

Response to reviewer 1:

Reviewer comments:

Aspects that must or can be improved:

- Background and references
- Research design
- Method description
- Clarity of results
- Conclusions more connected to the results.

Dear author,

There are many paragraphs that need to rewrite to avoid plagiarism. please check the comments in the paper.

Equations 3, 4, 5, 6 need to be mentioned in the paper

The paper did not follow the journal's format.

There is no acknowledgment.

There is no Declare for Conflict of Interest before References.

At the end of the References, authors need to check the format again.

Response:

Thanks for the suggestions, we completely agree. The paper has undergone a major revision in all its sections (including the abstract). In the revised version, we improve all the aspects that the reviewer marked as improvable to the best of our ability given the 10-day deadline (English, rewriting several paragraphs, references, introduction, description of the solution, methods, results and conclusions). We also fixed the aspects mentioned by the reviewer.

We believe that the reviewer will find a remarkable improvement in clarity now, and hope that the paper is now at the full satisfaction of the reviewer.

Article

Energy-efficient UAVs Deployment for QoS-guaranteed VoWiFi Service

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Version July 16, 2020 submitted to Sensors

Abstract: Unmanned Aerial Vehicles (UAVs) equipped with WiFi access points can be used to provide wireless communication services in open geographical areas. This paper formulates a new problem for UAVs the optimal deployment to provide QoS-guaranteed real-time placement of Unmanned Aerial Vehicles (UAVs) geared towards wireless coverage provision for Voice over WiFi (VoWiFi) communications. service to a set of ground users confined in an open area. Our goal objective function is to find constrained not only by coverage but also by VoIP speech quality and minimizes the ratio between the number of UAVs (and their positioning) deployed and energy efficiency in UAVs, hence providing the layout that minimizes requires less UAVs per hour of service. Solutions provide the UAV turnover rate while considering coverage number and QoS constraints. We propose position of UAVs to solve the optimization problem through be deployed, and are found using well-known heuristic search methods, methods such as genetic algorithms (used for the initial deployment, deployment of UAVs), or particle swarm optimization (used for periodical updates in dynamic scenarios. Then, an example scenario is solved and obtained results are validated via simulation. Via numerical results, we proved that radio communications represent about 15 update of the UAV power, which highlights positions). We examine two services of potential interest: (a) one bidirectional VoWiFi channel per user; (b) single broadcast VoWiFi channel for announcements. For these services, we study the benefits results obtained for an increasing number of considering energy consumption users confined in the optimization problem.

Keywords: UAV; Voice over IP; Wireless LAN; IEEE 802.11; Voice over IP over WiFi; VoWiFi; Quality of service (QoS). Service; Energy

1. Introduction

The WiFi mac-sublayer imposes more restrictive bounds over the number use of concurrent users who can enjoy QoS-guaranteed real-time Unmanned Aerial Vehicles (UAVs) for wireless communications than simply considering signal coverage [1,2]. In fact, there is have experienced a maximum number rapid growth in a broad range of VoIP flows application domains [3]. On-board communication devices enable UAVs to enhance coverage, capacity, reliability or energy efficiency of wireless networks. Note however, that an AP can handle with QoS guarantees, namely, VoIP capacity [4–7]. For example, an AP performing IEEE 802.11b can handle the drone communication technology has a maximum of 15 simultaneous calls [7], even though decisive impact on the number of stations associated data rate and range usable in the mission [8]. The predominant technology in UAV-related literature is cellular (i.e., UAVs are used as aerial base stations) [9], but it is not uncommon to find

studies with other technologies for UAV-to-ground communication such AP could be multiple times greater.

In a previous as WiFi [10] or Bluetooth [13]. This work [14] we took a first step into considering the mac-sublayer and QoS takes WiFi as enabling technology for UAV-to-ground communication, which provides a constraint in the optimal initial deployment problem, defining an objective function that minimized the number data range of UAV-mounted APs to be launched (and their position) while considering both, signal coverage 11Mbps-1Gbps and VoIP capacity in a service fitted for search and rescue missions. The behaviour range of the WiFi mac-sublayer was accounted for (i.e. modeled) up to predict network performance and radio power consumption at ground user's terminals. As such, among solutions with the same number of APs, the one with the least power consumption at 250 m (depending on the user terminal was preferred since prolonging casualties phone battery is valuable in disaster scenarios. However, albeit first of its kind, this work exhibits some limitations. First, it considers only a two-channel VoIP service which (although adequate revision).

Deploying UAVs for rescue missions) may result wireless networks brings in new opportunities such as creating a large number of UAVs required. Secondly, provisional communication infrastructures in Search and Rescue (SAR) missions [3,15], but it disregards the fact that UAVs have to be replaced Autonomous charging for UAVs also brings multiple challenges such as optimal 3D placement, performance analysis, path planning, backhaul connectivity or energy limitation, just to enable long-endurance missions [16] could be an alternative approach not considered in name a few [9,17]. In this work, due work, we are going to battery exhaustion after 15-20 min. The number deal with the challenge of UAVs finally launched will depend on both, optimal multi-UAV 3D placement in the number context of creating a provisional WLAN (i.e., UAVs required are used as aerial Access Points - AP) to provide the ground users with VoIP over WiFi (VoWiFi) service. A distinctive characteristic of this service and their endurance.

UAVs endurance is that 3D placement has to consider not only coverage (e.g., [1,2]) but also the VoIP speech quality [14] as the mac-sublayer of the communication protocol limits the number of simultaneous VoIP flows that APs can handle with quality of experience¹. This limit is known as VoIP capacity [4].

The optimal 3D placement of UAVs is a challenging task that has received significant attention from the ratio research community [9,17-19]. The problem has to take into account multiple factors such as the terrain, location of users, UAV-to-ground channel characteristics or radio interference between UAVs, and in our case, the energy available (i.e. battery capacity) Quality of Service (QoS). According to Sharkoor et al. [20], another factor to be carefully taken care of "when deploying UAVs is their flight time and required power [21]. Energy energy constraints". Indeed, the authors provide an excellent review of literature with emphasis on the energy efficiency perspective, dissecting the factors affecting energy consumption models take into consideration every power draw in UAVs such as hovering, climbing, UAV placement, UAV-user association, flight-time, mobility, trajectory, and UAV communication and mechanical energy. Although optimal 3D placement has been extensively addressed, the comparison between works is difficult as they have different objective functions and constraints. In general, we can classify them roughly as (a) those that minimize the number of UAVs deployed [22-25] (i.e. minimize deployment cost); (b) those maximize energy efficiency or providing a communications service [26,27]. battery lifetime [28-30] i.e., UAV endurance models have been used in energy-aware [21]). Energy-aware UAV optimal deployment problems to account for typically considering the power consumption either due to the flight [28] or due to either radio transmission [29,30]. Before battery exhaustion, UAVs need communication [29,30] or mechanical energy [28] using energy consumption models [26,27]. The reader is encouraged to be replaced read the surveys [8,20,31]

¹ For example, an AP performing IEEE 802.11b can handle a maximum of 15 simultaneous calls [7], even though the number of stations associated to such AP could be defined multiple times greater.

for service continuity. a more detailed list of works and references that address the problem of 3D placement with emphasis in energy consumption.

Motivation

Long-duration activities may require drone hot replacement due to battery exhaustion. Our previous work was fitted for search and rescue missions in which extending users' phones battery life was In the priority. However, requirements may be different in other non-critical scenarios (e.g., concerts) in which context of this work, we would like to deploy aerial APs to provide a QoS-guaranteed VoIP VoWiFi service to ground users (not necessarily all of them) during a in an outdoor long-duration activity (e.g. concert or similar longer time. 20-25 min) that will likely require drone hot replacement due to battery exhaustion. In this context, the following considerations should be taken into account:

- A low drone turnover rate (e.g., UAVs/hour) is desirable As mentioned earlier, besides coverage, the multi-UAV 3D optimal placement has to minimize consider VoWiFi speech quality for which the deployment cost in long-duration scenarios. Thus, mac-sublayer of the communication protocol is crucial. To the best of our knowledge, the only work that considers this factor [14] sets the focus only in addition to minimize minimizing the number of UAV launched at UAVs deployed² disregarding energy expenditure at UAVs (e.g., flight, communications), which efficiency in turn determines their operation lifespan. UAVs.
- Voice applications require QoS guarantees to avoid a general degradation The number of users' experience, so a correct estimation UAVs required for the mission depends not only on the UAVs initially deployed but also on the number of UAVs launched for the VoIP capacity is crucial replacement of those in battery exhaustion. Thus, besides minimizing the deployment number of VoWiFi services. UAV initially deployed, we should also seek the placement that maximizes the UAVs operation lifespan, considering UAV communication and mechanical energy.
- Long-duration events must should consider users' mobility, so users mobility. So besides the initial 3D placement, there should be a dynamic method in place so that UAV dynamically relocate themselves for UAVs relocation is required. service continuity.

Contribution

This paper defines and solves a new optimization problem that finds the number and position of UAVs to be deployed to cover over an user-defined portion of ground users that provides the minimum drone turnover rate with guaranteed VoIP QoS. This can be applied area to provide VoIP VoWiFi service to a set of ground users confined in known areas (i.e. with limited bounds) where users. Our optimal 3D placement minimizes the number of users and their location is known (i.e. semi-static), or periodically executed on dynamic scenarios where a fixed number UAVs deployed over time (i.e., rate of users are moving (an external location tracking system is required). drones per hour of service) while satisfying coverage and QoS constraints.

The contributions of this paper can be summarized as follows:

- We mathematically formulate a new UAV optimal deployment problem that accounts for UAVs turnover rate, coverage, and quality of service.
- We provide an analytical model that predicts the speech quality in a IEEE 802.11 WLAN for a set of VoIP traffic sources.
- We provide an analytical model that predicts UAV energy expenditure due to wireless communications. This information is used along with flight energy consumption to predict UAVs endurance.

² If multiple solutions with similar number of drones were found, the initial deployment, we should also consider one that extended the battery life of served users was chosen, overlooking the UAV power expenditure.

- We solve the UAV optimal deployment problem by using well-known heuristic methods such as genetic algorithm and/or particle swarm optimization.

2. Related works

The deployment

There are multiple survey papers that address the optimal placement of UAVs to conform a communications network has been extensively studied over the for wireless communications. In this section, we scrutinize four recent years. Each work however, models the problem in its own way surveys and sets the focus on specific aspects of the deployment. In those complement them with other related works devoted applicable. Our goal is to UAV-to-ground communication (i.e. the radio coverage clarify how our work compares with state of ground users is always considered), there is diversity in art related works.

The authors in [8] review the variables optimised on each work literature for multiple drone applications such as number of drones drone base-stations, search and rescue, or surveillance and monitoring, which is a challenging tasks due to be deployed versus fixed number the disparity of drones, or goals and constraints. Regarding energy efficiency and 3D placement, in drone versus ground user terminal. Besides [30] the optimization problem, there may be differences authors suggest an algorithm that minimizes transmit power in some aspects such as radio channel interferences, the application (e.g., VoIP versus data), or the mobility 3D placement of ground users. Table 1 summarizes the main related works one drone and shows how they can be compared with ours. assess their approach by simulation. 3D placement of one aerial base station was also proposed in [29]. In this case, the authors proposed an placement algorithm that maximizes the number of covered users using the minimum transmit power. In both cases, only the power related to radio communication was taken into account. In [32] the authors propose a placement algorithm for a set of UAV-mounted 5G aerial base stations that maximizes the capacity boost provided by the UAVs in each considered time frame and extends the battery life of the served mobile users. Unfortunately, the authors did not model the energy consumption and simply stated that "intuitively, less power is needed if the Gateway is closer to the users". In a context similar to ours, in [14] we proposed a 3D placement algorithm that minimized the number of aerial APs deployed to provide VoWiFi to ground users. As such, it is the only related work in which speech quality has been considered as a constraint. However, the subject of minimization was the number of deployed UAVs, and only if multiple solutions with similar number of drones were found, the algorithm selected the layout that extended the battery life of served users, overlooking the power expenditure in UAVs.

The survey paper [9] addresses the use of UAVs for wireless networks. The paper provides a state of art in optimal deployment of UAVs as flying base stations. In their previous work [33], the authors addressed the optimal deployment and mobility of multiple UAVs for energy-efficient data collection. In this case, the authors minimize the total transmit power of IoT devices (i.e., ground users) during UAVs trajectories. Other works such as [19,24,25,34–36] address the 3D optimal placement problem considering coverage of ground users using several different approaches, but ignore energy efficiency. Some of these works consider interference between UAVs[34].

Another excellent paper is [31], where the authors survey recent research addressing 1-3D placement optimization for aerial base stations. The authors highlight the diversity of objectives in the optimization problem such as maximizing the system capacity, minimizing the required number of UAVs [35], or minimizing the total transmit power of the entire aerial system [40]. The algorithms used for optimal placement also exhibit diversity and includes force brute search [38], Genetic Algorithms [41], K-means clustering [42] or transport theory [40]. This survey also provides a review of power-efficient operation of aerial base stations emphasizing that researchers typically work on either reducing communication energy (i.e., minimize the transmission power) of either the drone or ground users [18], or reducing mechanical energy of UAVs. For the latter is necessary to count with an energy consumption model [23] which largely depends on hovering. As the authors put it, "one

paper	objective	multi-UAV	UAV-to-ground technology	UAV mechanical power	UAV radio power	user radio power	speech quality constraint
[30]	minimize transmit power	no	cellular	no	yes	no	no
[29]	maximize coverage with minimum transmit power	no	cellular	no	yes	no	no
[32]	maximize capacity and extend battery life of mobile users	yes	cellular	no	yes	yes	no
[33]	minimize transmit power of mobile users (deployment and mobility)	yes	cellular	no	no	yes	no
[24]	minimize number of UAVs	yes	cellular	no	no	no	no
[40]	minimize the total transmit power of the entire aerial system	yes	cellular	no	yes	no	no
[43]	minimize total power consumption given predicted traffic	yes	cellular	yes	yes	no	no
[44]	minimize total power consumption	yes	cognitive radio	yes	yes	no	no
[14]	minimize number of UAVs	yes	WiFi	no	no	yes	yes
this paper	minimize the ratio between the number of UAVs and UAVs' endurance	yes	WiFi	yes	yes	no	yes

Table 1. Comparison of main works assume that a sufficient signal strength (e.g. SNR) is enough to guarantee QoS requirements, which is not a valid assumption in IEEE 802.11 networks [7]. Our previous work in [14] proposed a new optimization problem that provided a QoS-guaranteed VoWiFi service related to 3D optimal placement of UAVs for communication

solution to control the energy consumption of AUVs is to regulate their height. However, changing the height might reduce the performance of UAVs". This trade-off is also applies to this work and it will be addressed in the next Section. Finally, the survey provides a list of testbeds and real experiments in the literature. Interestingly, although most UAV communication research is focus on deploying UAVs as aerial base stations (i.e., cellular technology such as 3G/4G/5G), the majority of testbeds use WiFi (IEEE 802.11 b/g/a) as communication protocol such as in this work.

Only in [20] one can find a review of the literature with particular emphasis on the energy-efficiency perspective. Besides pointing to +20 other UAV communication-related existing surveys, the authors discuss the main factors affecting UAVs' energy consumption. One of these factors is UAV placement. As such, the authors review energy-efficiency algorithms for optimal UAV placement in the literature. In [43] use Machine Learning for optimal placement of UAV-mounted base stations given the predicted traffic. In their approach, they first find the optimal partitions of service areas. Next, the optimal location of each UAV that minimises the total power consumption is derived. While the authors model the transmit power of all UAVs needed to satisfy the data demand, they fail to use a mechanical energy model and simply minimize UAVs travel distance, assuming that the mechanical power is proportional to it. In [44] propose a solution to minimize UAV's mechanical and communication energies while integrating cognitive radio technology. The optimisation problem is solved with a deterministic algorithm based on the Weber formulation and its performance is compared to that of a meta-heuristic algorithm, namely particle swarm optimization algorithm (PSO). In this case, the authors model The total energy consumption of a drone with two components, namely the hover and transition energies needed for its movement and the communication energy needed to transmit.

Finally, Table 1 compares the main related works with our proposal. The uniqueness of this work lays on a new objective function for the problem of multi-UAV optimal 3D placement. The consideration of WiFi and its mac-sublayer on the speech quality (as a constraint) can only be found in [14]. However, [14] does not model the energy consumption in the UAVs and has a different objective function, as so does other works that model the mechanical and communication power in UAV-installed base stations such as [43,44].

3. QoS and UAVs Endurance in VoWiFi Networks

The optimization problem addressed in this work provides the number and position of a set of UAVs to be deployed over a known area to provide VoWiFi service to a set of ground users at known positions. Our objective function minimizes the ratio of drones per hour required to provide

this service constrained to both user's coverage and user's speech quality (i.e., QoS). In this section we study the relationship between drone position, QoS and UAV endurance. Figure 1 illustrates two

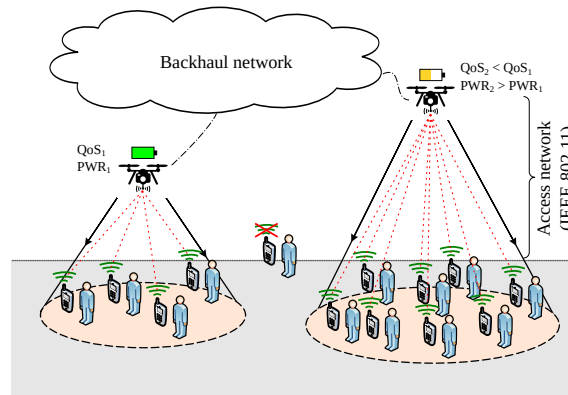


Figure 1. UAV-based VoWiFi network

UAV-mounted APs providing VoWiFi to ground users³. On the leftmost part, a lower-altitude drone provides coverage to four users. Their traffic (red lines show VoIP traffic flows) is aggregated at the UAV-mounted AP and this traffic load may influence not only the QoS perceived by these users, but also the power consumption of the UAV due to the transmission/reception of packets. The rightmost UAV however, is covering eight ground users so its AP aggregates more traffic which may have an impact on the QoS perceived by ground users. Hovering at a higher altitude and servicing more users will likely result in more energy expenditure due to both hovering and more transmission/reception. Thus, the rightmost drone is expected to be replaced earlier than the leftmost drone due to earlier battery exhaustion. This simple example illustrates how the decision variables of the optimization problem (i.e., number and position of drones) have an impact on both, the level of speech quality perceived by VoIP users and UAVs' energy expenditure.

Next, we provide the analytical expressions used to model VoWiFi's QoS and UAV's energy expenditure as both aspects are central in the problem's objective function.

3.1. Modeling QoS in VoWiFi

Each UAV-mounted AP and its associated stations can be studied as an independent IEEE 802.11 system as illustrated in Figure 2. Although all stations have a common Medium Access Control protocol (i.e. MAC sub-layer), the Modulation and Coding Scheme (MCS) set on each station is automatically self configured seeking the greatest possible data bit-rate achievable with the present signal strength. Table 2 shows different MCSs defined for OFDM modulations (e.g. 802.11 a/g) and the minimum signal strength required for each one.

Speech VoIP is a mature technology that counts with several methods for the assessment of voice quality [45]. At the planning stage, the method predominately used in literature for QoS assessment is the E-Model [46] since it allows one to estimate the speech quality can be estimated by using coming down to the effect that the VoIP traffic load has on network performance in terms of packet loss and delay. The E-model [46], which provides a quality score termed *R* factor from 0 (poor) to 100 (excellent).

³ Note that only the UAV-to-user communication is considered and the communication between UAVs or with the data network backhaul is taken for granted.

Modulation	Coding rate	Data rate (Mb/s)	Sensitivity (dBm)
BPSK	1/2	6	-82
BPSK	3/4	9	-81
QPSK	1/2	12	-79
QPSK	3/4	18	-77
16-QAM	1/2	24	-74
16-QAM	3/4	36	-70
64-QAM	2/3	48	-66
64-QAM	3/4	54	-65

Table 2. 802.11 sensitivity relations for OFDM modulations with 20 MHz channels.

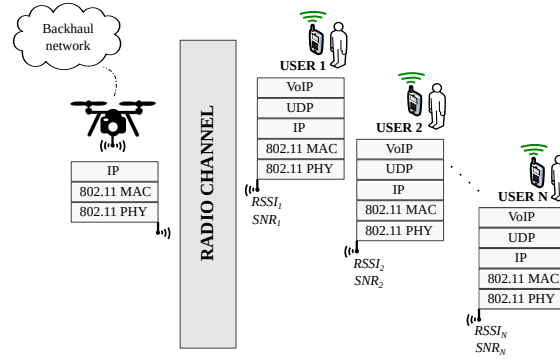


Figure 2. Communication system for each drone

A conversation is generally acceptable when its R factor is above a minimum value ($R_{\min}$). The QoS-level of VoIP (excellent) which can be readily obtained using the following expression [14,47,48]:

$$R = R_0 - I_e + (95 - I_e) \underbrace{\frac{P_{pl}}{\frac{P_{pl}}{BurstR} + B_{pl}}}_{I_{e,eff}} - \underbrace{(0.024d + 0.11 \cdot (d - 177.3) \cdot H(d - 177.3))}_{I_d} \quad (1)$$

where:

- $I_{e,eff}$ represents a combination between impairment equipment parameter at zero packet loss (I_e), and a function of I_e that is dependent on I_e , the packet loss rate, and packet loss behaviour. I_e is a codec-dependent constant associated with codec compression degradation⁴, B_{pl} represents the codec packet loss robustness, which also has a specific value for each codec (listed in ITU-T Rec. G117 Appendix I), P_{pl} represents the packet loss rate (in %) in the WiFi channel and finally $BurstR$ characterizes the burst ratio (i.e. equals 1 if packet loss is random and greater otherwise). In this paper, we use the G.711 codec ($I_e = 0$ and $B_{pl} = 25.1$) and assume that losses are random (i.e. $BurstR = 1$).
- I_d accounts for all impairments due to associated with the delay in the communication chain. A widely accepted approximation for I_d can be obtained from one-way delay in the communication path, path d , where H is the Heaviside function⁵. The one-way delay d (in milliseconds) is

⁴ A list of values from ITU-T codecs were presented in ITU-T Rec. G.113 Appendix I.

⁵ $H(x) = 0$ for $x < 0$ and $H(x) = 1$ for $x > 0$. In our case $x = d - 177.3$.

further composed of includes the delay in the WiFi network delay plus 20 ms that accounts for the packetization interval of the codec.

Finally, one can substitute P_{pl} and d with All terms in (1) are known but the network delay d and packet loss rate P_{pl} . The values for these two factors will be obtained from our WiFi mac-sublayer analytical model to calculate the R factor for each UAV in deployed⁶ (and its associated users). R is one of the constraints of our problem objective function, and its computation will be addressed in Section 5.2.2.

3.2. Modeling UAV endurance

Commercial UAVs for high-power

Endurance can be described as the total time taken during flight (T_{Flight}) until the UAV's battery is depleted. High-power performance commercial UAVs are typically powered by LiPo batteries, whose energy density varies between 150 and 300 Wh/Kg. UAVs endurance is commonly limited by In this work, the power consumption due UAV energy expenditure will consider two factors: flight and radio communication, being the former dominant in the energy budget.

According to [26], the drone's rotor-based configuration [26].

The energy (in Wh) required during UAV flight associated with flying can be broken down into three different flight stages [26]: stages:

$$E_{\text{Flight}} = E_{\text{Climb}} + E_{\text{Translational}} + \underbrace{P_{\text{Hover}} \cdot T_{\text{Hover}}}_{E_{\text{Hover}}} \quad (2)$$

where E_{Climb} represents the energy required stands for the energy associated with vertical climbing movement, climbing, $E_{\text{Translational}}$ is the energy spent in lateral transitions and E_{Hover} accounts for the energy spent while hovering (i.e. static). However, as As proved in [49], considering the hovering as dominant factor (i.e. $T_{\text{Hover}} = T_{\text{Flight}}$ is clearly dominant and $E_{\text{Climb}} = E_{\text{Translational}} = 0$), overshadows the other two, and thus, the expression in (2) can be simplified to its last term.

While Equation 2 only accounts for energy related to flying-related tasks, we must also consider to its last term.

Besides (2), the other contributing factor to energy consumption is the power spent by on the AP radio in providing used by the VoWiFi service. Therefore, the total energy E spent by the UAV can be expressed as follows:

$$E_{\text{Radio}} = P_{\text{Hover}} \cdot T_{\text{Flight}} + E_{\text{WiFi}} E_{\text{WiFi}} + E_{\text{Backhaul}} E_{\text{Radio}} E_{\text{Backhaul}} \quad (3)$$

where E_{WiFi} represents the energy consumed by the wireless IEEE 802.11 card of the Access Point (AP) and E_{Backhaul} accounts for the energy consumed by the radio link to used for the backhaul network.

Assuming no Power Saving (PS) mechanism is being used, E_{WiFi} that network cards are not running power saving mechanisms, the first term of (3) (E_{WiFi}) can be further decomposed as:

$$E_{\text{WiFi}} = P_{\text{WiFi}} \cdot T_{\text{Flight}} = \rho_{\text{tx}} \cdot T_{\text{tx}} + \rho_{\text{rx}} \cdot T_{\text{rx}} + \rho_{\text{idle}} \cdot T_{\text{idle}} \quad (4)$$

where T_{tx} , T_{rx} and T_{idle} stand for the time spent by the network interface spends card on transmission, reception and idle states respectively (their sum must be T_{Flight}); and ρ_{tx} , ρ_{rx} and ρ_{idle} stands stand for the respective power consumption of coefficients (which depend on the network interface during those states. card). The time spent taken on each state depends on the traffic handled processed by the AP during the flight duration, flight, which in turn will depend depends on the VoIP traffic

⁶ We assume that backhaul networks do not introduce any negative impacts into QoS (i.e., infinite bandwidth), or it can be considered as a constant in R

pattern, the MCS used Modulation and Coding Scheme (MCS) at each station, and retransmissions that may occur due to noise or collisions. Consequently, the aforementioned analytical modelling of In Appendix A we derive closed-form expressions for the mac-sublayer will also let us calculate this factor.

Although temporal factors in Equation (4) for the energy consumption at IEEE 802.11 mac sub-layer.

Regarding the second factor in (3),⁷ we could assume that in general it is will be proportional to the WiFi consumption:

$$E_{\text{Backhaul}} = \underbrace{K \cdot P_{\text{WiFi}}}_{P_{\text{Backhaul}}} \cdot T_{\text{Flight}} \quad (5)$$

where K is a constant that represents the relation between both radio consumptions. In the rest of the paper we use $K = 1$ so $P_{\text{Backhaul}} = P_{\text{WiFi}}$.

Therefore, the total energy E spent by the UAV can be expressed as follows:

$$E = E_{\text{Flight}} + \underbrace{E_{\text{WiFi}} + E_{\text{Backhaul}}}_{E_{\text{Radio}}} \quad (6)$$

Finally, assuming hovering as the dominant factor in Equation (2), the expected flight duration (in hours) of the UAV can be expressed as:

$$T_{\text{Flight}} = \frac{E_{\text{Battery}}}{P_{\text{Hover}} + (1 + K) \cdot P_{\text{WiFi}}} \quad (7)$$

where E_{Battery} represents the battery energy in Watts per hour. T_{Flight} is one of the factors of our objective function and its computation will be addressed in detail in Section 5.2.3.

4. Problem Statement

4.1. Terminology and assumptions

Figure 3 illustrates how As in most related works, we discretize the flying zone is discretized. space such as illustrated in Figure 3. The collection of edges of the drawn grid form a set of $\mathbb{R}^3$ coordinates we denote denoted as $\mathcal{P}$. These edges define potential locations for UAVs. Each element UAV mounts one AP. As such, the words UAV and AP may be used interchangeably for the remainder of this set defines a potential location for an UAV. work.

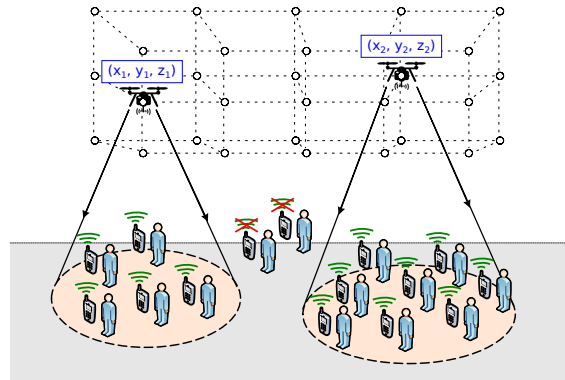


Figure 3. UAVs placement scenario.

⁷ The backhaul radio link depends is out of the scope of our this work and the radio power will depend on the used technology, particular technology used. However, the assumption indicated in Equation (5) is acceptable for the sake of completeness

In Throughout this paper, we follow use the following definitions and terminology we describe below: terminology:

- UAVs Drones are denoted by the set $\mathcal{D} = \{1, 2, \dots, D\}$. Their location is given by the set $\mathcal{X} = \{x_1, x_2, \dots, x_D | x_i \in \mathcal{P}, i \in \mathcal{D}, x_i \neq x_j | \forall j \neq i\}$, where $x_i \in \mathcal{P}$ represents the three-dimensional coordinates of drone i .
- Each user in the system is Ground users are denoted by the set $\mathcal{U} = \{1, 2, \dots, U\}$. Their location is given by $\{w_k | k \in \mathcal{U}\}$, where $w_k \in \mathbb{R}^3$ represents the coordinates of user k .
- The subset of users that are (i.e., WiFi clients) associated to the AP installed at drone $i \in \mathcal{D}$ is given denoted by $\mathcal{C}(i) \subset \mathcal{U}$. Consequently, Thus, the number of ground users that are associated to the WiFi network (i.e. to any AP) covered is given by $C = \sum_{i=1}^D |\mathcal{C}(i)|$.
- $R(i)$ represents the expected speech quality level (from 0 to 100) for users associated to the AP mounted installed at UAV drone $i \in \mathcal{D}$.
- $T_{\text{Flight}}(i)$ is the expected flight duration for the UAV tagged as drone i (i.e. see (7)). Moreover, $\bar{T}_{\text{Flight}}$ represents the (see (7), UAV endurance). The average flight duration for all deployed UAVs, which could be calculated as: of the set of UAVs deployed, $\bar{T}_{\text{Flight}}$, is:

$$\bar{T}_{\text{Flight}} = \frac{1}{D} \cdot \sum_{i=1}^D T_{\text{Flight}}(i) \quad (8)$$

For simplicity's sake, we consider the sake of simplicity and tractability, the following assumptions:

User positions assumptions are known. considered:

- Scenario The terrain has known dimensions are bounded and known. There it is a maximum an open area.
- The number of drones available for the initial deployment has an upper bound D_{max} .
- Users Ground users have a smartphone with a compatible VoIP application installed (i.e. using a known codec).
- Channelisation between APs User positions are known. This assumption is done commonly found in literature and could be implemented though user's smartphones GPS or image processing.
- APs' channelisation is set in such a manner that interferences between adjacent radio channels are negligible.

4.2. Problem definition

Our goal is deployment problem prov⁷ the optimum number and position of UAVs for VoWiFi service provision to ground users. We aim to minimize the number of UAVs launched (e.g. rate deployed over time (i.e., rate of drones per hour) required to provide VoIP service to ground users during the service duration hour of service) while satisfying coverage and QoS constraints. For example, for a service duration of one hour, a solution with 3 drones that last 30 minutes (6 drones/hour) will be preferred to one that with 2 drones that last 15 minutes (8 drones/hour). Therefore, we define an our objective function that minimizes the ratio between the number of

required UAVs deployed (D) and their average endurance expectations expectation ($\bar{T}_{\text{Flight}}$). Thus, the optimization problem This can be formulated as follows:

$$\begin{aligned}
 \min_{\mathcal{X}} \quad & \frac{D^2}{\sum_{i=1}^D T_{\text{Flight}}(i)} \\
 \text{subject to} \quad & \sum_{i=1}^D |\mathcal{C}(i)|/U \geq C_{\min} \\
 & R(i) \geq R_{\min}, \forall i \in \mathcal{D} \\
 & x_i \in \mathcal{P}, \forall i \in \mathcal{D} \\
 & D \leq D_{\max}
 \end{aligned} \tag{9}$$

where D represents the number of UAVs needed to provide the service, deployed, $T_{\text{Flight}}(i)$ accounts for drone i expected flight duration, $C_{\min}$ is stands for the minimum ratio of users that must be covered, and $R_{\min}$ is a constant that defines the minimum acceptable speech quality (e.g. 65 as proposed in ITU-T G.107 [46]).

5. Solving a Pseudo-static Scenario

The objective function in (9) For small flying spaces, solutions could be evaluated found through exhaustive search by assessing the objective function (i.e., see (9)) for every possible combination grid edge for an increasing number of UAV positions UAVs, starting with one UAV ($D = 1$). Then, if If no valid solutions are found, the number of drones should be increased to $D = 2$, evaluating every new candidate solution. This procedure should be repeated and so on until a solution is found, or a maximum number of UAVs is reached ($D_{\max}$). ($D = D_{\max}$). Once a solution is found ($D = D^*$), found, the search method has also to consider launching an extra drone ($D = D^* + 1$) to ensure that the objective function value cannot be further reduced (i.e., increasing the number of UAVs could result into higher flight duration, which in turn could reduce reducing the UAV turnover rate).

Although the previous procedure could be executed exhaustively, our previous work demonstrated that brute force However, although exhaustive search is feasible in very small areas, it is not generally feasible in most real-life scenarios [14]. For example, it would require to evaluate $\sum_{d=1}^{D+1} (|\mathcal{P}|/d)$ possibilities scenarios, for assessing a solution with D drones. Consequently, we propose drones would require to solve evaluate $\sum_{d=1}^{D+1} (|\mathcal{P}|/d)$ possibilities. For this reason, we suggest the optimization problem through a use of heuristic search algorithm. algorithms as a general method to find solutions to our optimization problem. Although many several other metaheuristic methods are applicable, we opt for using Genetic Algorithms to find a sub-optimal solution due to its simplicityThe simplicity and proven effectiveness in similar problems [14,41,50], since the contribution of this work is not focused on the performance of the metaheuristics method and proven effectiveness in similar problems [14,50]. method.

5.1. Search algorithm: GA

A genetic algorithm is a heuristic search method inspired by the process of natural selection. In GA, a A population of individuals (i.e., candidate solutions, named individuals, solutions to the problem at hand) are evolved through evolutionary operators (e.g., crossover, mutation) toward better solutions. This evolution typically starts from an initial population of randomly generated individuals, which is improved in an iterative process building For every new generations. In each generation, each individual in the population is evaluated and scored.

Each individual presents its own characteristics, named genes. scored according to a fitness function and best individuals a passed to the next generation. This process typically starts with a first generation of random individuals.

In our problem, each individual **can be represented as a** represents the location of D drones **as** $\mathcal{X} = \{x_1, x_2, \dots, x_D | x_i \in \mathcal{P}, i \in \mathcal{D}, x_i \neq x_j | \forall j \neq i\}$, where $x_i \in \mathcal{P}$ **accounts stands** for the **3D** location of **UAV drone** i . For example, consider a scenario with $D = 3$ drones; then, **any individual could individuals would** be represented by the following sequence of genes:

$$\mathcal{X}|_{D=3} = \underbrace{\{x_1, y_1, z_1\}}_{x_1}, \underbrace{\{x_2, y_2, z_2\}}_{x_2}, \underbrace{\{x_3, y_3, z_3\}}_{x_3} \quad (10)$$

Algorithm 1 shows the pseudocode **for of** our **GA-based** search **algorithm, which is a genetic algorithm implementation to solve our problem. method.** The input of the algorithm is the set of ground users ($\mathcal{U}$) and their location (w_k), the set of edges ($\mathcal{P}$), **minimum** coverage ($C_{\min}$) **and constraint** ($C_{\min}$), **minimum speech** quality ($R_{\min}$) **constraints, constraint** ($R_{\min}$), and the maximum number of **available** drones ($D_{\max}$). **Our** The algorithm starts **looking for by seeking** solutions **for** $D = 1$ **drones with one drone** ($D = 1$) and then increases the number of UAVs (**up to** $D_{\max}$) until a sub-optimal solution is **found. found** (until an upper bound of $D_{\max}$). On each iteration, the genetic algorithm (lines from 3 to 18 in Algorithm 1) **is executed aims** to find the best solution that meets the problem constraints. **Each Every** time that the genetic algorithm is **restarted, initiated**, an initial population of candidate solutions (i.e. individuals) is created as $\mathcal{I}$ by the *GA_InitialPopulation* function. Then, every individual in $\mathcal{I}$ is evaluated **by using** the *Check* **function, which function.** This function returns the objective function value (see Equation 9) including the ratio of coverage and QoS-level. If one individual meets the problem constraints and improves the **last best found value of the** objective function **value** (f_{obj}^*), the individual is recorded as a candidate solution. After **the assessment of one generation is evaluated, generaion**, the next one is created. In **the** next generation, **part of the some** individuals are a copy of the best individuals from parents (function *GA_Elite*), **some others come from are created** applying operations of Crossover-and-Mutation (function *GA_CM*) and Self-Reproduction and Mutation (function *GA_SRM*) to the parents [51,52]. This process is repeated until maximum number of generations is reached without **finding** any improvement (exit criteria).

The remainder of this section, elaborates on **how the assessment of** individuals **are evaluated** (i.e. *Check* function). GA implementation and related functions (*GA_InitialPopulation*, *GA_Elite*, *GA_CM*, and *GA_SRM*) are discussed in **Appendix B. Appendix B.**

5.2. Checking the fitness of individuals: Check function

The **pseudocode in Algorithm 2 (Check function)** shows how a candidate positioning (i.e. an individual) **objective of this function is evaluated to determine its coverage, QoS level compute all the factors of the objective function of the problem for a candidate solution, i.e., the constraints of coverage and endurance capabilities. The speech quality, and the value of the objective function. As shown in Algorithm 2, the** input of the *Check* function is the 3D coordinates of D drones ($\mathcal{X}$) and **each user users'** location $\{w_k | k \in \mathcal{U}\}$. Each **UAV-mounted AP drone in the candidate solution is analysed separately analyzed separately**, and the evaluation is **assessed considering done in three steps by** three different **stages. functions.** First, the collection of **associated ground** users **associated to the AP** is determined through the *Associate* function. Then, the QoS level **of** associated users is evaluated with the *QoS_eval* function. Finally, UAV endurance is determined (i.e. *Endurance_eval* function). Next, we elaborate on these functions.

5.2.1. Signal Coverage Evaluation (Associate)

The first stage consists of associating (*Associate* function) 

This function **associates** each **ground** user to an UAV-mounted AP. A successful association requires that the Received Signal Strength Indicator (RSSI) and the Signal-to-Interference-plus-Noise-Ratio (SINR) are above minimum levels. If multiple access points were available, each user will associate with the AP which provides the **highest strongest** RSSI.

Input: $\mathcal{P}, \mathcal{U}, \{w_k\}, D_{\max}, C_{\min}, R_{\min}$
Output: $\mathcal{L}^*$ (location), f_{obj}^* (obj. value)
Initialization: $D = 1, \text{finish} = \text{False}, \mathcal{L}^* = \emptyset, f_{\text{obj}}^* = \text{Inf}$

```

1 while (!finish and  $D \leq D_{\max}$ ) do
2   finish = True;
3   /* Build initial population */
4    $\mathcal{I} = \text{GA\_InitialPopulation}(\mathcal{U}, \{w_k\});$ 
5   while !(exit criteria met) do
6     /* Evaluate each individual */
7     for individual  $i = 1$  to  $|\mathcal{I}|$  do
8        $\mathcal{X} = \mathcal{I}(i);$ 
9        $[f_{\text{obj}}(i), C, R] = \text{Check}(D, \mathcal{X}, \mathcal{U}, \{w_k\});$ 
10      if ( $f_{\text{obj}}(i) < f_{\text{obj}}^*$  and  $C \geq C_{\min}$  and  $R \geq R_{\min}$ ) then
11         $\mathcal{L}^* = \mathcal{X};$ 
12         $f_{\text{obj}}^* = f_{\text{obj}}(i);$ 
13        finish = False;
14      end
15    end
16    /* Build next generation */
17     $\mathcal{I}_{\text{elite}} = \text{GA\_Elite}(\mathcal{I});$ 
18     $\mathcal{I}_{\text{CM}} = \text{GA\_CM}(\mathcal{I});$ 
19     $\mathcal{I}_{\text{SRM}} = \text{GA\_SRM}(\mathcal{I});$ 
20     $\mathcal{I} = \mathcal{I}_{\text{elite}} \cup \mathcal{I}_{\text{CM}} \cup \mathcal{I}_{\text{SRM}};$ 
21    /* Get best individuals */
22    /* Apply Crossover-and-Mutation */
23    /* Apply Self-Reproduction & Mutation */
24    /* Update population */
25  end
26   $D++;$ 
27 end

```

Algorithm 1: GA-based search pseudocode

Input: $D, \mathcal{X}, \mathcal{U}, \{w_k\}$
Output: f_{obj}, C, R

```

1 for  $j = 1$  to  $D$  do
2    $\mathcal{C}(j) = \text{Associate}(\mathcal{U}, \{w_k\}, \mathcal{X});$ 
3    $R(j) = \text{QoS\_eval}(\mathcal{C}(j), x_j, \{w_k\});$ 
4    $T_{\text{Flight}}(j) = \text{Endurance\_eval}(\mathcal{C}(j), x_j, \{w_k\});$ 
5 end
6  $C = \sum_{i=1}^D |\mathcal{C}(i)|;$ 
7  $R = \min_{k=1..D} \{R(k)\};$ 
8  $f_{\text{obj}} = D^2 / \sum_{i=1}^D T_{\text{Flight}}(i);$ 

```

Algorithm 2: Check function pseudocode

Therefore, the  output of the *Associate* function is the set of users that are associated to drone j , $\mathcal{C}(j)$, so their coverage constraints are satisfied and their RSSI is maximized: $\mathcal{C}(j)$:

$$\mathcal{C}(j) = \{i \in \mathcal{U} \mid \gamma_{ik} = 1, \text{RSSI}_{ij} > \text{RSSI}_{ik}, \forall k \neq j\} \quad (11)$$

where γ_{ij} as a boolean that represents if user $i \in \mathcal{U}$ satisfies minimum thresholds (i.e. both, $\text{SINR}_{ij} \geq \text{SINR}_{\min}$ and $\text{RSSI}_{ij} \geq \text{RSSI}_{\min}$) when associated to UAV $j \in \mathcal{D}$. The resultant  Observe that the user-to-AP association also determines the Modulation and Coding Scheme (i.e. $\text{MCS}^{(i)}$) used at the physical layer of each user's terminal, WiFi station, which depends on both, the received $\text{RSSI}^{(i)} = \max_{j=1..D} \{\text{RSSI}_{ij}\}$ and the required minimum sensitivity for each MCS. Next, we develop how RSSI and SINR are computed for each ground user.

UAV-to-Ground Channel Model

Previous Most works [24,34,53] consider that ground users receive three different groups of signals that could be classified as: (a) Line-of-Sight (LoS), (b) Non-Line-of-Sight (NLoS), and (c) other reflected components which cause multipath fading. Each group has its own probability of occurrence depending on the environment, density, height and elevation angle; so their impact to the overall path loss expression can be averaged. According to [54], the probability of fading is significantly lower than the probability of receiving LoS (P_{LoS}) and NLoS (P_{NLoS}) components. Therefore, the UAV-to-Ground path loss can be represented by:

$$L(d, \theta) = P_{\text{LoS}}(\theta) L_{\text{LoS}}(d) + P_{\text{NLoS}}(\theta) L_{\text{NLoS}}(d) \quad (12)$$

which is dependent of depends on the distance d between the UAV and the ground terminal, and θ that represents the elevation angle (in radians). L_{LoS} and L_{NLoS} represent the average path loss for LoS and NLoS components, respectively; and can be expressed as [53]:

$$L_{\text{LoS}}(d) = 20 \log_{10} \left(\frac{4\pi f_c d}{c} \right) + \xi_{\text{LoS}} \quad (13)$$

$$L_{\text{NLoS}}(d) = 20 \log_{10} \left(\frac{4\pi f_c d}{c} \right) + \xi_{\text{NLoS}} \quad (14)$$

where the first term account for the free space propagation loss, ξ_{LoS} and ξ_{NLoS} represent any additional losses due to the environment (a list of values can be found in [24]), and f_c is the channel frequency.

Finally, the probability of receiving each component is given by [55]:

$$P_{\text{LoS}}(\theta) = \frac{1}{1 + \alpha e^{-\beta\theta \cdot 180/\pi + \beta\alpha}} \quad (15)$$

$$P_{\text{NLoS}}(\theta) = 1 - P_{\text{LoS}}(\theta) \quad (16)$$

where α and β are environment dependent constants (e.g. rural, urban, etc.) as defined in [24] (e.g., $\alpha = \beta = 0$ if no buildings).

Obtaining RSSI and SINR

The Received Signal Strength Indicator (RSSI) represent represents the power received at a the ground terminal. Let us consider a generic user i and an access point the AP installed at drone j . Then,

$RSSI_{ij}$ can be **deduced calculated** by subtracting the UAV-to-Ground path loss to the total transmitted power:

$$RSSI_{ij} = P_{tx} + G_{ij} - L(\|w_i - x_j\|, \theta_{ij}) \quad (17)$$

$$G_{ij} = 10 \log_{10} \left(10^{G_{max}/20} \cdot \cos^2 \theta_{ij} \right) \quad (18)$$

where P_{tx} (dBm) represents the power delivered by the transmitter **antennas; antenna**; G_{ij} (dB) stands for the gain of the antenna between user i and **UAV drone** j as indicated in (18) **which (which is** bounded by G_{max} ; G_{max}); $L(d, \theta)$ **represent represents** the path loss function **we** introduced in (12); and $\|w_i - x_j\|$ is the Euclidean distance between user i and drone j .

The Signal-to-Interference-plus-Noise-Ratio ($SINR_{ij}$) can be calculated by subtracting every noise and co-channel interferences to the received signal strength. To do so, let us declare $\mathcal{Z}_j$ as the collection of drones that may cause interferences⁸ to the network deployed by UAV j . Then, the SINR (in dB) can be expressed as:

$$SINR_{ij} = RSSI_{ij} - F - N - \sum_{k \in \mathcal{Z}_j} (RSSI_{ik}) \quad (19)$$

$$N = -174 + 10 \log_{10}(C_{BW}) \quad (20)$$

where N is the thermal noise, F accounts for the receiver's noise figure, and C_{BW} represents the signal bandwidth, which depends on the IEEE 802.11 standard version under consideration.

5.2.2. Quality of Service Evaluation (QoS_eval function)

After establishing the association between users and APs (i.e. drones), which enables the verification of the coverage constraint, the second step consists of assessing the speech quality level (and hence, enable the verification of the second constraint in (9)) by computing the R factor (as introduced in Section 3). To do so, we evaluate the network performance on each set of users plus its corresponding UAV (i.e., $\mathcal{C}(j)$ + AP at drone j). This evaluation is based on a model of the IEEE 802.11 MAC sub-layer and provides delay and packet loss in the WiFi network, which allows one to calculate the R factor for each drone.

After establishing the association between users and APs (i.e. drones), which enables the verification of the coverage constraint, the second **stage step** consists of **evaluating assessing** the **QoS constraints we described speech quality level** (and hence, enable the verification of the second constraint in Section 3 (9)) by **estimating computing** the **R factor. factor** (as introduced in Section 3). To do so, we **model the IEEE 802.11 MAC sub-layer of evaluate** the network **composed by the performance on each** set of **stations $\mathcal{C}(j)$ users** plus **the its corresponding UAV (i.e., $\mathcal{C}(j)$ + AP j (from now, set $\mathcal{S}$), which allows to estimate some performance metrics such as at drone j). This evaluation is based on a model of the IEEE 802.11 MAC sub-layer and provides delay and packet **loss, loss** in the WiFi network, which **are required allows one** to calculate the **R factor. factor** for each drone.**

The IEEE 802.11 MAC sub-layer features a distributed access mechanism called DCF (i.e. Distributed Coordination Function), whose performance has been largely studied in literature [56–59]. In **summary, a nutshell**, each contending station **must sense senses** the medium during a period of **time** (DIFS) before transmitting **in order** to avoid collisions. If the channel is busy, the station waits a random backoff interval before trying again (up to M **retries**). **attempts**). The backoff procedure is also triggered between two consecutive transmissions. During the backoff process, **time is discretized** (T_{slot}) and a **random** number of **discretized** time slots (T_{slot}) between 0 and $2^i W_o$ is **randomly chosen**,

⁸ Channel planning is out of the scope of this paper

$$\eta = (1-r) + \frac{r^2 W_o (W_o + 1)}{2(1 - (1-r)^{W_o})} + \frac{W_o + 1}{2(1-q)} \left(\frac{r^2 q W_o}{1 - (1-r)^{W_o}} + rp(1-q) - rq(1-p)^2 \right) + \frac{p}{2(1-q)(1-p)} \left(\frac{r^2 W_o}{1 - (1-r)^{W_o}} + qr(1-p)^2 \right) \left(2W_o \frac{1-p-p(2p)^{m-1}}{1-2p} + 1 \right) \quad (22)$$

421 selected, where W_o accounts for the minimum contention window value, and i increases by one in
 422 with each failed attempt up to a ceiling reaching an upper bound m .

In this paper we have adapted a mix of analytical some existing models of the DCF behaviour [60–63] to consider develop an analytical model fit for our context of heterogeneous traffic sources, non-saturated stations and a non-ideal channel, which are based on Markov chains that represent the behaviour of the DCF channel. The key central variable in DCF models is named τ , which refers to stands for the probability that an observed station attempts to transmit during a randomly chosen time slot. We use the one expression proposed in [60]:

$$\tau = \frac{1}{\eta} \frac{1}{1-q} \left(\frac{r^2 W_o}{(1-p)(1 - (1-r)^{W_o})} - qr(1-p) \right) \quad (21)$$

where η is defined in (22) and p is the probability that a packet suffers any transmission errors (i.e. collisions or noise). Traffic due to collisions and/or noise. The VoIP traffic is modelled⁹ through two variables, r and q variables; q , which account for the probability that at least one packet arrives during an idle state, and the probability that the MAC queue is not empty, respectively.

$$r = 1 - e^{-\lambda E[T]} \quad (23)$$

$$q = 1 - e^{-\lambda E[T]E[B]} \quad (24)$$

where $E[B]$ is the expected number of back-off slots that a packet waits before transmission and can be expressed as proposed in [63]:

$$E[B] = \frac{W_o}{2(1-p)} \left(\frac{1-p-(2p)^m}{(1-2p)} - 2^m p^{M+1} \right), \quad (25)$$

423 and $E[T]$ is the average slot duration, which represents the expected length of any state of the Markov
 424 chain. It can be calculated by averaging the duration of each type of event with its probability
 425 (i.e. success, collision, corruption or idle) as proposed in [14,62].

In order to consider heterogeneous sources, Recall that each station in $\mathcal{S}$ presents its the system composed of drone $i + \mathcal{C}(i)$ (from now on termed set $\mathcal{S}$) has its own τ expression, so since we consider heterogeneous sources. So let us tag each station as $i \in \{1, \dots, S\}$ and let the superscript (i) relate each variable to the i -th station. Then, $p^{(i)}$ is the probability that a packet from station i suffers any transmission error:

$$p^{(i)} = \left(1 - P_i^{(i)} \right) \cup FER^{(i)} = 1 - P_i^{(i)} + P_i^{(i)} \cdot FER^{(i)} \quad (26)$$

$$P_i^{(i)} = \prod_{j=1, i \neq j}^{|S|} \left(1 - \tau^{(j)} \right) \quad (27)$$

⁹ We assume Poisson packet arrivals and the small queue assumption as discussed in [59] [59].

where $P_i^{(i)}$ represents the probability that no more stations are attempting to transmit, and $FER^{(i)}$ stands for the Frame Error Rate¹⁰ (i.e. channel noise), which can be obtained as:

$$FER^{(i)} = 1 - (1 - P_e^{(i)})^L \quad (28)$$

where L is the size of the packet (considering preamble, headers and payload), and $P_e^{(i)}$ represents the bit error rate of station i , which can be calculated by considering the user's modulation and coding scheme (i.e. MCS⁽ⁱ⁾) as proposed in [64,65].

Finally, one can solve the non-linear equation system formed by (21) and (26). Since the downlink performance is the dominant factor in QoS as demonstrated in [7], the packet loss and delay¹¹ from the access point (tagged as $i = AP$) will represent the worst case, and those case. For this reason it will be used to calculate the QoS. QoS for the set $\mathcal{S}$. Then, the packet loss ratio and delay can be expressed as:

$$PL = 1 - \frac{(1 - FER^{(AP)}) \tau^{(AP)} \prod_{j=1, j \neq AP}^{|\mathcal{S}|} (1 - \tau^{(j)})}{\lambda^{(AP)} E[T]} \quad (29)$$

$$DEL = E[B^{(AP)}] \cdot E[T] \quad (30)$$

Substituting PL and $(DEL + 20)$ ¹² in the terms P_{pl} and d from Equation 1 provides the output of the QoS_Eval function: the R factor quality level. factor.

5.2.3. Endurance Evaluation (Endurance_eval function)

This function estimates the expected UAVs endurance. As introduced in Section 3, the flight duration has two main components: the power (in Watts) required to hover the drone (P_{Hover}), and the power consumption at both radio links (i.e. proportional (i.e. recall from Section 3.2 that it was proportional to P_{WiFi}).

P_{Hover} in rotor-based aircrafts can be easily derived from the Momentum Theory ([27]) as:

$$P_{Hover} = \frac{g^{\frac{3}{2}}}{\eta_{ps} r_p \sqrt{2 N_R \rho_a \pi}} m^{\frac{3}{2}} \quad (31)$$

where g accounts for gravity acceleration, m represents the mass of the aircraft, η_{ps} is the rotorcraft propulsion system efficiency, N_R is the number of rotors, r_p represents the radius of each rotor and finally ρ_a represents the density of air. N_R , r_p and η_{ps} are UAV-specific. While the first two are fixed and can easily be obtained from manufacturer manuals, the latest is variable (although a constant value is generally adopted) and requires experimental determination or estimation [49].

¹⁰ In the access point case, MCS and FER are dynamically changed according to its communication partner. Our approach is to average its data bit-rate and FER

¹¹ The small queue assumption allows us to neglect the queuing delay and DEL can be approximated by the channel access delay

¹² Recall that the delay includes the a codec packetization delay of 20ms.

Regarding P_{WiFi} , the power related to the network interface card P_{WiFi} at the access point point, the power can be expressed as:

$$P_{\text{WiFi}} = \frac{1}{E[T]} \cdot \left(\underbrace{J_{\sigma} P_i}_{\text{idle interval}} + \underbrace{J_{\text{tx},s} P_{\text{tx},s} + J_{\text{tx},e} P_{\text{tx},e} + J_{\text{tx},c} P_{\text{tx},c}}_{\text{transmission interval}} + \underbrace{J_{\text{rx},s} P_{\text{rx},s} + J_{\text{rx},e} P_{\text{rx},e} + J_{\text{rx},c} P_{\text{rx},c}}_{\text{reception interval}} \right) \quad (32)$$

where J_{σ} represents the energy spent during an idle interval; $J_{\text{tx},s}$, $J_{\text{tx},e}$, and $J_{\text{tx},c}$ represent the average energy consumption (in Joules) during a successful, erroneous or collided transmission at the access point respectively; and $J_{\text{rx},s}$, $J_{\text{rx},e}$ and $J_{\text{rx},c}$ represent the expected energy consumption during a successful, erroneous or collided reception respectively. The terms P_i , $P_{\text{tx},s}$, $P_{\text{tx},e}$, $P_{\text{tx},c}$, $P_{\text{rx},s}$, $P_{\text{rx},e}$ and $P_{\text{rx},c}$ indicate the probability of such events. A detailed expression of the remainder factors in (32) based on the traffic and our model of the mac-sublayer is deduced in Appendix A.

Finally, P_{Flight} and P_{WiFi} can be substituted into Equation (7) in order to calculate the expected flight duration T_{Flight} for of a given drone. particular drone can be calculated by substituting the expressions of P_{Flight} and P_{WiFi} in Equation (7).

5.3. Example solution

In this paper, section we have implemented offer a first example solution and validate the Algorithm 1 models used in Matlab[®]. Then, we have generated and solved a squared scenario (100 m × 100 m) the previous Section with the network-simulator ns-3. We define an scenario where 40 ground users are randomly placed users to introduce it as an example. The rest in a square area of the used (100 m × 100 m). The parameters used in the scenario are listed in Table 3. Unless otherwise specified, such parameters are common to all experiments in this paper.

IEEE Standard		Scenario		Traffic		Constraints		Energy	
Revision	802.11n	Users	40	Calls/hour/user	5	RSSI _{min}	-82 dBm	E_{Battery}	60 Wh
GI	800 ns	Size	100 m × 100 m	Call length	180 s	SNR _{min}	20 dB	P_{Hover}	120 W
Preamble	Greenfield	X-Y-Z step	1 m	VoIP codec	G.711	R_{min}	65	ρ_{tx}	16 W
Bandwidth	20 MHz	Altitude layers	{10, ..., 40} m	On/Off times	CBR	C_{min}	0.9	ρ_{rx}	9.7 W
Retries	7	Prop. Exponent	3.3	Packet interval	20 ms			ρ_{idle}	9.7 W

Table 3. Example solution input parameters

The solution to the optimization problem has been found by implementing Algorithm 1 in Matlab[®]. A graphical representation of the solution is provided in Figure 4. Notice that different colors represent different WiFi associations between users and UAVs.

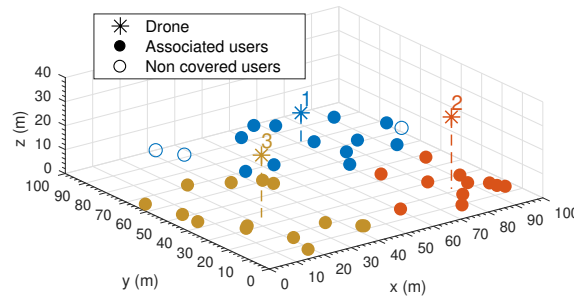


Figure 4. Example solution.

The resultant scenario (including the UAVs) has been simulated with the ns-3 network simulator. In the simulation, no interferences between APs have been considered and transmission buffer sizes have been set to one packet to match the small queue assumption we made in 5.2.2. Presented results represent the average value from 30 different runs where users have been placed randomly.

Finally, the

The results obtained are summarized in Table 4, which shows the most relevant performance measurements (location, flight time, quality level and radio power). We have performed 30 runs of simulation and results presented represent average values.

Drone	x_i	$ C(i) $	T_{Flight} (min)	Algorithm 1 / Simulation	
				R	P_{Radio} (W)
1	(69, 77, 14)	12	25.61	89 / 88	20.56 / 20.27
2	(83, 22, 30)	11	25.64	90 / 89	20.42 / 20.16
3	(24, 36, 26)	14	25.56	87 / 85	20.86 / 20.53

Table 4. Algorithmic and simulation results

Results in Table 4 indicate that the solution meets both coverage and speech quality constraints, and the QoS and energy models used in Algorithm 1 are aligned with simulation results, which validates the models proposed in Section 5.2.2.

6. Solving a Dynamic Scenario

So far, we have applied the GA-based search algorithm in Section 5 for solving the problem of initial deployment of drones to provide service to a set of users who are assumed to be static at known positions. However, in some activities (e.g., outdoor concerts) users are free to move within a bounded area. Consequently, the problem constraints may not hold after a while due to users's movement unless deployed UAVs are relocated continuously. One approach to do this is to perform periodic updates of the user's positions every $T = T_{\text{sample}}$ seconds, (re)solve the optimization problem and update UAVs locations, as illustrated in Figure 5. A central assumption in this approach (and our work hypothesis) is that the set of UAVs initially deployed and their position will suffer small changes (assuming that the trajectories always minimize UAVs displacement) if the sampling period is short enough.

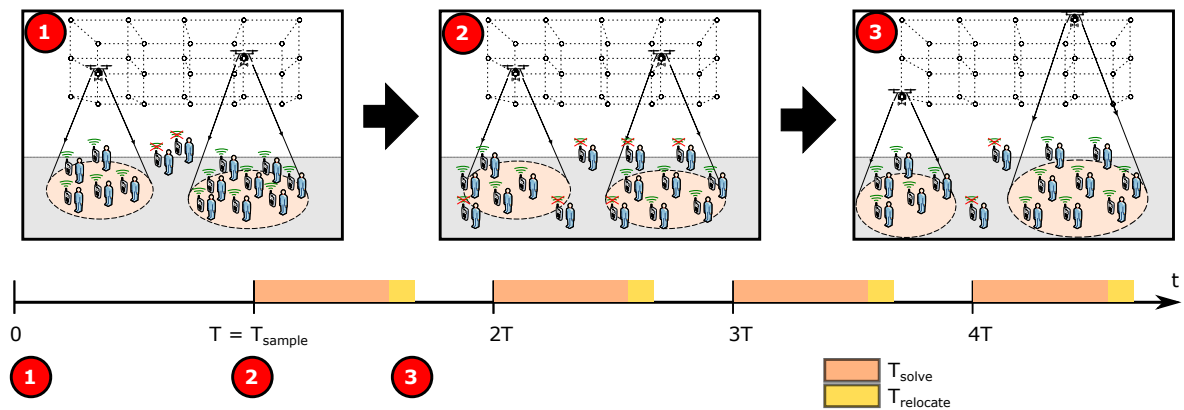


Figure 5. Dynamic scenario

Besides Between two consecutive relocation periods T , one has to consider the relocation delay, T_{delay} , which represents the time elapsed since a relocation is requested until it finishes (i.e., drones updated their location), and includes:

- The time required to solve the problem, T_{solve} , which in turn depends on the performance of the algorithm used algorithm. to find the solution to the problem.

- The time required to relocate UAVs, $T_{relocate}$, which depend on the distance travelled by UAVs and their speed. Small UAVs typically travel at speeds below 15 m/s [31].

Consequently, valid T values are bounded as follows:

$$T \geq \underbrace{T_{solve} + T_{relocate}}_{T_{delay}} \geq T_{sample} \quad (33)$$

In our previous work [14], we introduced a preliminary study that considered the periodical execution of a GA-based search method to consider dynamic scenarios. It was proved that greater T values lead to bigger discrepancies between the theoretical and actual position of users, which impacts the overall time that constraints are satisfied. Moreover, our previous work considered off-line computations ($T_{solve} = 0$), so the requirements in (33) were assumed.

In this paper, we propose to split the complexity of the dynamic scenario in two different phases with unique search methods: (a) initial deployment,

Under our assumption that AUVs will complete self relocation in a short time due to high speed and (b) periodical updates. The short distance, the main goal limiting factor for fast sampling of user positions is the time required to solve the problem. For this reason, we want to reduce the execution time spent in solving of the problem (T_{solve}), further enabling a lower T value. The initial deployment can be solved as we already discussed in Section 5. Next, we propose a new heuristic search method algorithm for periodical updates periodic relocation.

According to [66], search algorithms based on a Particle Swarm Optimization (PSO) algorithm. According tend to [66], both PSO and be computationally more efficient than algorithms based on GA are able to faster converge; however, although both metaheuristics provide similar effectiveness (i.e., solution quality) but PSO is more computationally efficient than GA (i.e., it requires less iterations to converge). However, quality), it is also known that PSO is more prone than GA to get stuck on local solutions than GA [67]. Assuming that periodical updates are frequent (e.g., $T \approx 30$ s), the position of UAVs between two consecutive updates should not vary significantly. Under solutions. For this hypothesis, reason, we propose to use a PSO-based search algorithm for periodical updates, but keep using the GA-search algorithm we introduced in from Section 5 only for the initial deployment deployment, but then use a PSO-based algorithm to avoid getting local solutions. solve the UAVs placement for the remainder of the mission. PSO algorithms have been successfully used for the problem of optimal 3D placement of UAVs before [44].

6.1. Periodical search algorithm: PSO

Particle Swarm Optimization (PSO) is a heuristic search method inspired by social behaviour of bird flocking or fish schooling. In PSO, each candidate solution is represented as a particle that moves around in the search-space towards better solutions. Initially, a collection of particles with random positions in the search-space is created. Each particle is represented by its position (i.e., collection of characteristics, similar to GA individuals), individuals in GA), and a velocity. In each iteration, each particle updates its position based on its velocity, its best known position, and the global best location.

Algorithm 3 shows the pseudocode for our PSO-based search algorithm. The input of the algorithm is the previous positioning ($\mathcal{D}$ and $\mathcal{L}_{old}$), the set of ground users ($\mathcal{U}$) and their location ($\{\mathcal{w}_k\}$), the set of edges ($\mathcal{P}$), coverage (C_{min}) and quality (R_{min}) constraints, and the maximum number of drones (D_{max}). The algorithm assumes that the number of deployed drones (D) does not change between two consecutive executions, and relocates them. To do so, it initializes the swarm of particles ($\mathcal{W}$) with the function *PSO_InitSwarm* around the previous positioning ($\mathcal{L}_{old}$). Then, each particle is updated through the function *PSO_UpdateParticle*, which receives as an argument input the best known position for that particle. Then, the candidate position ($\mathcal{X}$) is evaluated through the function *Check* from Section 5. Finally, if the particle improves its result, we store the new position as $\mathcal{W}(i)$ and, if the best solution is improved, we record it at $\mathcal{L}^*$, which is the output of the algorithm. This procedure

Input: $\mathcal{D}, \mathcal{L}_{old}$ (old location), $\mathcal{P}, \mathcal{U}, \{w_k\}, D_{max}, C_{min}, R_{min}$
Output: $\mathcal{L}^*$ (new location), f_{obj}^* (obj. value)
Initialization: $\mathcal{L}^* = \mathcal{L}_{old}, f_{obj}^* = \text{Inf}$

```

/* Create the initial swarm */
1  $\mathcal{W} = \text{PSO\_InitSwarm}(\mathcal{L}_{old});$ 
2  $\mathcal{B} = \mathcal{W};$  // Initialize best-known locations
3  $\mathcal{F}(i) = \text{Inf } \forall i;$  // Initialize best-known obj. function values
4 while  $!(\text{exit criteria met})$  do
5   for particle  $i = 1$  to  $|\mathcal{W}|$  do
6     /* Update the  $i$ -th particle */
7      $\mathcal{W}(i) = \text{PSO\_UpdateParticle}(\mathcal{W}(i));$ 
8     /* Evaluate the  $i$ -th particle */
9      $[f_{obj}, C, R] = \text{Check}(D, \mathcal{W}(i), \mathcal{U}, \{w_k\});$ 
10    /* Record results */
11    if  $(f_{obj} < \mathcal{F}(i) \text{ and } C \geq C_{min} \text{ and } R \geq R_{min})$  then
12       $\mathcal{B}(i) = \mathcal{W}(i);$  // Update best-known particle's location
13       $\mathcal{F}(i) = f_{obj};$  // Update best-known particle's obj. function value
14      if  $f_{obj} < f_{obj}^*$  then
15         $\mathcal{L}^* = \mathcal{W}(i);$  // Store best-known global position
16         $f_{obj}^* = f_{obj};$ 
17      end
18    end
19  end
20 end

```

Algorithm 3: PSO-based search pseudocode

is repeated until the exit criteria is met. PSO implementation and its functions (*PSO_InitSwarm* and *PSO_UpdateParticle*) is discussed in Appendix C.

6.2. Convergence speed

Our previous work considered that the GA-based search could be executed periodically to update drones locations.

In this paper, section we propose to replace the GA-based search in periodical executions with a PSO-based one. Let us compare the convergence speed of both approaches.

In this experiment, we place our two heuristics (GA and PSO) to validate the faster convergence speed of PSO and justify the goodness of selecting PSO as preferred method for periodical updates.

We have performed the following experiment. We have placed 100 users on a variable different sized scenario areas (from 1000 to 10000 m²), that 10000 m²). Ground users move according to a correlated random walk model¹³. Each ground user moves at a walking speed of 5.3 km/h with a probability of 0.8 and in such case, the direction remains unchanged with probability 0.8. Users rotate 180 degrees when they reach the area bounds. Algorithm 1 is used for the initial deployment and the number of drones deployed D remains unchanged for the remainder of the simulation (15 min). To achieve this we limit subsequent solutions to the best possible solution found with D drones (even though problem constraints were not satisfied). Every 30 seconds ($T = 30$), we update drones' location by executing one of the resolution methods: (a) GA, or (b) the PSO-based search we introduced in this section. Figure 6 illustrates the obtained results (x-axis represents the sparsity of users in m²/U).

¹³ The rest of parameters are in Table 3

With every new solution drones are relocated (considering a speed of 60 Km/h) so that the sum of the distances travelled by all drones is the minimum possible.

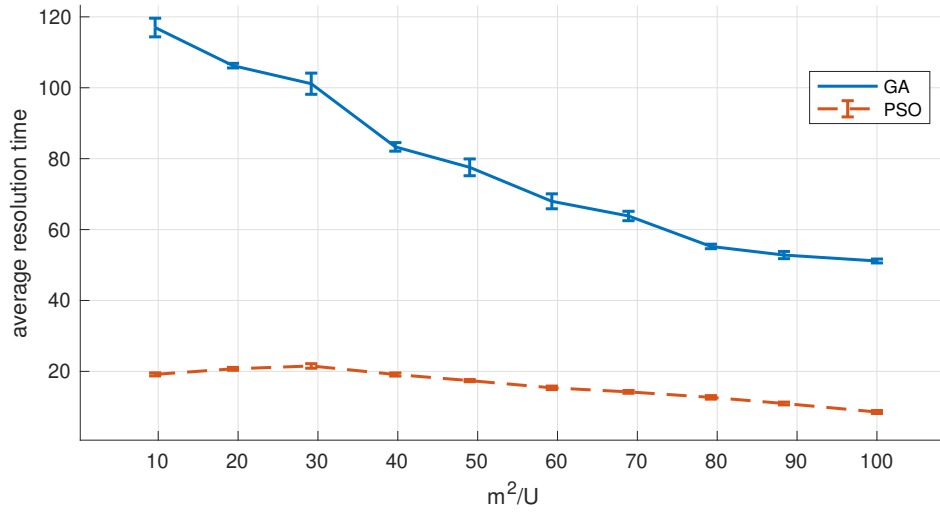


Figure 6. Resolution time (T_{solve})

Obtained results clearly prove that using the PSO-based search on periodical updates vastly algorithm significantly improves the convergence speed, reporting up to a 80% improvement in the resolution time. With the PSO-based search, the resolution time (T_{solve}) is never greater takes longer than 25 seconds, which validates its use with the observation our preferential sampling time we chose ($T = 30$ s). Results also show that high sparse scenarios with high user sparsity are easier to solve and the algorithm requires less time to converge to solutions.

7. Numerical Results

In this section we provide a numerical analysis using the proposed search algorithm. Results are provided as the average of 30 executions and a 95 confidence interval. On each execution, users disposition was randomly generated. We study the results obtained with our optimal placement method for two different scenarios according to a potential VoWiFi communication service: services.

- Individual VoIP channels. Each associated ground user handles an independent bidirectional VoIP conversation.
- Broadcasting channels. Broadcast channel. Every ground user receives a single shared unidirectional VoIP flow.

For each VoWiFi service, we study the results obtained for an increasing number of users confined in a small area of 100 m^2 as well as in a large area of $10\,000 \text{ m}^2$. The results provided are the average of 30 simulation runs and exhibit a 95% confidence interval. On each run, users location was randomly generated.

7.1. Individual VoIP channels

In this experiment, each user has an individual bidirectional VoIP channel. We vary the number of ground users from 10 to 100 over two terrain sizes (100 m^2 and $10\,000 \text{ m}^2$) using the rest of parameters we listed in Table 3. Then, we want to study the evolution of f_{obj} , f_{obj} (i.e., average rate of drone per hour of service), the power spent on communications P_{Radio} and the total required power, power (i.e. communication and hovering).

Figure 7a illustrates the drone turnover rate (f_{obj}) in UAVs/hour. As introduced in Section 4, this value is the ratio between the number of drones D and the average flight duration $\bar{T}_{\text{Flight}}$. Results suggest that scenarios with large user sparsity (m^2/U) tends tend to demand a higher number more of drones. For example, from 10 to 50 users, the $10\,000 \text{ m}^2$ scenario requires a greater number of more

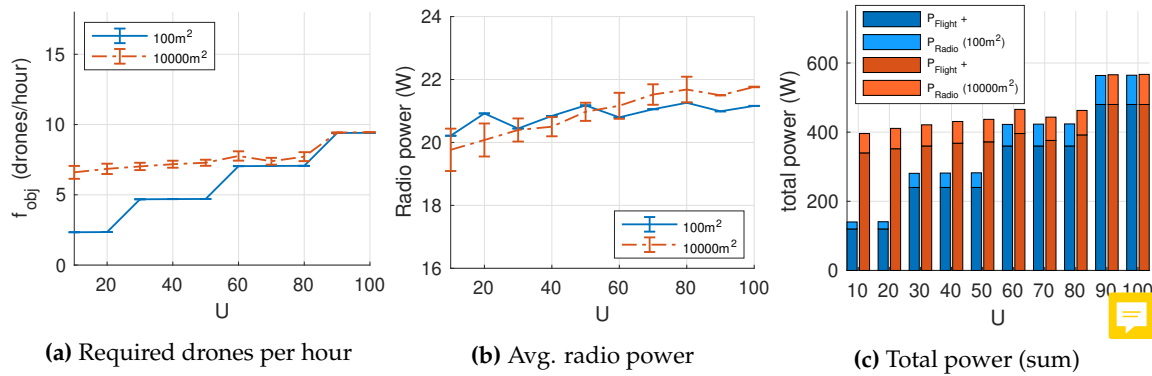


Figure 7. Results for both curves. the individual VoIP channels experiment

582 drones to satisfy the coverage constraint ($C \geq C_{min} \cdot U$) than that of $100 m^2$. Results indicate that the
 583 The average drone flight duration is was around 25 minutes.

584 Figure 7b shows the average power expended in communications (i.e. P_{Radio}). In this graph we
 585 can identify two behaviours:

- 586 • Less For less than 50 users. The users, UAVs in the smaller scenario requires spend more radio
 587 power than in the larger one. This can be explained as follows: while in the bigger scenario can
 588 exclude up to $(1 - C_{min}) \cdot U$ users can be excluded from coverage by locating drones far away
 589 from them, the smaller one has not enough terrain for the drones to exclude people ($C = U$),
 590 which in turn increases the number of users associated to each drone.
- 591 • More For more than 50 users. When user density is high enough, users, the previous behaviour
 592 gets inverted, so a greater power is needed in inverted when the largest scenario. user density
 593 is high enough. This is attributable to a solutions where droned are placed at higher drone
 594 altitude in the solutions. altitude. In general, drones increase their altitude to cover a larger area
 595 (i.e. antenna directivity), which in turn reduces the received signal strength and the achievable
 596 data bit-rate (i.e. a slower MCS is selected), so transmissions last longer. Thus, longer the time
 597 to complete data transmission times translate is longer which translates into higher energy
 598 consumption.

599 Finally, Figure 7c represents the overall total power used by all UAVs broken down by total
 600 into mechanical power invested in flight (i.e. P_{Flight}) and the power required for communications
 601 power (i.e. P_{Radio}). In our experiment, P_{WiFi} represents between the 14% and 16% of the total power
 602 expenditure, scaling with user density. This ratio is highly dependent on drone characteristics
 603 (including its radio power consumption) and radio interfaces the power expenditure. consumptions
 604 of the radio network interfaces. A careful selection of these aspects is a key factor for reducing the
 605 number of required UAVs per unit hour of time service.

606 7.2. Broadcasting Broadcast channels

607 Our second experiment considers a single broadcast voice channel instead of individual VoIP
 608 channels. VoWiFi channel. This is a one-way communication service (i.e. from the access point to
 609 the VoIP terminals) uses the parameters listed in Table 3 that could be used for announcements to
 610 ground users. In order to be able to compare both VoWiFi services, we set up the same range of users
 611 and terrain sizes as in our previous experiment (and continue using the parameters listed in Table 3).
 612 As a particularity, broadcast channels are transmitted over the lowest available bit-rate modulation
 613 (i.e. MCS0 in IEEE 802.11n) to maximize coverage.

614 The results in Figure 8a show that the drone turnover rate (f_{obj}) increases with user sparsity
 615 (i.e. scenario size) but however, the number of users does not affect negatively in the broadcasting
 616 experiment since problem constraint related to QoS is no longer an obstacle (i.e. there is only one traffic
 617 flow from the AP to all its associated users).

Figure 8 shows the results for f_{obj} , P_{WiFi} and the total power consumption. The average drone turnover rate (f_{obj}) shown in Figure 8a depends on the size of the terrain, but the number of served users does not affect negatively since the problem constraint related to QoS is no longer an obstacle due to the scarce traffic load (i.e. there is only one traffic flow from the AP to all its associated users).

In terms of energy consumption, Figure 8b shows that communications power is close to idle consumptions ($P_{Radio} \approx 2 \cdot \rho_{idle}$), which demonstrates that the channel occupation is very low: G.711 bandwidth requires 64 Kbps (around 80 Kbps at physical layer) and the considered physical data bit-rate is 6.5 Mbps. As a result, P_{Radio} represents a 14% of the total required power (see Figure 8c).

In terms of energy consumption, Figure 8b shows that the power spent in radio communications is close to the power consumption of the radio idle state ($P_{Radio} \approx 2 \cdot \rho_{idle}$). This suggest that the channel occupation is very low. Indeed, the codec G.711 requires a throughput of 64 Kbps (around 80 Kbps at physical layer) and the available data bit-rate is 6.5 Mbps. As a result, P_{Radio} represents a 14% of the total required power (see Figure 8c).

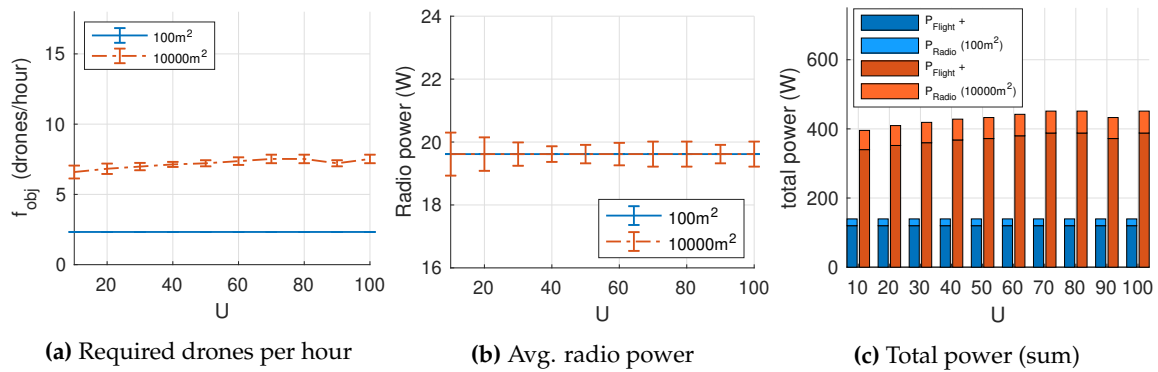


Figure 8. Results for the broadcast VoIP channels experiment

Finally, let us compare the total required power in both experiments (see Figures 7c and 8c). Since the VoWiFi broadcast service require less drones, the total power consumption is also improved. Energy savings are reduced up to 20% on the largest scenario and up to a 75% on the low-sized one. As expected, energy savings increase with user density and thus, QoS-constrained scenarios take advantage from replacing individual VoIP channels with a unique broadcast channel.

7.3. Comparing with other approaches

As shown in Section 2, there are several research works addressing the optimal 3D deployment of UAVs for communications. Unfortunately, comparing our results with these works is very difficult due to: (a) the objective function and constraints are different; (b) the radio access network (WLAN versus cellular) is also different which affects coverage and QoS. But for the sake of completeness, we compare our results with the following approaches:

- A search method based on K-means clustering that seeks for the minimum number of UAVs that satisfies the optimization problem in this paper, i.e. (9). K-means clustering has also been used for 3D optimal placement in [42].
- Our previous work [14] for optimal 3D placement in search and rescue missions. This GA-based search algorithm is the only related work that has comparable constraints (i.e., speech quality in WiFi) although the objective function is not the same and does not model UAVs endurance (see Table 1 for details).

For the comparison, we vary the number of ground users from 10 to 100 over a 10 000 m² terrain, using the rest of parameters we listed in Table 3¹⁴. Then, we analyse the evolution of the drone turnover rate (f_{obj}) and the total power expenditure (i.e., sum of all UAVs in the solution).

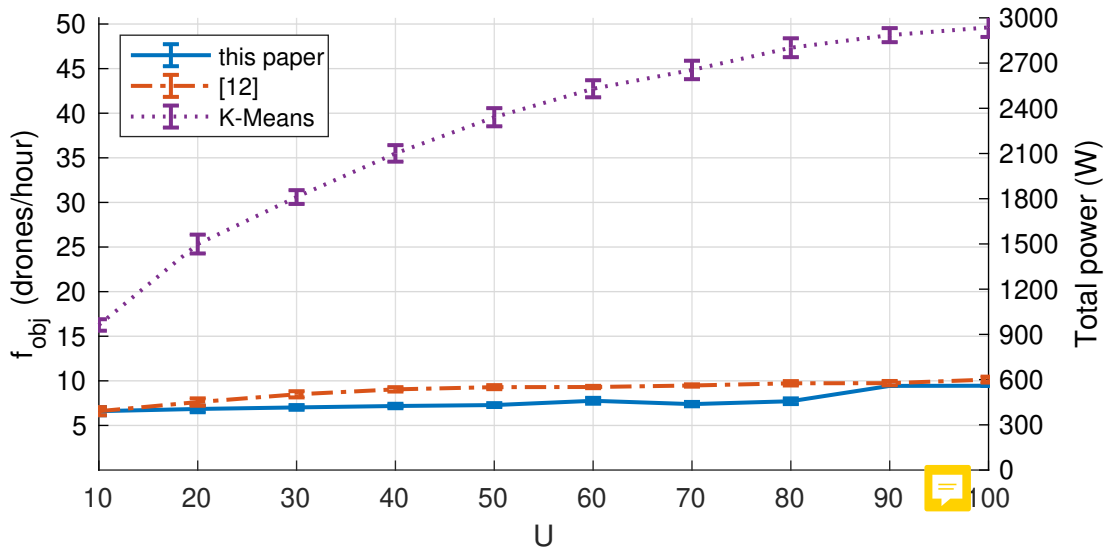


Figure 9. Comparison against other approaches

Figure 9 illustrates how the UAV turnover rate (left axis) and the total power expenditure (right axis) change while the number of ground users increases. As expected, both variables are interrelated, and scale up with the number of ground users. Results suggest that our new proposal can reduce both, UAVs turnover rate and energy consumption. Compared to the K-means search method, our method saves 60% of the energy consumption for $U = 10$, and 80% for $U = 100$. Compared to [14], our method provides also energy savings, although this is reduced up to 22%. In general, our method also reduces the number of UAVs per hour required to complete the mission (e.g., reduced from 9 to 7 in $U = 70$).

8. Conclusions and future research

This paper formulates a new UAV optimal deployment problem to offer VoWiFi services with guaranteed QoS. Our goal is to minimize the UAV turnover rate while covering a fixed ratio of users. Then, two search methods are provided to solve the problem: (a) a genetic algorithm is proposed for the initial deployment, and (b) a particle swarm optimization algorithm is proposed for updating UAVs' location in dynamic scenarios where users' can freely move.

This paper formulates a new problem for the optimal 3D placement of UAVs to offer VoWiFi services with guaranteed speech quality to ground users confined in a known area. Our objective function minimizes the ratio between the number of UAVs initially deployed and their average endurance expectation, providing the layout that require less drones per hour of service. Solutions are found using two well-known search methods: (a) a genetic algorithm is proposed for the initial deployment, and (b) a particle swarm optimization algorithm is proposed for updating UAVs' location in scenarios with users mobility.

A numerical analysis is provided to compare two different scenarios: using individual VoIP channels or a single broadcasting one. Results suggest that the drone turnover rate is related to both, users' sparsity and the number of associated users (when using individual VoIP channels). In terms of energy consumption, radio communications represent around 15% of the total power draw,

¹⁴ Some parameters, such as coverage ratio, are not supported by our previous work [14]

which reinforces the idea that energy efficiency is a key factor to consider when deploying UAV-based communication infrastructures.

A numerical analysis compares the results of our optimal placement algorithm for unicast and broadcast VoWiFi services. Our results for the unicast service show that the drone turnover rate is related to both, users' sparsity and the number of associated users to each drone. In terms of energy consumption, radio communications represent between a small part (between 14% and 16%) of the total power consumption depending on the density of users served per drone, and large areas tend to locate drones at higher altitudes which increases UAVs mechanical energy consumption. The broadcast VoWiFi service generates a very low traffic load which translates into a significant reduction of the number of UAVs deployed and total power consumption (between 20% and 75%), and less sensitivity to the number of served users.

The next step in our work is to consider two new aspects in this field: (a) interferences between APs, so that overlapping channels could negatively impact on QoS; and (b) using 5G instead of WiFi as the enabling technology for the UAV-to-Ground access network.

Author Contributions: Conceptualization, Vicente Mayor and Rafael Estepa; methodology, Vicente Mayor; software, Vicente Mayor; validation, Vicente Mayor, Rafael Estepa and Antonio Estepa; formal analysis, Vicente Mayor and Rafael Estepa; investigation, Vicente Mayor and Rafael Estepa; resources, Germán Madinabeitia; data curation, Vicente Mayor; writing—original draft preparation, Antonio Estepa and Vicente Mayor; writing—review and editing, Antonio Estepa and Vicente Mayor; visualization, Vicente Mayor; supervision, Rafael Estepa; project administration, Rafael Estepa; funding acquisition, Rafael Estepa. All authors have read and agreed to the published version of the manuscript.

Funding: This work is partially funded by the research grant number 2020/00000172 from the Regional Government of Andalusia (European FEDER 2014-2020 Andalusia Tech program).

Acknowledgments: None.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A Consumption Events on WiFi

The expected energy consumption per slot can be computed by averaging each consumption event with its probability of occurrence as proposed in (32). Each state on the WiFi NIC (transmission, reception or idle) presents a different power consumption termed as ρ_{tx} , ρ_{rx} and ρ_{idle} ; respectively. In addition, some frame exchanges may last longer than others depending on their result (success, collision or corruption). Consequently, the following events can be identified:

The absence of transmission attempts results into an idle channel event, whose consumption (in Joules) is represented by $J_{\sigma}^{(j)}$ for the j -th station¹⁵ and its probability of occurrence P_i is common to every station in the network:

$$P_i = \prod_{j=1}^S (1 - \tau^{(j)}) \quad (A1)$$

$$J_{\sigma}^{(j)} = \rho_{idle}^{(j)} \cdot \sigma \quad (A2)$$

A successful packet transmission event happens when a single station attempts to transmit while the rest remain silent. Let us define its consumption by $J_{tx,s}^{(j)}$ with a probability of $P_{tx,s}^{(j)}$:

$$P_{tx,s}^{(j)} = (1 - FER^{(j)}) \cdot P_s^{(j)} \quad (A3)$$

$$J_{tx,s}^{(j)} = \rho_{tx}^{(j)} \cdot T_{tx,data}^{(j)} + \rho_{rx}^{(j)} \cdot T_{ack} + \rho_{idle}^{(j)} \cdot (SIFS + 2\delta + DIFS) \quad (A4)$$

¹⁵ Notice that consumptions may differ between stations and access points

where $P_s^{(j)}$ represents the probability of success of station j :

$$P_s^{(j)} = \tau^{(j)} \prod_{i=1, i \neq j}^{|S|} (1 - \tau^{(i)}) \quad (\text{A5})$$

We consider a corrupted transmission event when a transmission does not collide but fails due to noise influence:

$$P_{\text{tx},e}^{(j)} = \text{FER}^{(j)} \cdot P_s^{(j)} \quad (\text{A6})$$

$$J_{\text{tx},c}^{(j)} = \rho_{\text{tx}}^{(j)} \cdot \bar{T}_{\text{data}|c} + \rho_{\text{idle}}^{(j)} \cdot (\text{EIFS} + \delta) \quad (\text{A7})$$

Analogously, the probability that station j suffers a collision transmission event is given by $P_{\text{tx},c}^{(j)}$, whose consumption is defined by $J_{\text{tx},c}^{(j)}$:

$$P_{\text{tx},c}^{(j)} = \tau^{(j)} \cdot \left(1 - \prod_{i=1, i \neq j}^S (1 - \tau^{(i)}) \right) \quad (\text{A8})$$

$$J_{\text{tx},c}^{(j)} = \rho_{\text{tx}}^{(j)} \cdot \bar{T}_{\text{data}|c} + \rho_{\text{idle}}^{(j)} \cdot (\text{EIFS} + \delta) \quad (\text{A9})$$

The reception probabilities can be derived from the aforementioned transmission probabilities. Notice that stations and access points may behave different. For example, the successful packet reception event is characterised by consumption $J_{\text{rx},s}^{(j)}$ with probability $P_{\text{rx},s}^{(j)}$:

$$\begin{cases} P_{\text{rx},s}^{(j)} = \sum_{i=1, i \neq j}^S (P_{\text{tx},s}^{(i)}), & \text{if } j = AP \\ P_{\text{rx},s}^{(j)} = P_{\text{tx},s}^{(AP)} \cdot \lambda_{\text{rx}}^{(j)} / \lambda^{(AP)}, & \text{if } j \neq AP \end{cases} \quad (\text{A10})$$

$$\begin{aligned} J_{\text{rx},s}^{(j)} &= \rho_{\text{rx}}^{(j)} \cdot T_{\text{rx,data}}^{(j)} + \rho_{\text{tx}}^{(j)} \cdot T_{\text{ack}} \\ &\quad + \rho_{\text{idle}}^{(j)} \cdot (\text{SIFS} + 2\delta + \text{DIFS}) \end{aligned} \quad (\text{A11})$$

In addition, stations may hear frames whose destination are not themselves, we term this event as overhear:

$$\begin{cases} P_{o,s}^{(j)} = 0, & \text{if } j = AP \\ P_{o,s}^{(j)} = \left(\sum_{i=1, i \neq j}^S P_{\text{tx},s}^{(i)} \right) - P_{\text{rx},s}^{(j)}, & \text{if } j \neq AP \end{cases} \quad (\text{A12})$$

$$\begin{aligned} J_{o,s}^{(j)} &= \rho_{\text{rx}}^{(j)} \cdot \bar{T}_{\text{data}|s} + \rho_{\text{tx}}^{(j)} \cdot T_{\text{ack}} \\ &\quad + \rho_{\text{idle}}^{(j)} \cdot (\text{SIFS} + 2\delta + \text{DIFS}) \end{aligned} \quad (\text{A13})$$

Corrupted receptions (to any destination) can be calculated by summing external corruption transmission events:

$$P_{\text{rx},e}^{(j)} = \sum_{i=1, i \neq j}^S P_{\text{tx},e}^{(i)} \quad (\text{A14})$$

$$J_{\text{rx},c}^{(j)} = \rho_{\text{rx}}^{(j)} \cdot \bar{T}_{\text{data}|c} + \rho_{\text{idle}}^{(j)} \cdot (\text{EIFS} + \delta) \quad (\text{A15})$$

Finally, the event on hearing collisions (to any destination) can be calculated as follows:

$$P_{rx,c}^{(j)} = 1 - P_i - P_{tx,c}^{(j)} - \sum_{i=1}^S P_s^{(i)} \quad (A16)$$

$$J_{rx,e}^{(j)} = \rho_{rx}^{(j)} \cdot \bar{T}_{data|e} + \rho_{idle}^{(j)} \cdot (EIFS + \delta) \quad (A17)$$

707 The previous expressions rely on transmission and reception times, which depend on the data
708 bit-rate and the operation mode (individual VoIP channels or broadcast):

- One individual VoIP bi-directional channel per station:

$$\begin{cases} T_{tx,data}^{(j)} = \\ PLCP + (L_{header}^{(j)} + L_{data}^{(j)}) / R_b^{(j)}, & \text{if } j \neq AP \\ T_{tx,data}^{(j)} = \sum_{i=1, i \neq j}^S (\lambda^{(i)} \cdot T_{tx,data}^{(i)}) / \lambda^{(j)}, & \text{if } j = AP \end{cases} \quad (A18)$$

$$T_{rx,data}^{(j)} = T_{tx,data}^{(j)} \quad (A19)$$

- One unique broadcast channel:

$$\begin{cases} T_{tx,data}^{(j)} = 0, & \text{if } j \neq AP \\ T_{tx,data}^{(j)} = PLCP + (L_{header}^{(j)} + L_{data}^{(j)}) / R^{(j)}, & \text{if } j = AP \end{cases} \quad (A20)$$

$$\begin{cases} T_{rx,data}^{(j)} = T_{tx,data}^{(AP)}, & \text{if } j \neq AP \\ T_{rx,data}^{(j)} = 0, & \text{if } j = AP \end{cases} \quad (A21)$$

where R_b (physical data bit-rate) depends on the MCS and R corresponds to the lowest bit-rate (i.e. at MCS 0). Finally, the ACK duration is constant and given by:

$$T_{ack} = PLCP + \frac{L_{ack}}{R} \quad (A22)$$

709 In the previous equations $T_{data}^{(j)}$ and $T_{ack}^{(j)}$ indicate the duration of the reception/transmission of a
710 data packet or ACK at station j ; $\bar{T}_{data|c}$ and $\bar{T}_{data|e}$ and $\bar{T}_{data|s}$ represent the average duration of the
711 transmission of a data packet known that it has collided, suffered error or successfully transmitted
712 respectively.

713 In the previous equations $T_{data}^{(j)}$ and $T_{ack}^{(j)}$ represent the duration of the reception/transmission of a
714 data packet or ACK at station j ; $\bar{T}_{data|c}$ and $\bar{T}_{data|e}$ and $\bar{T}_{data|s}$ account for the average duration of a
715 collided, erroneous or successful transmission, respectively.

$$\bar{T}_{data|s} = \frac{1}{\sum_{j=1}^S P_{tx,s}^{(j)}} \cdot \sum_{j=1}^S P_{tx,s}^{(j)} T_{tx,data}^{(j)} \quad (A23)$$

$$\bar{T}_{data|e} = \frac{1}{\sum_{j=1}^S P_{tx,e}^{(j)}} \cdot \sum_{j=1}^S P_{tx,e}^{(j)} T_{tx,data}^{(j)} \quad (A24)$$

The expression of $\bar{T}_{data|c}$ is more complex as, if a collision between two stations occurs, it must preserve the longest duration collision time (the slowest stations negatively affect to the fastest ones).

To capture this effect we take the terminology from [62], where $d \in \{1, \dots, N_c\}$ represents different traffic groups ordered from greater to lower occupation times, in the set of stations considered.

$$\bar{T}_{\text{data}|c} = \frac{\sum_{d=1}^{N_c} \left(P_c^{\mathcal{N}(d)} + P_c^{\mathcal{H}(d)} \right) T_{\text{tx,data}}^{(d)}}{\sum_{d=1}^{N_c} \left(P_c^{\mathcal{N}(d)} + P_c^{\mathcal{H}(d)} \right)} \quad (\text{A25})$$

where $P_c^{\mathcal{N}(d)}$ and $P_c^{\mathcal{H}(d)}$ represent the probability that a station collides with any station from the same or higher (faster) class, respectively, and can be calculated as indicated in [14].

Appendix B Genetic Algorithm Implementation

We have implemented the Algorithm 1 using the Matlab[®] R2017A Global Optimization Toolbox. As any other Genetic Algorithm, it can be studied as a sequential collection of steps based on GA operators. Next, we elaborate on those steps and other basic concepts.

Appendix B.1 Individuals

Every candidate positioning that represent a possible solution for the problem is called an individual. Thus, each individual can be represented as a location of D drones as $\mathcal{X} = \{x_1, x_2, \dots, x_D | x_i \in \mathcal{P}, i \in \mathcal{D}, x_i \neq x_j | \forall j \neq i\}$, where $x_i \in \mathcal{P}$ accounts for the 3D location of UAV i . For example, consider a scenario with $D = 3$ drones; then, any individual could be represented by the following sequence of genes:

$$\mathcal{X}|_{D=3} = \left\{ \underbrace{x_1, y_1, z_1}_{x_1}, \underbrace{x_2, y_2, z_2}_{x_2}, \underbrace{x_3, y_3, z_3}_{x_3} \right\} \quad (\text{A26})$$

Appendix B.2 Algorithm steps

The GA implementation considers an evolutionary process where a series of individuals are evaluated and replaced (or combined) based on their score (according to the objective function). This process is repeated until the algorithm converges to a sub-optimal solution as we illustrated in Algorithm 1. Then, each step can be summarized as follows:

1. Initial population. An initial collection of p individuals is created¹⁶.
2. Evaluation. Each individual from the current generation is evaluated (and scored) based on the objective function of the problem (9).
3. Selection. A collection of parents is selected from the current generation based on their score and rank, so best individuals are more prone to be chosen as parents.
4. Next generation. This step slightly differs from the canonical GA by distinguishing between three different sources of individuals. However, convergence is improved according to [51,52].
 - Elite individuals. Best 5% individuals from current generation are preserved to the new generation.
 - The remaining population (95%) is created as follows:
 - Self-reproduction and Mutation (GA_SRM). 20% of the remaining population is created by directly applying a random mutation with probability p_m^{SRM} over selected parents.
 - Crossover-and-Mutation (GA_CM). The rest (80%) is created by combining the genes of two parents (crossover) and applying a mutation to these new individuals with probability p_m^{CM} .

¹⁶ The population size p also affects convergence and performance. Experimentally, we found that $p = 200$ provided results that could not be improved in the scenarios tested

5. Exit criteria: in our implementation, the algorithm ends when the score of the best individual found could not be improved after $Gen_{\max}$ consecutive generations¹⁷ by 10^{-3} . Otherwise, the algorithm returns to step 2.

Appendix B.3 Creating the initial population ($GA_InitialPopulation$)

The initial population could be generated randomly but if individuals are prone to be fit, the performance of the GA is improved [68]. To do so, our starting individuals are created based on the k -means clusterization method:

1. First, we apply a two-dimensional k -means algorithm, as illustrated in Figure A1, to define D clusters so that the average distance from each user to its closest centroid is minimized.
2. Then, we convert the 2D centroids to 3D ones by initializing the height coordinate to the mean altitude of the grid. These centroids will represent the first individual.
3. Finally, the rest of the initial population ($p - 1$ individuals) is created by randomly placing each drone (of each individual) among the spatial regions we created around each centroid. In particular, each region is a 3D cube that represents the D -th part of the grid volume.

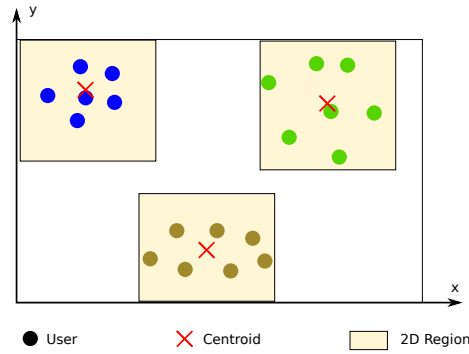


Figure A1. 2D regions for initial population creation ($D = 3$)

The spatial regions are only used when creating the initial population, so genes carried by individuals from future generations could be at any edge in $\mathcal{P}$ with no restrictions.

Appendix B.4 Operators

The following operators have been used:

- **Evaluation and ranking:** the quality of the individuals must be evaluated to distinguish between good and bad candidates. First, each individual is scored by evaluating the objective function in (9), resulting in a raw fitness score. Then, solutions are ranked according to their raw fitness score. Those individuals that do not meet the problem constraints are penalized so that they are placed at the tail of the ranking according to the ratio of users that meet the constraints. Finally, if an individual is in the n position in the ranking, it is assigned a new scored termed expectation value of $1/\sqrt{n}$.
- **Parent selection:** parents are selected through a stochastic uniform selection process among individuals, according to their expectation value. For example, for $p = 200$ individuals, 342 parents (152×2 for CM operations plus 38 for SRM) are selected. By applying the proposed selection method, best individuals may be chosen multiple times as parents.

¹⁷ Observe that $Gen_{\max}$ has a great impact on performance and convergence. Experimentally, we have found that $Gen_{\max} = 50$ is a good balance between performance and precision

- **Mutation:** this operator consists of replacing genes of an individual for random coordinates within $\mathcal{P}$ with probability $p_m^{SRM} = (3D)^{-1}$ or $p_m^{CM} = p_m^{SRM}/2$ for SRM and CM, respectively.
- **Crossover:** this operator randomly combines the genes of two parents to create a new individual.

Appendix C Particle Swarm Optimization Implementation

We have implemented the Algorithm 3 using the Matlab® R2020A Global Optimization Toolbox, which is described in [69] and uses some of the modifications suggested in [70,71].

Appendix C.1 Algorithm steps

The particle swarm algorithm begins by creating an initial population of particles defined by their position and velocity (i.e., function `PSO_InitSwarm`). Then, the algorithm iteratively evaluates and modifies each particle in the swarm:

1. It chooses new velocities, based on the current velocity, particles' best location and the global best location.
2. It obtains a candidate new position for each particle (i.e., function `PSO_UpdateParticle`), considering the its best known location and its velocity.
3. It evaluates each particle, and determines the best known function value and its position.
4. It updates particles' and global best locations if improved.

This procedure is repeated until an exit criteria (e.g., the best known objective function does not improve after a number of iterations) is satisfied.

Appendix C.2 Initializing the swarm of particles (`PSO_InitSwarm`)

Similar to the GA implementation we described in Appendix B, choosing an initial population not fully random but including particles prone to be fit can accelerate convergence, with is one of the desired goals when using PSO in our search algorithm.

Given the fact that consecutive solutions (i.e., UAVs positioning) are likely to be close in the search-space, the previous solution is included as the first particle in the initial swarm. The rest of particles is randomly generated (e.g., uniform distribution) over the n-dimensional search-space.

Appendix C.3 Updating particles (`PSO_UpdateParticle`)

Let us define p_i as the best known position for the i -th particle, and g as the best global known location. In each iteration, the velocity of a particle with position x_i is updated by considering the previous velocity (v_i), the difference between the current position and the best position the particle has seen ($p_i - x_i$), and the difference between the current position and the best position that the algorithm has seen ($g - x_i$) as:

$$v_i = W v_i + y_1 u_1 (p_i - x_i) + y_2 u_2 (g - x_i) \quad (\text{A27})$$

where W_i is the inertia, u_1 and u_2 are uniformly chosen in the range $(0, 1)$, and y_1 and y_2 represent the self and social adjustment weight, respectively. Initial values are illustrated in Table A1. Inertia is updated on each iteration within its bounds depending on the number of consecutive improvements over the observed particle (i.e., see Matlab® R2020 online documentation). Finally, the position of the particle is updated by $x_i = x_i + v_i$.

Parameter	Default value	Range
u_1 and u_2	$U(0, 1)$	–
SelfAdjustmentWeight (y_1)	1.49	–
SocialAdjustmentWeight (y_2)	1.49	–
Inertia (W)	1.1	$[0.1, 1.1]$

Table A1. PSO default parameters

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