# Learn-As-You-Fly: A Distributed Algorithm for Joint 3D Placement and User Association in Multi-UAVs Networks

# Learn-As-You-Fly: A Distributed Algorithm for Joint 3D Placement and User Association in Multi-UAVs Networks

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*Abstract*—In this paper, we propose a distributed algorithm that allows unmanned aerial vehicles (UAVs) to dynamically learn their optimal 3D locations and associate with ground users while maximizing the network's sum-rate. Our approach is referred to as 'Learn-As-You-Fly' (LAYF) algorithm. LAYF is based on a decomposition process that iteratively breaks the underlying optimization into three subproblems. First, given fixed 3D positions of UAVs, LAYF proposes a distributed matching-based association that alleviates the bottle-necks of bandwidth allocation and guarantees the required quality of service. Next, to address the 2D positions of UAVs, a modified version of K-means algorithm, with a distributed implementation, is adopted. Finally, 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 interference, the UAVs altitudes game is a potential game where UAVs can maximize the limited interference sum-rate by only optimizing a local utility function. Our simulation results show that the network's sum-rate is improved as compared to both a centralized suboptimal solution and a distributed approach that is based on closest UAVs association.

*Index Terms*—UAV-assisted networks, UAV-user's association, 3D placement, matching game, potential game, best-response dynamics, K-means.

## I. Introduction

The first development and testing of drones, also known as *unmanned aerial vehicles (UAVs)*, can be traced back to the inter-world-war period where the British army built radio-controlled aircrafts to use them as targets during military trainings [1]. Since then, the use of drones has been gradually expanded to cover a countless number of applications that range from military services to humanitarian purposes and commercial applications [2], [3], [4]. As an example, one of the most beneficial applications of drones is for search and rescue operations where UAVs can access remote areas, provide supplies, and find missing people [5]. The continuous advancement in technology has also extended the use of drones to shipping applications that allow customers to receive their requested products rapidly through drone delivery services [6] (see some UAVs use cases in Fig. 1).

Telecommunications are another important area where drones powered solutions are flourishing [7], [8]. The use of drones as ad-hoc networks that provide on-demand connectivity to the ground users has drawn significant attention from researchers in both

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academia and industry in the last few years. Essentially, drones can be used as temporary support to the terrestrial network for different use cases. As an example, UAVs can be useful to replace damaged cellular infrastructure after a natural disaster. They can also be used to extend coverage to remote areas where natural obstacles may restrain operators from deploying a ground cellular network [9], [10]. In temporary mass events (sport games and festivals), UAVs can be easily deployed to satisfy the high demand for mobile data and expand the cellular network capacity. By virtue of their high flexibility, drones can also serve as dynamic relays that move toward the ground users (e.g. Internet of Things devices), collect data and transmit it to an out-of-range receiver (e.g. sink node) [11].

However, deploying UAVs poses a number of challenges [12], [13]. Clearly, when a drone is used to accomplish a number of tasks, it is essential to design its trajectory [14], minimize its energy [15], and maximize the profit of its mission [16]. Furthermore, in order to control the drone remotely and communicate with ground users, it is important to study the nature of the air-to-ground channel [17], [18], manage interference [19], and achieve the quality of service that satisfies the communication requirements [20].

In the context of multi-UAVs systems, two fundamental challenges arise. The first is how to position UAVs optimally in a way that guarantees a balanced tradeoff between the shadow-fading effects, the path loss and the interference. Previous studies have shown that increasing the UAV's altitude has a double effect: on one hand, it improves the probability of line-of-sight (LoS) between the drone and the ground user, on the other hand, it results in additional path loss [21], [19]. In a multi-UAVs system, more complexity is added to the network as drones positioning should also be favorable to a reduction of the overall interference [22]. The second challenge naturally follows from the first one. Indeed, in order to reap the benefits of a multi-UAVs system, reduce interference and improve the network performance, drones should either (i) rely on a centralized ground controller that has a global view on the network and defines the optimal drone strategies, or (ii) autonomously decide about their positions based on local observations of the surrounding environment [23], [24], [25].

With the growing size of today's networks and the dynamic characteristic of connected systems, a distributed realization is considered as the best solution to cope with the ever-changing nature of the wireless environment, especially in UAVs-assisted networks where UAVs need to quickly adapt to the user's density variations, a base station failure, communication bottlenecks, etc. In such a context, distributed algorithms present numerous

Fig. 1: UAVs use cases in the context of smart cities.

advantages against centralized ones that we summarize as follows.

- **Scalability**: the architecture of a decentralized system is very flexible and more adapted to large scale networks. The network can be expanded by adding new UAVs that will autonomously converge to a stable and efficient state without resulting in additional load to a centralized entity (as it is the case for centralized networks).

- **Robustness to failure**: in centralized networks, a failure of the centralized node may result in the failure of the whole system as the network architecture depends on a single centric point (e.g. a ground base station) that computes the best strategies for all the UAVs. In contrast, in distributed schemes, if a UAV node fails, only its neighbors have to update their strategies.

- **Robustness to bottlenecks**: centralized networks are sensitive to bottlenecks as a large amount of overhead needs to be exchanged from the UAVs to the centralized entity and vice versa. A decentralized approach makes it easier to UAVs to communicate with each other without overloading a particular component of the network.

- **Computational efforts**: centralized schemes require high computational efforts to process the collected information, whereas distributed ones necessitate less computational capacity as computations are distributed among all the network agents (i.e. UAVs).

- **Synchronization**: unlike centralized approaches where a global clock is needed to synchronize the centralized entity with the UAV nodes, a distributed realization allows to each UAV to build its strategy depending on its own clock. Therefore, each UAV can decide about its strategy by collecting local information without any need of synchronization with the entire system.

Moreover, in most multi-UAVs systems, the UAV-user's association rule is an important component. This is because the overall network performance relies on the number of connected users and their perceived quality of service [26]. Thus, the 3D placement is tightly coupled with the UAV-user's association problem. It would,

therefore, be a requirement to define a practical association rule that can jointly operate with the 3D placement algorithm in order to enhance the number of connected users, satisfy their quality of service, and respect the maximum bandwidth allowed for each aerial vehicle.

Although a number of recent works have provided various approaches to approximately solve 3D placement problems, 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 such 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.

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 downlink sum-rate of the network. Being non-convex and NP-hard, the studied problem cannot be solved using classical convex optimization methods. Therefore, we propose an algorithm referred to as 'Learn-As-You-Fly' (LAYF) that iteratively breaks the underlying optimization problem into three subproblems: 2D UAVs positioning, the altitude optimization, and the UAV-user's association. At each iteration,

1) LAYF addresses the UAV-user's association by leveraging a distributed matching scheme that alleviates the bottlenecks of the bandwidth and guarantees the required quality of service.
2) It also updates the 2D coordinates using a modified K-means approach where UAVs dynamically change their 2D positions in order to reach the barycenter of the served ground users.
3) Finally, LAYF adjusts UAVs altitudes by only optimizing a local utility function based on a neighborhood structure that depends on interference.
4) The last step of the algorithm is justified by the fact that under fixed UAVs 2D coordinates, a predefined association scheme,

and limited interference, the UAVs altitudes subproblem can be seen as a non-cooperative *potential game* where the players (UAVs) can reach the optimum of the limited-interference sum-rate by only looking for a Nash equilibrium of a local utility function.

5) Our simulation results show that a good performance can be reached as compared to both a centralized suboptimal solution and a distributed approach that is based on closest UAVs association.

This paper builds on our short version of the work in [27] where we present a distributed approach for joint 3D placement and UAV-user's association. In the current paper, we discuss the convergence aspect of the proposed algorithm, provide more details on its implementation and exhibit its qualitative properties. This version also includes extensive simulation results where comparison is performed with a centralized approach.

The rest of the paper is organized as follows. The next section presents related work. Section III describes the studied system model. Section IV presents the general optimization problem. Section V decomposes the underlying optimization problem and provides local solutions to each subproblem. In section 3 the global approach is described and its qualitative properties along with its limitations are provided. Simulation results are described in Section VII. Finally, concluding remarks and possible extensions of this work are provided in section VIII.

**Notations:** 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 drones are used interchangeably.

## II. Related Work

Several optimization problems that are related to UAVs placement and resource allocation can be found in the literature. We classify them into three categories: *resource allocation for fixed UAV positions*, *3D placement and UAV trajectory optimization*, and *joint resource allocation and UAV 3D placement*. In the following, we review the papers that are the most relevant to our work. A summary of this review is provided in TABLE I.

**Resource allocation for fixed UAV positions:** In [26], authors present a distributed greedy approach to improve the users sum-rate under backhaul capacity, bandwidth constraint, and maximum number of links limitation. The optimal power and spectrum allocation are investigated in [28] where the authors minimize the mean packet transmission delay for uplink communications. In [29], the authors goal is to minimize the maximum energy needed to ensure a certain bit error rate target. To this end, they propose a global scheduling technique using standard optimization, and provide a light version of the algorithm to reach a suboptimal solution.

**3D placement and UAV trajectory:** Unlike the previous works where the 3D placement of UAVs is not considered, authors in [31] investigate the 3D placement of UAVs while maximizing the number of covered users. The UAV horizontal and vertical locations are optimized separately. The optimal altitude is found by solving a convex decoupled optimization problem, while the optimal 2D location is achieved by finding a solution to the

smallest enclosing circle problem. In [34], authors optimize the UAV trajectory to accurately learn the environment propagation parameters. They introduce a map compression method and use dynamic programming to efficiently design the UAV trajectory. The optimal UAV position to maximize the end-to-end throughput is studied in [35] where information provided by the signal strength radio map is leveraged. In line with the previous cited work, authors in [33] provide an online algorithm, based on the theory of asynchronous stochastic approximation, for a fast deployment of flying relays, that minimizes the power consumption under constraints of outage probability and number of deployed drones.

**Joint resource allocation and 3D placement:** When considering the 3D placement, the aforementioned works either assume 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 interference, an additional constraint should be considered as any improper adjustment of UAVs locations may severely affect the network performance. Authors in [37] present a heuristic particle swarm optimization algorithm to find the 3D placement of UAVs in order to maximize, under interference, 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. Under this assumption, the optimal proportion of resources allocated to UAVs backhaul is determined through a decomposition process that yields in a convex optimization problem. 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 [38]. 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 cluster centers in order to reach a good network configuration. Furthermore, the algorithm focuses on the 2D positions and does not optimize the UAVs altitudes.

Although the problems of resource allocation and UAV 3D placement have been widely discussed in the literature, the majority of existing works either consider a single UAV or assume an interference-free environment. Under such assumptions, the sum-rate problem is quickly reduced to a disk coverage optimization. The closest works to our paper are [37] and [38] where interference, joint association and UAV positioning are considered. Unlike [37], we propose a distributed algorithm and thoroughly discuss its practical implementation. Our paper is also different from [38] as it deals with the downlink sum-rate, instead of the coverage region, and optimizes the UAVs altitudes as well.

It is important to note that, in general, meta-heuristic approaches can be proposed to study NP-hard problems [40]. However, these approaches are generally designed to solve either discrete or continuous optimization. When considering the joint association and 3D placement problem, both discrete (association matrix) and continuous (3D positions) variables are involved. This re-

| Type of problem | Reference | Objective | Technique | Comment |
|---|---|---|---|---|
| Resource allocation for fixed UAVs positions | [26] | -Maximize the sum-rate | -Greedy knapsack algorithm | -Distributed algorithm for UAVs small-cells association |
| | [28] | -Minimize the mean packet transmission delay | -Bisection method and gradient descent | -Centralized approach for power & spectrum allocation |
| | [29] | -Minimize the maximum energy | -Transform to standard integer programming | -Centralized approach for users scheduling |
| 3D placement and UAV trajectory optimization | [30] | -Maximize a lower bound of the uplink sum-rate | -Line search based algorithm | -Centralized and offline for the trajectory of a UAV |
| | [31] | -Maximize the number of covered users | -Decoupling horizontal and vertical positions and convex optimization | -Centralized and designed for a single UAV |
| | [32] | -Minimize the deployment delay | -Dynamic programming | -Centralized algorithm for multiple UAVs deployment |
| | [33] | -Minimize the power consumption | -Online algorithm based on the theory of stochastic approximation | -A learning algorithm for a single UAV |
| | [34] | -Build a LoS map | -Dynamic programming and map compression method | -Centralized and online for a single UAV to optimize the channel measurements |
| | [35] | -Maximize the end-to -end throughput | -Convex optimization | -Centralized and online for a single UAV |
| Resource allocation and 3D placement | [36] | -Maximize the sum-rate | -Adaptive weighted coordinates based on gradient ascent | -Centralized approach for joint power allocation and 3D placement |
| | [37] | -Maximize sum-rate | -Particle swarm optimization | -Centralized approach for user's association and 3D placement |
| | [38] | -Maximize the coverage region of drones | -Matching and control theory | -Distributed approach for user's association and 2D placement, altitude is not optimized |
| | [39] | -Collision avoidance | -Conflict detection framework | -Distributed alerting algorithm |

TABLE I: Summary of the state of the art.

sults, in addition to the NP-hardness, in a mixed integer non-linear programming (MINLP) problem that can be solved using advanced software such as CPLEX and SCIP from IBM (mainly based on hybrid meta-heuristics) [41]. However, the convergence to the global optimum is not guaranteed as the software can halt at a local optimum. Furthermore, the convergence time can be long and the implementation is definitely centralized. Throughout this article, our objective is to propose a practical, distributed and easy-to-use algorithm to reach an efficient sum-rate of the downlink communication in a multi-UAVs environment. Although the proposed approach relies on combining existing algorithms, it suggests a feasible way to implement and merge them, and it investigates their global convergence. Furthermore, to the best of our knowledge, this is the first time the altitudes problem is shown to be a potential game where the UAVs can reach the optimum of the limited-interference sum-rate by only looking for a Nash equilibrium of a local utility function.

## III. 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 $K$ of drones, randomly scattered in the 3D area, is deployed. The optimal number of required drones can be estimated roughly by taking into account the number of ground users, the average capacity of the network and the average target rate of the users. More advanced techniques, based on heuristics, can also be used as proposed in reference [42].

Let $\mathcal{B}^G$ be a realization of $\Phi_G$ and $\mathcal{B}^A$ the set of UAVs. We denote by $(\mathbf{x}^A, \mathbf{y}^A, \mathbf{h})$ the 3D positions matrix of all UAVs, with $(\mathbf{x}^A, \mathbf{y}^A)$ the 2D locations of UAVs and $\mathbf{h}$ their altitudes vector. Let $\mathcal{U}$ be the set of ground users that need to be served by the UAVs. Although not all the GBSs are overloaded/damaged, we assume, throughout the paper, that ground users are allowed to associate with UAVs only in order to avoid any additional load to the terrestrial network. An illustration of the system model is given in Fig. 2 (a).

### 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 UAV. 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 plan, the probability of LoS is given by [43]

$$p_{ij}^{\text{LoS}}(r_{ij}, d_{ij}) = \frac{1}{1 + \epsilon \cdot \exp\left(-\beta \frac{180}{\pi} \arctan \frac{\sqrt{r_{ij}^2 - d_{ij}^2}}{d_{ij}} - \epsilon\right)}, \quad (1)$$
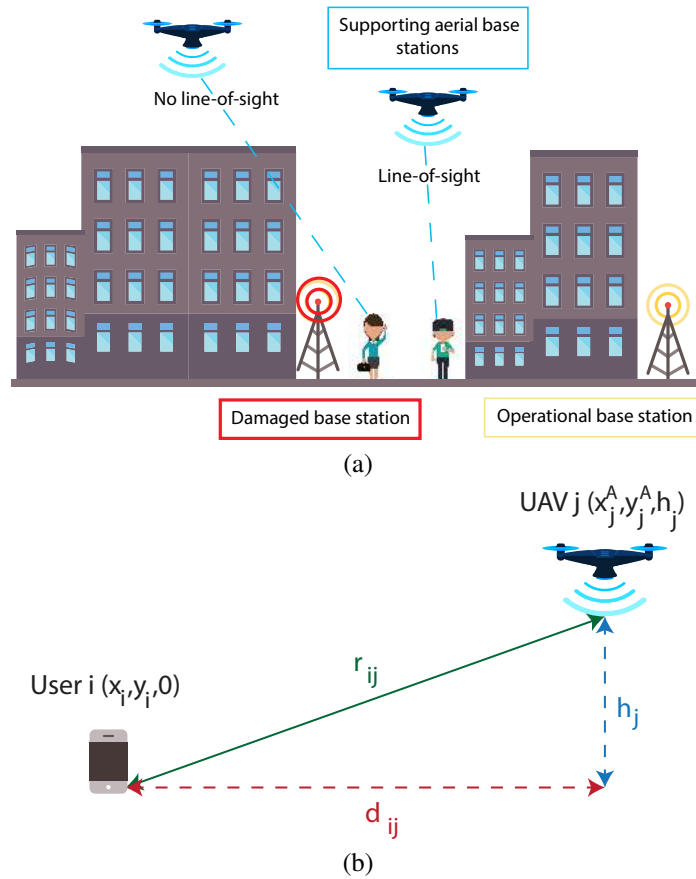
Fig. 2: (a) System model, (b) distances notations.

with $d_{ij}$ the distance from the projected position of the UAV on the 2D plane, $\epsilon$ and $\beta$ are environment dependent parameters. Accordingly, the path loss between UAV $j$ and user $i$, can be written

$$L_{ij}(r_{ij},d_{ij}) = \left(\frac{4\pi f r_{ij}}{c}\right)^{-\alpha}\left(\zeta_{\text{LoS}} p_{ij}^{\text{LoS}}(r_{ij},d_{ij}) + \zeta_{\text{NLoS}}(1 - p_{ij}^{\text{LoS}}(r_{ij},d_{ij}))\right)^{-1}, \quad (2)$$

where the first term formulates the free space path loss that depends on the carrier frequency $f$, the speed of the light $c$ and the path loss exponent $\alpha$. Parameters $\zeta_{\text{LoS}}$ and $\zeta_{\text{NLoS}}$ represent the additional losses due to LoS and NLoS links respectively. The distance notations are described in Fig 2 (b).

It is worth noting that to account for interference 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 the downlink channel and assume that each ground/aerial base station $j$ transmits with power $P_j$. Hence, when a frame is transmitted by a UAV $j$, it is received at user $i$ with the power $P_j g_{ij} L_{ij}(r_{ij}, d_{ij})$, where $g_{ij}$ accounts for the multipath fading that is considered to follow an exponential distribution with mean $\mu$[1]. We assume that the drones move sequentially. Therefore, during their stopping periods, the communication channels are

[1]Our proposed approach is independent of the small-scale fading model. Our simulation results show that the proposed approach is also valid for a Rician channel.

supposed stationary and known at both the UAVs and the users. The quality of the wireless link is measured in terms of signal-to-interference-and-noise-ratio (SINR), $\gamma_{ij}$, defined as follows

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

where $\sigma^2$ represents the power of an additive Gaussian noise. Accordingly, the average spectral efficiency received at a user $i$ from a UAV $j$, $\eta_{ij}$, can be defined using Shannon's capacity bound as the following

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

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 $R_i = b_{ij}\eta_{ij}$.

### IV. PROBLEM FORMULATION

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

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

$$\text{subject to} \quad R_i = b_{ij} \eta_{ij}, \quad \forall i \in \mathcal{U}, \forall j \in \mathcal{B}^A, \quad \text{(5b)}$$

$$\sum_i a_{ij} b_{ij} \leq B_j, \quad \forall j \in \mathcal{B}^A, \quad \text{(5c)}$$

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

$$x^{\min} \leq x_j^A \leq x^{\max} \quad \forall j \in \mathcal{B}^A, \quad \text{(5e)}$$

$$y^{\min} \leq y_j^A \leq y^{\max} \quad \forall j \in \mathcal{B}^A, \quad \text{(5f)}$$

$$h_j \in \mathcal{H} \quad \forall j \in \mathcal{B}^A, \quad \text{(5g)}$$

$$\sum_j a_{ij} \leq 1, \quad \forall i \in \mathcal{U}, \quad \text{(5h)}$$

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

Constraint (5b) guarantees that the requested rate can be provided by the UAV. Constraint (5c) ensures that the limitation on the bandwidth resource of each UAV is respected (each UAV $j$ has a bandwidth limit $B_j$). Constraint (5d) guarantees that the average spectral efficiency is no less than a predefined threshold $\eta^{\min}$. Constraint (5e) and (5f) show that it is necessary that the UAV 2D coordinates belong to the target area. Moreover, constraint (5g) ensures that the UAVs altitudes will belong to the allowed flying altitude values described in the set of discrete UAVs altitudes $\mathcal{H}$. Constraints (5h) and (5i) restrict the ground user to be associated, at most, with one UAV.

In practice, problem (8) 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 MINLP that is, moreover, NP-hard (due to the UAV-user's association that can be formulated as the well-known knapsack problem [44]). Finding the global optimal solution to such a problem may involve searching over 3D coordinates for all UAVs and for every possible UAV-user's association. In the following, we propose a distributed approach based on a decomposition process to achieve a suboptimal, yet efficient, solution that costs few numbers of iterations. To this purpose, the studied optimization is decoupled into three subproblems. First, the association problem is solved while assuming fixed 3D locations of UAVs. This subproblem is described as follows.

$$\underset{\mathbf{A}}{\text{maximize}} \quad \sum_{j \in \mathcal{B}^A} \sum_{i \in \mathcal{U}} a_{ij} R_i \quad \text{(6a)}$$

$$\text{subject to} \quad R_i = b_{ij} \eta_{ij}, \quad \forall i \in \mathcal{U}, \forall j \in \mathcal{B}^A, \quad \text{(6b)}$$

$$\sum_i a_{ij} b_{ij} \leq B_j, \quad \forall j \in \mathcal{B}^A, \quad \text{(6c)}$$

$$\frac{a_{ij}}{\eta_{ij}} \leq \frac{1}{\eta^{\min}}, \quad \forall (i,j) \in \mathcal{U} \times \mathcal{B}^A, \quad \text{(6d)}$$

$$\sum_j a_{ij} \leq 1, \quad \forall i \in \mathcal{U}, \quad \text{(6e)}$$

$$a_{ij} \in \{0, 1\}, \quad \forall (i,j) \in \mathcal{U} \times \mathcal{B}^A. \quad \text{(6f)}$$

Second, we deal with the 2D positioning of UAVs for fixed

altitudes and association, which is expressed as follows,

$$\underset{(\mathbf{x}^A, \mathbf{y}^A)}{\text{maximize}} \quad \sum_{j \in \mathcal{B}^A} \sum_{i \in \mathcal{U}} a_{ij} R_i \quad \text{(7a)}$$

$$\text{subject to} \quad x^{\min} \leq x_j^A \leq x^{\max} \quad \forall j \in \mathcal{B}^A, \quad \text{(7b)}$$

$$y^{\min} \leq y_j^A \leq y^{\max} \quad \forall j \in \mathcal{B}^A. \quad \text{(7c)}$$

Finally, we optimize the UAVs heights given fixed 2D coordinates of the UAVs and a predetermined association scheme. The sum-rate is therefore maximized with respect to the UAVs altitudes as follows

$$\underset{\mathbf{h}}{\text{maximize}} \quad \sum_{j \in \mathcal{B}^A} \sum_{i \in \mathcal{U}} a_{ij} R_i \quad \text{(8a)}$$

$$\text{subject to} \quad h_j \in \mathcal{H} \quad \forall j \in \mathcal{B}^A. \quad \text{(8b)}$$

## V. PROPOSED APPROACH

As stated before, the problem under analysis is mathematically challenging. Finding a global optimal solution cannot be achieved using classical convex optimization methods. Our idea is to break the studied problem into subproblems that are locally solvable using combined low-complexity algorithms, and iterate the process in order to reach a stable solution.

### A. Efficient UAVs-Users Matching

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**Algorithm 1** Users-UAVs Matching

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

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To deal with the target optimization, we first assume fixed 3D locations of UAVs and propose a suitable distributed mechanism for UAV-user's association. The proposed mechanism is achieved using Gale-Shapley matching [45] 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 UAVs that satisfy constraint (5d), and sorts them in a decreasing order by comparing their spectral

efficiencies. At this step, each user has its own list of preferred UAVs (line 2). Similarly, each UAV establishes its list of preferred users by comparing the requested bandwidths (line 3). Each user sends a request to connect to its most preferred UAVs (line 6). Each UAV accepts its most preferred users one by one until its bandwidth limit is reached and rejects the remaining users (lines 7 and 8). Each rejected user attempts to connect to its second most preferred UAV, if no more bandwidth is left on this UAV, the drone can disconnect a less desired user and replace it by the new one (lines 10 and 11)). Otherwise, the user and UAV are mutually removed from their respective preference lists (line 13). The algorithm stops when all UAVs have reached their bandwidth limit or each user has been either connected, or rejected by all its preferred UAVs (line 14).

The number of iterations needed for convergence is, at most, equal to $|\mathcal{U}| \times |\mathcal{B}^G|$, since each user can propose to at most $|\mathcal{B}^A|$ UAVs.

### 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 UAV-user's association scheme is the one described in Subsection V-A and that the altitudes for all UAVs are fixed at some random values. The UAVs altitudes are addressed separately in Subsection V-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.

To this end, we propose a modified version of $K$-means algorithm [46] (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.

---

**Algorithm 2** 2D Placement Optimization

1: **Initialization**
2: For each UAV $j$, $(x_j^A(0), y_j^A(0))$ are chosen randomly within the target area $\mathcal{A}$
3: For each UAV $j$, $C_j = \varnothing$
4: **repeat**
5:     **for** $j$ in $\mathcal{B}^A$ **do**
6:         **for** $i$ in $\mathcal{U}$ **do**
7:             Update $\eta_{ij}$, update $\mathbf{A}$ with **Algorithm** 1
8:             **if** $a_{ij} = 1$ **then**
9:                 $C_j = C_j \cup \{i\}$
10:         $x_j^A \leftarrow \frac{1}{|C_j|} \sum_{i \in C_j} x_i$, $y_j^A \leftarrow \frac{1}{|C_j|} \sum_{i \in C_j} y_i$
11: **until** UAVs cannot improve their 2D locations or number of iterations reaches a predetermined value.

---

Given $K$ initial positions of UAVs $(\mathbf{x}^A(0), \mathbf{y}^A(0))$ (line 2), the algorithm groups the users with their serving UAVs using the association scheme described in **Algorithm** 1 (line 7). Accordingly, each UAV's 2D position is updated as a barycenter of its cluster $C_j$ (lines 10). When the position of the UAV is updated, the user's 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).

### C. Altitude Optimization

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

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

- **Neighborhood**: two base stations $j$ and $k$ are considered neighbors if there exist two heights $h_j$ and $h_k$, where at least one user is covered by both base stations. In mathematical words, the neighborhood of a UAV $j$ can be defined as follows.

$$\mathcal{N}_j(\tau) = \{k \in \mathcal{B}^A \cup \mathcal{B}^G, \exists i \in \mathcal{U} \text{ s.t. } \exists (h_j, h_k) \in \mathcal{H}^2$$
$$P_j L_{ij}(r_{ij}, d_{ij}) > \tau \quad \text{and} \quad P_k L_{ik}(r_{ik}, d_{ik}) > \tau \}, \quad (9)$$

where $\tau$ is the received signal threshold. Note that such a threshold is defined on the received power averaged over small-scale (multipath) fading. For ease of notation, we will remove the 'dependency' on $\tau$ in the rest of the paper, and note $\mathcal{N}_j$ instead of $\mathcal{N}_j(\tau)$. Furthermore, let us denote by $\tilde{\mathcal{N}}_j$ the neighboring UAVs of UAV $j$, therefore

$$\tilde{\mathcal{N}}_j = \mathcal{B}^A \cap \mathcal{N}_j. \quad (10)$$

- **Local sum-rate function**: is the function that computes the sum-rate over a local neighborhood set. Thus, instead of considering the social welfare of all base stations with interference, only rates from neighboring base stations with limited interference (coming from neighbors) are considered. Accordingly, for each UAV $j$, the local sum-rate is given by

$$U_j(\mathbf{h}) = \sum_{l \in \tilde{\mathcal{N}}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \mathbb{E}_g \left[ \log_2 \left(1 + \frac{P_l g_{il} L_{il}(r_{il}, d_{il})}{\sigma^2 + \sum_{\substack{k \in \mathcal{N}_l, \\ k \neq l}} P_k g_{ik} L_{ik}(r_{ik}, d_{ik})} \right) \right]. \quad (11)$$

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)** [47]: a strategy profile $\mathbf{h}$ is a Nash equilibrium of a game $\mathcal{G}$ if for each player $j$, $\forall h_j \neq h_j^*$

$$U_j(h_j^*, \mathbf{h}_{-j}^*) \geq U_j(h_j, \mathbf{h}_{-j}^*), \quad (12)$$

where $\mathbf{h}_{-j}$ refers to the altitude vector of UAVs other than $j$.

- **Potential game** [48]: in game theory, an interesting class of games called *potential* games has a specific property: the NE is a local optimum of the social welfare function also called 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 exists a potential function $F : \mathcal{X} \longrightarrow \mathbb{R}$ such that for each player $j$, $\forall (h_j, \mathbf{h}_{-j})$ and $(h_j', \mathbf{h}_{-j}) \in \mathcal{X}$

$$F(h_j, \mathbf{h}_{-j}) - F(h_j', \mathbf{h}_{-j}) = U_j(h_j, \mathbf{h}_{-j}) - U_j(h_j', \mathbf{h}_{-j}). \quad (13)$$

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

$$F(\mathbf{h}) = \sum_{j \in \mathcal{B}^A} \sum_{i \in \mathcal{U}} a_{ij} b_{ij} \mathbb{E}_g \Big[ \log_2 \big( 1 + \frac{P_l g_{ij} L_{ij}(r_{ij}, d_{ij})}{\sigma^2 + \sum\limits_{\substack{k \in \mathcal{N}_j, \\ k \neq j}} P_k g_{ik} L_{ik}(r_{ik}, d_{ik})} \big) \Big]. \quad (14)$$

In order to account for the neighborhood and altitudes in the average spectral efficiency, we set the following notation

$$\eta_{ij}^{\mathcal{N}_j}(h_j, \mathbf{h}_{-j}) = \mathbb{E}_g \Big[ \log_2 \big( 1 + \frac{P_l g_{ij} L_{ij}(r_{ij}, d_{ij})}{\sigma^2 + \sum\limits_{\substack{k \in \mathcal{N}_j, \\ k \neq j}} P_k g_{ik} L_{ik}(r_{ik}, d_{ik})} \big) \Big], \quad (15)$$

where $L_{ij}$ is the path loss when UAV $j$ is at altitude $h_j$. Hence, when a UAV $j$ changes its altitude given fixed altitudes of its opponents, the difference in the limited-interference sum-rate can be written

$$F(h_j, \mathbf{h}_{-j}) - F(h'_j, \mathbf{h}_{-j}) = \sum_{l \in \mathcal{B}^A \backslash \tilde{\mathcal{N}}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \eta_{il}^{\mathcal{N}_l}(h_j, \mathbf{h}_{-j}) +$$
$$\sum_{l \in \tilde{\mathcal{N}}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \eta_{il}^{\mathcal{N}_l}(h_j, \mathbf{h}_{-j}) - \sum_{l \in \mathcal{B}^A \backslash \tilde{\mathcal{N}}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \eta_{il}^{\mathcal{N}_l}(h'_j, \mathbf{h}_{-j}) -$$
$$\sum_{l \in \tilde{\mathcal{N}}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \eta_{il}^{\mathcal{N}_l}(h'_j, \mathbf{h}_{-j}). \quad (16)$$

Notice that the term $\sum\limits_{l \in \mathcal{B}^A \backslash \tilde{\mathcal{N}}_j} \sum\limits_{i \in \mathcal{U}} a_{il} b_{il} \eta_{il}^{\mathcal{N}_l}(h_j, \mathbf{h}_{-j})$ is independent of $(h_j, \mathbf{h}_{-j})$ as it does not involve UAV $j$ neighborhood. Therefore,

$$F(h_j, \mathbf{h}_{-j}) - F(h'_j, \mathbf{h}_{-j})$$
$$= \sum_{l \in \tilde{\mathcal{N}}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \eta_{il}^{\mathcal{N}_l}(h_j, \mathbf{h}_{-j}) - \sum_{l \in \tilde{\mathcal{N}}_j} \sum_{i \in \mathcal{U}} a_{il} b_{il} \eta_{il}^{\mathcal{N}_l}(h'_j, \mathbf{h}_{-j})$$
$$= U_j(h_j, \mathbf{h}_{-j}) - U_j(h'_j, \mathbf{h}_{-j}). \quad (17)$$

The following **Proposition** arises from the previous analysis.

**Proposition 1.** *Let $\mathcal{G}$ be the game where the UAVs are considered as players and the altitudes are their playing strategies. The game $\mathcal{G}$ is a potential game where the function $F$ defined by equation (14) is the potential function.*

The following result is an immediate consequence of **Proposition 1** [48].

**Corollary 1.** *In a potential game, a global optimum of the potential function is a Nash equilibrium. Moreover, any Nash equilibrium is a local optimum.*

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 [49]. The best-response dynamics are based on computing the best strategy that maximizes the utility of the player (i.e. a UAV) for fixed strategies of its opponents. Since the set of altitudes is finite, this maximum is simply determined using exhaustive search over the set of altitudes.

Assume fixed 2D locations of UAVs (line 2), each UAV maximizes its utility $U_j$ over a set of discrete altitude's values $\mathcal{H}$ given fixed altitudes of other UAVs (line 6). Subsequent changes are therefore fed back to the neighbors resulting in updates of the

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

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

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association matrix using **Algorithm 1**. This process is repeated until convergence to a NE[2] (line 9). Such process results in a local optimum of $F$ given fixed 2D positions of the UAVs and the predefined association scheme.

## VI. LEARN-AS-YOU-FLY ALGORITHM (LAYF)

The general proposed approach to solve the joint 3D placement and association problem, LAYF algorithm, is described in details in Fig. 3. Indeed, the interdependency between the UAV-user's association problem and the 3D placement makes it conspicuously obvious that it is not possible to address each problem separately in only one shot. Our approach is built in a way that allows to the UAVs to test, as they fly, various association options and 3D locations while preserving the distributed aspect of both the association scheme and the placement policy. First, the matching-based association scheme is fully distributed as both users and UAVs rely on local information to make the association decision. Then the UAVs are moved, in the 2D plan, next to their served users to potentially improve the quality of the link, reduce the requested bandwidth, and free some resource to satisfy additional users demands. Furthermore, the altitudes are adjusted to reduce interference in the neighborhood of each UAV. This process is repeated until none of the UAVs positions is improved or the algorithm reaches a predefined number of iterations. Next, we analyze the complexity of the proposed algorithm, show its qualitative properties and discuss its limitations.

### A. Complexity Analysis

In this subsection we analyze the performance of LAYF algorithm in terms of worst case complexity. First, the worst case complexity of the matching algorithm is $N \times K$, where $N$ is the number of ground terminals and $K$ is the number of UAVs [50], whereas the time complexity of K-means algorithm is known to be equal to $O(N \times K)$ [51][3]. The complexity of the best response dynamics has been studied in [52] where the authors show that the worst case complexity of the algorithm is exactly $K \times |\mathcal{H}|^{K-1}$, where $|\mathcal{H}|$ is the set of discrete altitudes.

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[2]Convergence of best response dynamics to a NE has been proved in many works, e.g. [49].

[3]This complexity can be improved using directional movements of the clusters as shown in [51].
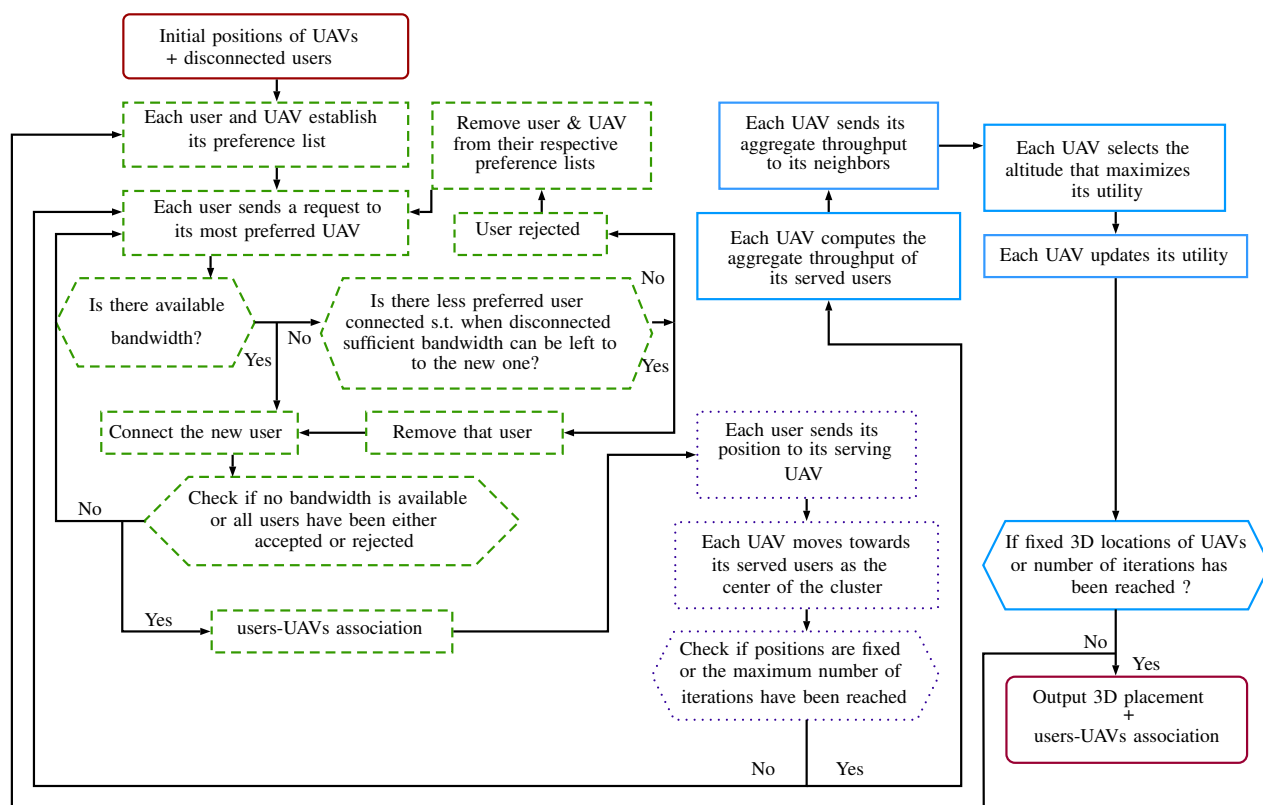
Fig. 3: LAYF algorithm. Dashed line boxes correspond to the matching-based association scheme, the dotted ones illustrate the modified K-means for UAVs 2D positioning, and the solid line rectangles correspond to the response-dynamics based altitudes adjustment.

Assume the number of running iterations of the algorithm is fixed, and is equal to $T$. Then the worst case complexity $Cp$ of LAYF is given by

$$Cp = TO(N \times K + N \times K + K \times |\mathcal{H}|^{K-1})$$
$$= TO(N \times K + K \times |\mathcal{H}|^{K-1}). \quad (18)$$

### B. Qualitative Properties

*1) Distributed Implementation:* Unlike centralized algorithms where UAVs need to know the 3D positions and associated users of all other UAVs at each time slot, LAYF algorithm assumes limited knowledge for all aerial base stations. Indeed, each UAV needs only to observe the result of the strategy (3D position) it has picked as well as the results of the strategies of its neighbors in order to estimate its utility, and decides its next strategy.

Depending on the stage of LAYF algorithm optimization (UAV-user's association, 2D placement or altitudes adjustment), the utility of a UAV $j$ is either based on the throughput of neighboring users (for association and 2D placement), or composed of the sum-rate of the tagged UAV in addition to the sum-rates of neighboring UAVs (for altitudes adjustment). Therefore, an overhead, first, occurs when a user sends its spectral efficiency and the required rate (or equivalently its throughput) to neighboring UAVs (the ones that satisfy the required quality of service). The second kind of signaling overhead is triggered when a neighboring UAV sends its sum-rate to the tagged UAV through its air interface.

In order to reduce exchanged messages, an overhead can be sent only when the throughput of a given user has changed (for association and 2D placement), or when the difference between the previous rum-rate of a neighboring UAV and its current one

has evolved (for altitudes adjustment). It is to be noted that, in order to optimize the overhead packet size, only the difference between current and previous state can be sent.

*2) Asynchronous Performance:* LAYF algorithm can be implemented on board of each UAV in an asynchronous way where each UAV updates its state depending on its own clock. Each UAV has two states: active and dormant. During the active state, the UAV updates its 3D coordinates. During the dormant state, the UAV sleeps in order to save its energy and reduce exchanged signaling messages.

### C. Limitations

*1) Convergence:* It is important to note that it is not guaranteed that the algorithm will iterate until reaching fixed UAVs positions. The reason is that when a UAV moves next to its served users, it might cause additional interference to neighboring UAVs. Although this issue might be bypassed by adjusting UAVs altitudes, the interference can trigger the movement of another UAV and thus, the algorithm can oscillate infinitely between these two states. To circumvent this problem, the algorithm can keep track of the number of iterations and halts if no significant improvement is noticed in the sum-rate function, or if the counter of iterations reaches a certain predetermined value.

*2) Dynamic Nature of the Environment:* LAYF algorithm assumes that when the UAV is fixed, the propagation channel is stable. Indeed, in UAV based networks, the dynamic nature of the propagation environment is tightly related to the type of the UAV application. For example, when a UAV hovers over a damaged area to provide connectivity, the propagation channel is most probably stable. Unlike when UAVs are deployed for search and rescue

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applications or as relays for IoT devices, the UAV has to constantly move over the field in order to take measurements and collect information. In these cases, it would be a requirement to design robust algorithms that considers the varying nature of the channel and selects the best UAVs moves in an uncertain environment.

*3) UAVs Trajectory Optimization:* Optimizing the UAVs trajectory is a challenging task as it involves various parameters including the energy consumption, the flights constraints and the mobility dynamics. In this work, we do not take into account the trajectory optimization of UAVs when they update their coordinates. Introducing such constraint (i.e. trajectory minimization) to the studied optimization problem is envisioned as a part of our future works.

## VII. SIMULATION RESULTS

In order to study the performance of LAYF algorithm, we consider a 150m × 150m area. Let $\mathcal{U}$ be the set of ground users assumed as a realization of a HPPP with intensity $\lambda_u = 16 * 10^{-4}$ user/m². To position ground base stations, we consider a realization of PPP with intensity $\lambda_G = 3.44 * 10^{-4}$ BS/m². Damaged/overloaded base stations are obtained with a thinning of probability $p = 0.45$. Next, UAVs are generated using a 3D PPP with intensity $p\lambda_G$. We assume the same transmit power $P = 10$ dBm for all base stations. In order to compute the average spectral efficiency in equation (4), we use Monte Carlo simulations with 5000 runs, the average is computed over the small-scale fading. The simulation settings are summarized in TABLE. II. To assess the performance of the proposed algorithm, we build 4 benchmarking scenarios.

1) LAYF scenario: for this scenario, we implement the proposed LAYF algorithm to solve problem (8).
2) LAYF-Nearest scenario: in this scenario, instead of the matching based association, we use the commonly adopted association scheme that assigns users to their nearest UAV. The remaining process is the same as for the proposed LAYF algorithm.
3) Centralized scenario: in this scenario, we sub-optimally solve the problem described in (8) by using a combined centralized approach. The approach alternates between solving the association problem using *intlinprog* (an optimization function from the integer-linear-programming toolbox of Matlab®), and the UAVs 3D positioning by using *fmincon* (an optimization function for continuous optimization from the Matlab® optimization toolbox, this function is based on the interior-point algorithm).
4) Random scenario: at each iteration, we generate a random feasible solution. To this end, we first create a random matrix of UAVs 3D positions within the studied area. Second, we randomly assign users to UAVs such that each user is assigned to exactly one UAV. Then, we check if the constraints on bandwidth and spectral efficiency are satisfied. If the spectral efficiency constraint is not satisfied for a given user, we disconnect it. Similarly, if the constraint on the bandwidth is not verified for a given UAV, we randomly disconnect users until the bandwidth limit of this UAV is respected.

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $R_i$ | Random in [90, 100] Mbps | P | 10 dBm |
| $\eta^{\min}$ | -3 dB | $\tau$ | -69 dBm |
| $\mu$ | 1 | $p$ | 0.9 |
| $\lambda_u$ | $16 * 10^{-4}$ user/m² | $\sigma^2$ | -100 dBm |
| Bandwidth | {1070, 1151, 927, 941, 1021, 1004}(MHz) | | |
| $\mathcal{H}$ | {100, 160, 120, 180}$m$ | | |

TABLE II: Simulation settings.

Fig. 4 plots the initial and final positions of UAVs for the first 3 studied scenarios. As depicted in Fig. 4(a), (b), (d), (e), (g), and (h), for all the studied scenarios, the UAVs dynamically change their positions starting from their initial points, and move towards their served users in a few steps before reaching their final best locations. Clearly, the number of users that are connected under LAYF scenario is higher than the number of served users under both LAYF-Nearest and centralized scenarios. This is mainly due to the fact that LAYF can better handle the bandwidth resource. Under the nearest UAV association, a user is either connected to its closest UAV or not connected if the UAV has already reached its bandwidth limit. On the other side, under the matching based association, a user has more potential serving UAVs as it can select among a list of preferred UAVs. It can also be seen from the figure that some users are left without connectivity either due to bandwidth limitation or quality of service constraint. The final heights of UAVs are better shown in Fig. 4(c), (f) and (i) 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 interference. For example, one can remark from Fig. 4(c) that UAVs 1 and 2 that are neighbors have converged to different height values in order to alleviate interference.

The occupied bandwidth of UAVs is plotted in Fig. 5. The figure shows that the bandwidth constraint is respected for all scenarios. Again, it can be seen from the figure that the number of connected users is higher when using LAYF approach. As depicted in Fig. 5(b), for LAYF-Nearest scenario, no user is served by UAVs 1 and 5 as the required bandwidth of nearby users is above the bandwidth limit of these UAVs. Furthermore, it can be seen from the figure that LAYF approach is favorable to more fairness in the network as the number of served users is higher and their required bandwidth is lower when compared with LAYF-Nearest and centralized scenarios.

Fig. 6 plots the convergence the sum-rate function vs the number of iterations under two small-scale fading models: Rayleigh channels in Fig. 6(a) and Rice channels in Fig. 6(b). The figures show how the sum-rate evolves over iterations. Clearly, LAYF approach significantly improves the overall sum-rate as compared with the studied scenarios. It can also be seen from the figure that the random approach always yields a suboptimal result.

In order to study the effect of the bandwidth constraint on the studied scenarios, we set all UAVs to the same bandwidth and plot the sum-rate vs bandwidth values for each UAV in Fig. 7(a). As depicted from the figure, in general, the sum-rate increases when the bandwidth per UAV increases, except for the random scenario, where the sum-rate decreases at some points of the curve. This is mainly due to the random suboptimal solutions that this scenario proposes. It can also be noticed that when enough bandwidth is supplied to the network, LAYF, LAYF-Nearest and centralized approaches provide the same solution which coincides with the maximum network sum-rate. Finally, in Fig. 7(b), we
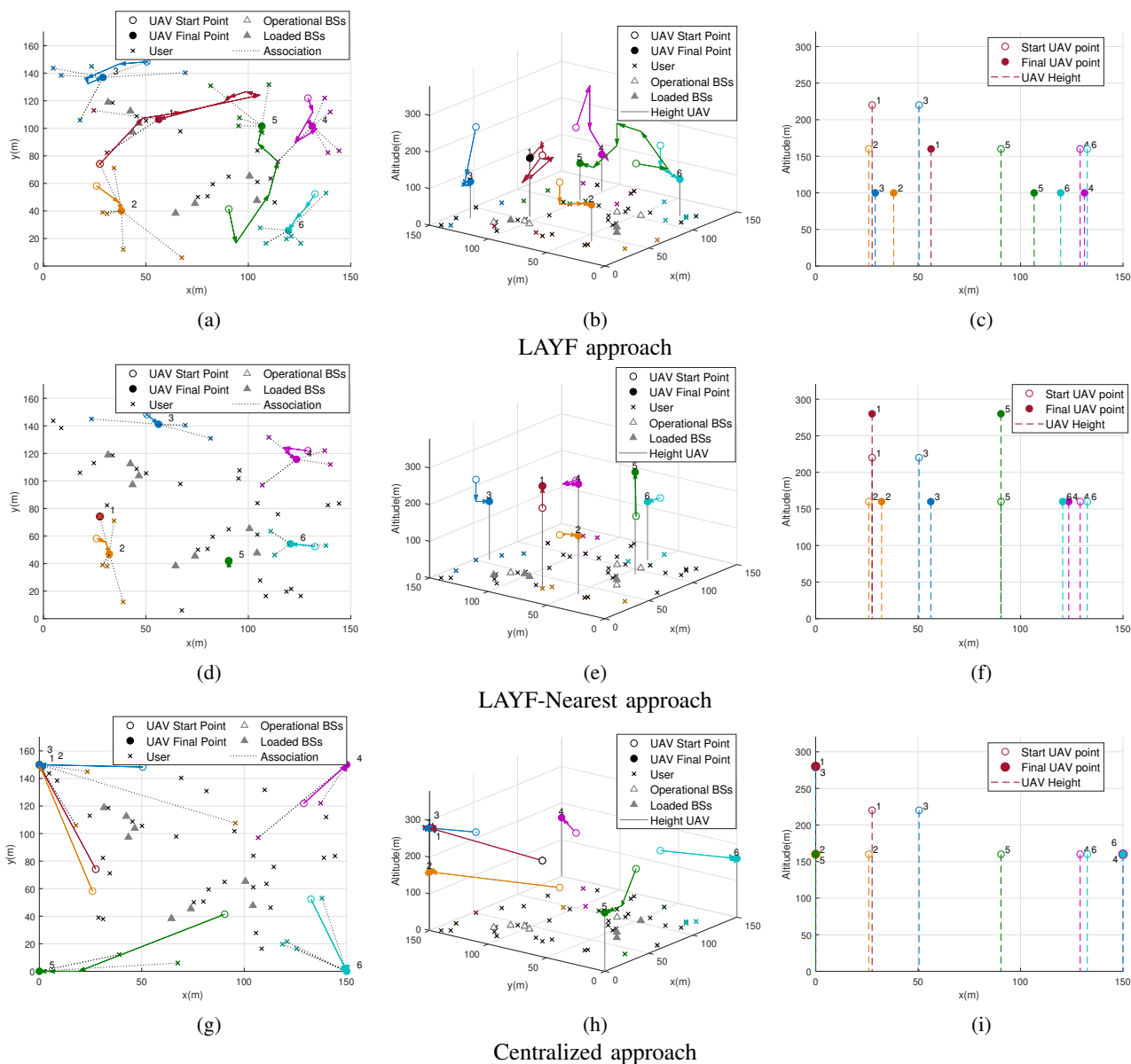
Fig. 4: (a) 2D configuration with UAVs trajectories for LAYF approach, (b) 3D network configuration for LAYF approach, (c) Heights of UAVs for LAYF approach (d) 2D configuration with UAVs trajectories for LAYF-Nearest approach, (e) 3D network configuration for LAYF-Nearest approach, (f) Heights of UAVs for LAYF-Nearest approach, (g) 2D configuration with UAVs trajectories for Centralized approach, (h) 3D network configuration for Centralized approach, (e) Heights of UAVs for Centralized approach.
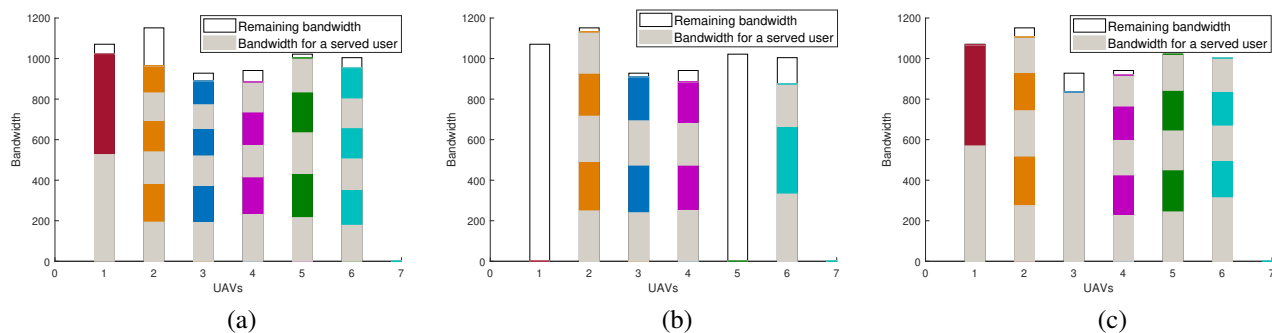


Fig. 5: Bandwidth allocation for (a) LAYF, (b) LAYF-Nearest, (c) Centralized approaches. Colored bars (gray, orange, red, blue, green, purple) are used to show the amount of bandwidth occupied by a served user. For example, graph (a) shows that 2 users are served by UAV 1, 6 are served by UAV 2, 6 are also served by UAV 3, etc..
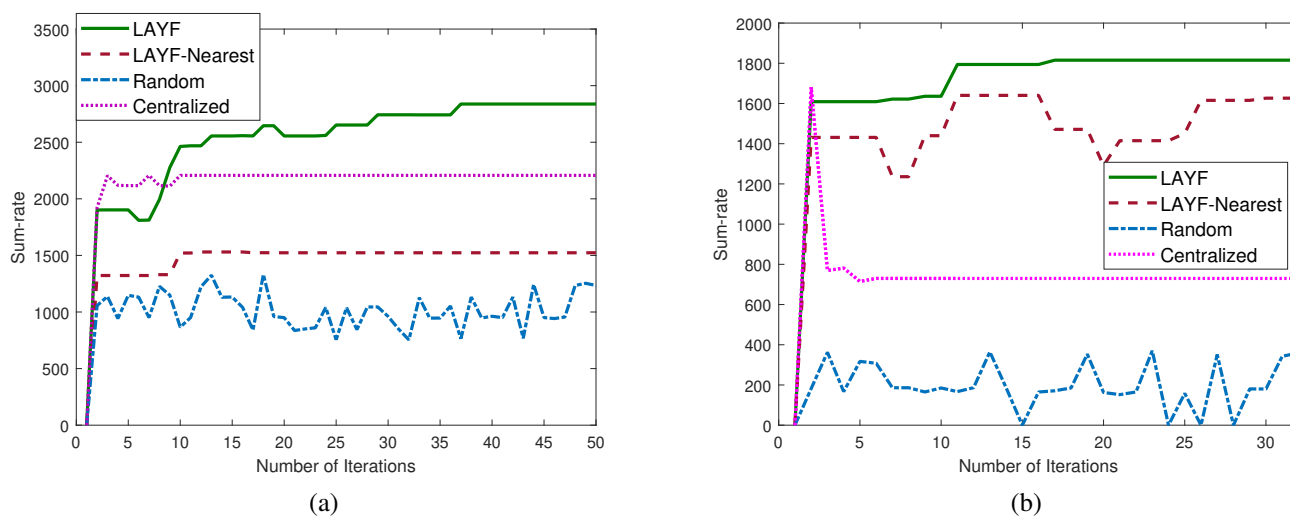
Fig. 6: Algorithms convergence over (a) Rayleigh channels, (b) Rician channels with parameters $K_r = 4$ .
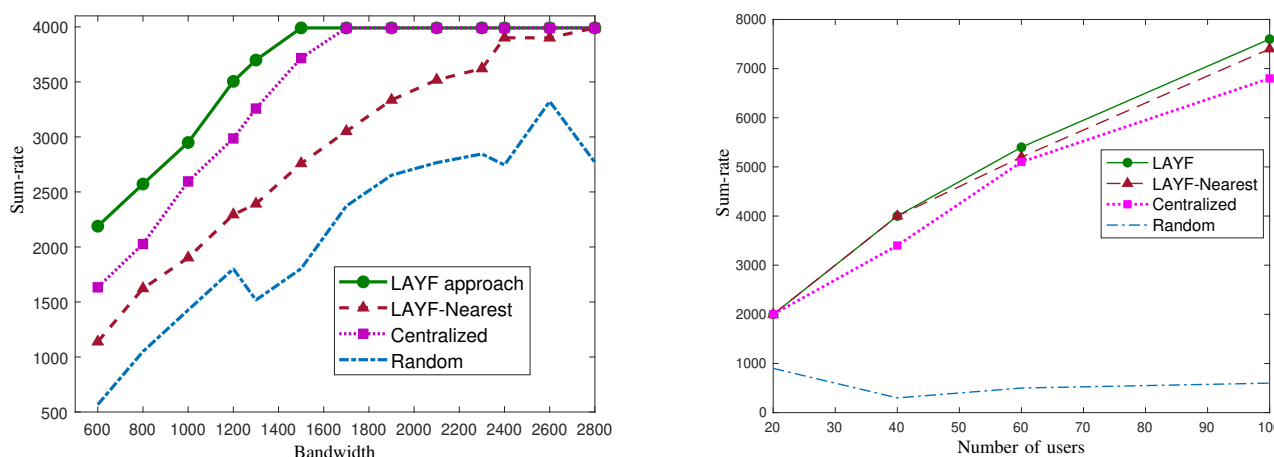


Fig. 7: (a) Bandwidth effect, (b) effect of the number of users.

also plot the final value of the sum-rate after convergence of the algorithms against the number of the ground users while assuming fixed bandwidth of the UAVs (450 MHz). The figure shows that LAYF approach provides a better performance as compared to centralized, LAYF-Nearest and random approaches.

## VIII. CONCLUSION

In this paper, we have studied the joint 3D placement and UAV-user's association in multi-UAVs networks. Our proposed LAYF algorithm relies on a iterative three steps mechanism that reaches an efficient and stable solution of the studied optimization problem. Indeed, in order to maximize the network sum-rate under bandwidth limitation and quality of service constraint, LAYF approach proposes a matching-based UAVs-users associations, a distributed version of K-means for the 2D positioning of UAVs, and dynamic best-response for altitudes adjustment. The whole approach is fully distributed and requires only a few iterations to reach an efficient network performance. Simulation results show that appreciable performance is obtained as compared with the trivial case where users are associated, over iterations, to the clos-est UAV, and when compared to a combined centralized approach where UAV-user's association and 3D positioning problems are solved separately using centralized metaheuristics.

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. We will also study UAVs trajectory optimization while updating UAVs coordinates.

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