal{G}$ be the game where the UAVs are considered as players, the altitudes are their playing strategies, and $U_j$ their utilities. The game $\mathcal{G}$ is a potential game where the function $F$ defined by equation (10) is the potential function.*

The proof of **Proposition** 1 as well as additional results can be found in the extended version of the paper in [14].

Accordingly, in order to reach a local optimum of the limited-interference sum rate $F$, we can only target a NE. To this end, we adopt **Algorithm** 3, based on best-response dynamics, to help UAVs to adaptively learn how to play a NE over iterations [15].

**Algorithm 3** Best-Response Dynamics for Altitudes Adjustment

**repeat**
  Let $(\mathbf{x}^A, \mathbf{y}^A)$ be the 2D locations vector obtained using **Algorithm** 2
  For each UAV $j$, determine its neighborhood
  **repeat**
    **for** $j \in \mathcal{U}$ **do**
      $h_j^* = \text{argmax}_{h \in \mathcal{H}} U_j(h, h_j)$
      Update $\eta_{ik}$ for all neighbors of $k \in \mathcal{N}_j$
      Update **A** using **Algorithm** 1
  **until** A NE is reached.
**until** Sum-rate is not significantly improved over a given number of iterations.

## V. Simulation Results

In order to study the performance of the proposed approach, we consider $1\text{km} \times 1\text{km}$ area where a number of GBSs with intensity $\lambda_G = 0.22 * 10^{-4}$ are randomly scattered. Assume $f_c =$ 2 GHz, $P_j = 10dBm$ for all base stations. In order to compute the average spectral efficiency, we use Monte Carlo simulations with 5000 runs. The simulation settings are summarized in TABLE. I.

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $R_i$ | Random from $[90, 100]$ Mbps | $\alpha$ | 9.61 |
| $\beta$ | 0.16 | $c$ | $3.10^8 m/s$ |
| $\zeta_{\text{LoS}}$ | 1 dB | $\zeta_{\text{NLoS}}$ | 20dB |
| $\eta^{\min}$ | -20 dB | $\tau$ | -69 dBm |
| $\mu$ | 1 | $p$ | 0.35 |
| $\mathcal{H}$ | $\{40, 100, 160, 220, 280, 340\}m$ | $\sigma^2$ | -100 dBm |
| UAVs bandwidth | $\{756, 696, 567, 737, 968, 631, 814, 573, 930, 796, 742, 767, 712\}$ MHz | | |

TABLE I: Simulation settings.

Fig. 1 plots the positions of UAVs in the 2D plan. As depicted in the figure, ABSs dynamically change their 2D positions. Starting from their initial points (dots in red), the UAVs move towards the served users in a few steps before reaching their final destination (dots in green) considered as the barycenter of their served users. Clearly, due to the bandwidth limitation and the quality of service constraint, some users are left without connectivity. It is important to note that the K-means algorithm convergence depends on the initial values of the network configuration. Some initialization procedures can however be used to improve the convergence results of K-means [11]. Fig. 2 shows the final 3D UAVs placement and users association. As expected, the UAVs stand at the center of the served users clusters. Notice that when an ABS has only one user to serve, it simply stands above the served user in order to improve the LoS probability (this is for example the case of ABS 3). The final heights of

ABSs are better shown in Fig. 3 where these altitudes are plotted vs UAVs x-coordinates. It can be seen from the figure that UAVs adjust their heights in order to reduce interferences. Fig. 4 plots the convergence of the proposed approach vs the number of iterations. The figure shows how the sum-rate evolves over iterations under our proposed scheme that adopts a UAVs-users matching association (as described by Algorithm 1) and under the trivial case where users are connected, at each iteration, to the closest ABS. Clearly, the proposed approach significantly improves the overall sum-rate. For the studied scenario, the sum-rate is improved by 200% compared with the nearest UAV association.

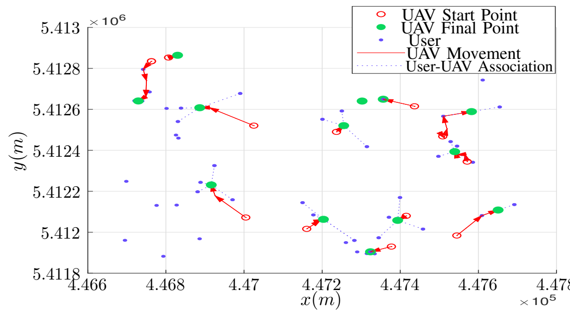


Fig. 1: Movement of UAVs in 2D plan.

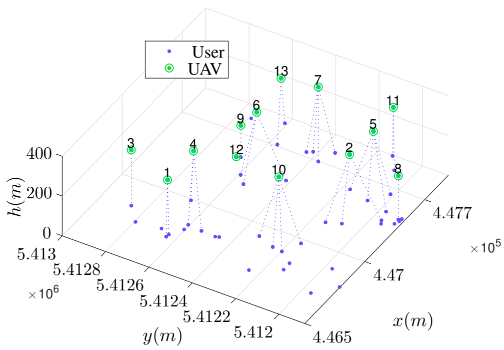


Fig. 2: Final 3D placement and UAVs-users association.

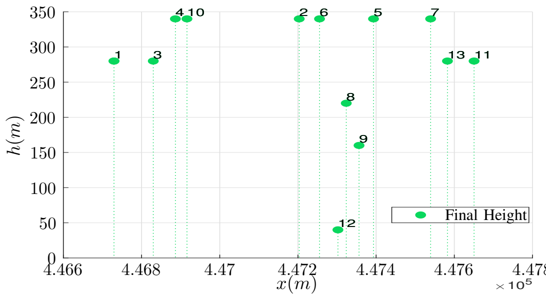


Fig. 3: Final heights of UAVs.

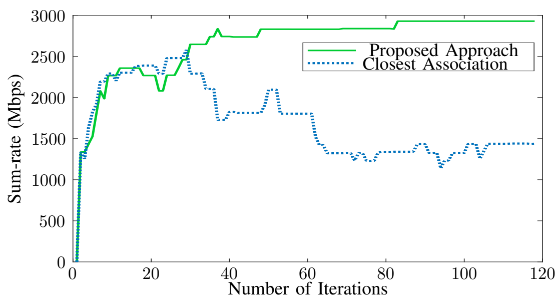


Fig. 4: Sum rate convergence.

## VI. Conclusion

In this paper, we have studied the joint 3D placement and UAVs-users association in UAV-assisted networks. We have proposed a 3 steps approach that iteratively reaches an efficient solution to the studied optimization problem in only a few number of iterations. In particular, the initial problem was broken into 3 subproblems: UAVs-users associations, 2D positioning of UAVs, and altitudes optimization. Each subproblem has been solved locally using a low-complexity algorithm. Our simulation results have shown appreciable performance of the proposed approach as compared with the trivial case where users are associated, over iterations, to the closest UAV.

The extended version of the paper in [14] is based on a more realistic system model where the number of buildings is introduced to account for shadowing. Extensive simulation results are carried out using real building footprints from Paris city 3D map. The concept of the price of ignorance is introduced and is used to show that a very good performance can be reached even when the UAVs neighborhood is reduced. In ongoing works, we will introduce more uncertainty to the system model and propose a robust approach that considers the dynamic nature of the network environment to reach an optimal UAVs 3D placement.

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