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Article

Centralized Unmanned Aerial Vehicle (UAV) Mesh Networks Placement Scheme: A Multi-Objective Evolutionary Algorithm Approach

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Abstract: In the past, Unmanned Aerial Vehicles (UAVs) were mostly used in the military operations to prevent pilot losses. Nowadays, the fast technological evolution enables the production of a class of cost-effective UAVs which can service a plethora of public and civilian applications, specially when configured to work cooperatively to accomplish a task. However, designing a communication network among the UAVs is challenging task. In this article, we propose a centralized UAV placement strategy, where UAVs are used as flying access points forming a mesh network, providing connectivity to ground nodes deployed in a target area. The geographical placement of UAVs is optimized based on a Multi-Objective Evolutionary Algorithm (MOEA). The goal of the proposed scheme is to cover all ground nodes using a minimum number of UAVs, while maximizing the fulfillment of their data rate requirements. The UAVs can employ different data rates depending on the channel conditions, which are expressed by the Signal-to-Noise-Ratio (SNR). In this work, elitist Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is used to find a set of optimal positions to place UAVs, given the positions of the ground nodes. We evaluate the trade-off between the number of UAVs used to cover the target area and the data rate requirement of the ground nodes. Simulation results show that the proposed algorithm can optimize the UAV placement given the requirement and the positions of the ground nodes in the geographical area.

Keywords: Unmanned Aerial Vehicles, Genetic Algorithm, Mesh Networks, Optimization, MOEA, NSGA-II

1. Introduction

Unmanned Aerial Vehicles (UAVs), also known as drones refer to aircrafts with no human pilot on board. These are either programmed and fully autonomous or remotely and fully controlled from another location, e.g., ground or space station. There are various types of UAVs (e.g., Fixed wing and multi-rotor) and they come in different sizes, raging from small (less than 5 kg) to large (over 4332 kg) [1]. Large UAVs are commonly used singly , for instance, in military operation such as border surveillance, strike and reconnaissance, whereas small UAVs may be utilized in swarms to accomplish a mission. With advancement in electronics and sensor technology, small UAVs are becoming massively present in many public and civilian application, such as in search and rescue operations [2], aerial surveillance [3], tracking targets[4], agriculture field monitoring [5], network extension or compensation [6], leisure, to mention a few.

The use of swarms of small UAVs has many advantages compared to a single and large UAV [7]. One of the key advantages is the cost to acquire and maintain small UAVs, which is generally much lower than the cost of a large UAV [8]. Swarms of UAVs can automatically reconfigure themselves in a case of node failure or link break, and accomplish the designated task. That is not possible with a single UAV. Additionally, when network coverage extension is needed, it may be easily achieved with swarms of UAVs by positioning additional UAVs in the target area and allow them to operate

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through other already existing UAVs, unlike single UAV network coverage which is limited by the communication range between the infrastructure and the UAV itself.

Although swarms of UAVs present many advantages, an important aspect to be considered when designing an application using multiple UAVs is the communication network, which poses many challenging issues as described in [9]. Depending on the purpose of the application at hand, UAVs may be semi-stationary and hovering over the area of operations or move around at high speed changing their relative positions. In the latter scenario, frequent topology changes are observed, which may lead to network partitioning and poor link quality. On the other hand, the commonly used wireless ad-hoc network communication protocols or algorithms (e.g., proactive and reactive routing) cannot be directly used for UAVs [10]. For instance, since proactive routing protocols need to update the routing tables periodically, in the presence of high degree of mobility and topology changes, it increases the number of control messages to be exchanged, which degrade the network performance. On the other hand, reactive protocols may introduce higher packet delivery delay each time they compute a new route to the destination node.

UAV placement schemes can help to mitigate the aforementioned issues by finding suitable positions to place UAVs while maintaining connectivity and improving the network performance. The UAV placement optimization schemes can be classified as centralized or distributed. The former assumes that the UAV positions are selected by a centralized entity and conveyed to the UAVs by means of special purpose long-range low bit rate radio interface. On the other hand, in distributed approaches, UAVs work cooperatively to adjust their position based on local interactions to achieve optimal coverage. This work extends our previous work [11], where we considered the use of a swarm of UAVs as flying access points forming a mesh network among themselves, providing connectivity to ground nodes (GNs). Our main goal is to optimize the placement of the UAVs by choosing deployment positions for the UAVs in order to provide adequate wireless communication coverage to GNs in a target area, while fulfilling their Quality of Service (QoS) requirements.

This work is more related with centralized placement optimization. It considers the following requirements and constraints:

- Minimization of the number of UAVs needed to service the GN, while ensuring that the QoS requirements (here measured as the physical data rate) are properly met.
- The number of available UAVs is limited and must not be exceeded;
- The inter-UAV links do not necessarily employ the same technology as GN-UAV links. Inter-UAV links are considered in an abstract way, but constrained to a maximum range.
- It is assumed that the throughput values of the links between UAVs are high enough not to constrain end-to-end inter-GN traffic. Only GN-UAV links impose limits to the satisfaction of QoS requirements (end-to-end QoS shall be addressed in future work);
- GN-UAV links are orthogonal. This can be achieved, for example, by assigning different frequencies or orthogonal channel codes.

Given the nature of the problem requirements, we consider using Multi-Objective Evolutionary Algorithm (MOEA) techniques to optimize the UAV node placement considering two main objectives, namely, to minimize the number of UAVs and the degree of dissatisfaction regarding the required data rate.

The paper is structured as follows. Section 2 presents the related work. In Section 3 the system model is presented. Section 4 presents the problem definition and formulation as a Multi-Objective Optimization Problem (MOP). Section 5 presents our MOAEA implementation. The simulation results are presented in Section 6. Section 7 presents the simulation results discussion and Section 8 concludes the paper.

2. Related Work

Optimal placement of UAVs has already been studied in the literature whether considering single or multi-UAV scenarios. In [2], a single-UAV was proposed for search and rescue application such

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as earthquake, flood or bomb blast. The goal is to deploy an UAV to a position where it can bridge communication between two static nodes on the ground. It is assumed that the UAV hovers the area in spiral or ladder search mode sending hello/beacon messages in regular interval. Upon receiving such a message, the GNs respond by sending their GPS positions back to the UAV. The UAV stores this information and continues hovering in the immediate surrounding to find a position based on the received signal strength (RSS) and distance between the UAV and nodes on the ground. Simulation results showed that the algorithm provides maximum throughput and low bit error rate (BER) once the UAV is fixed at an optimal position. The drawback of this system is that it is only validated for two GNs. Therefore, as the number of GN grows, the solution should consider energy constraints during the search process and bandwidth constraints when providing network access to GNs.

The authors in [12] have developed a framework named UAVNet. It is capable to autonomously deploy a wireless mesh network to interconnect two end systems using small quadrocopter-based UAVs with 802.11s nodes on board. Each UAV would act as access point and provides network access for regular IEEE 802.11g wireless devices. There are two positioning modes to place the UAVs between the end systems.The first one is the location based positioning mode. The latter uses the submitted GPS locations of the end systems and directs the UAV to the exact geographical position between these two GPS coordinates. The second one is the signal strength positioning mode. It extends the location positioning mode and includes also the received signal strength of the two end systems to calculate a more accurate position for the UAV. This takes the quality of the wireless link and other environmental factors into account.

Usually, the process of network densification in cellular networks uses fixed small cells (e.g., picocells and fentocells) to increase the network capacity based on the expected formation of hotspots. In places where temporary hotspots are formed, fixed small cells would remain under-utilized once the hotspots moved to a different location or disappeared. Authors in [13] proposed small cells mounted on UAVs to offload user equipments (UEs) from the microcell infrastructure. The optimum placement points of the UAVs are determined using K-means clustering algorithm. In their work, the performance metric where measured based on the RSS experienced by the UEs. The simulation results have shown that as UAVs are able to position themselves in real-time around actual UE position rather than expected UE hotspots, they outperform equivalent small cell deployment.

In [14], the authors present a model for an optimal placement of UAVs to cover a set of targets, i.e., GNs. They consider two cost metrics, namely, the number of UAV and energy consumption, seeking to minimize both metrics. The authors assume that each UAV has a minimum and maximum observation altitude. They also assure that the UAV's energy consumption is related to this altitude, since the higher the altitude, the larger the observed area, but also the higher the energy consumption. The optimization problem is mathematically solved by defining an integer linear and a mixed non-linear optimization model.

The authors in [15] use the same assumption as in [14] to model an optimized UAV placement and formulate it as a multi-objective linear problem. The main difference is that, in [15], the connectivity among UAVs is considered as an additional constraint. In [15], the following objectives are to be minimized: number of UAVs and the maximum flying altitude. Our work is closer to [15] though with some differences. Firstly, we consider using omnidirectional antennas instead of directional. Secondly, one of our objectives is to minimize the difference between the assigned and required data rate, whereas one of their objectives is to maximize the flying altitude.

3. System Model

We consider a wireless network consisting of two kinds of nodes, GNs and UAVs, which are represented by the sets **V** and **U**, respectively. All nodes are assumed to be located in a rectangular area $\mathcal{A}$ with length X_{max} and width Y_{max}. Nodes are equipped with omnidirectional transceivers and a GPS. Therefore, they know their positions in the aforementioned rectangular area at any time. The position of a GN v is assumed to be on the ground with coordinates $q^{v}_{(x,y,0)}$, while the position of an UAV node

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u is represented in the 3D plane as $q^u_{(x,y,h)}$, where h is the flying altitude of u. We assume that the main factor which affects the service quality offered by an UAV is path loss, as it is assumed that the links between a GN and its serving UAV are line-of-sight (LOS) links. We employ the free-space propagation model given by the Friis equation, as follows:

$$P_R = P_T G_T G_R \left(\frac{\lambda}{4\pi d} \right)^2 \tag{1}$$

where P_R is the received power, P_T is the transmission power, G_T and G_R are the transmitter and receiver antenna gains, respectively. $\lambda = \frac{c}{f}$ represents the wavelength of the carrier wave, where c is the speed of light and f is the carrier wave frequency. UAVs are assumed to have the same operating characteristics, featuring the same transmit power, antenna gains and altitude. GNs can only communicate with each other through UAVs. The parameter d in Equation (1) represents the distance between the transmitter and receiver antennas of the nodes. Assuming communication between a GN and an UAV, d is computed as the Euclidean distance between their transceivers as follows:

$$d = \sqrt{(x_u - x_v)^2 + (y_u - y_v)^2 + h_u^2} \tag{2}$$

The distance d should not be greater than the maximum communication range $\mathcal{D}$. We compute $\mathcal{D}$ based on the receiver sensitivity, denoted as $P_{RS_{dBm}}$. Considering $G_T = G_R = 1$ $(0\ dBm)$ in Equation (1), it yields:

$$\mathcal{D} = 10^{\frac{P_{T_{dBm}} - P_{RS_{dBm}} - 20\log(f) + 147.56}{20}} \ (m) \tag{3}$$

129 An overview of the proposed system is shown in Figure 1.

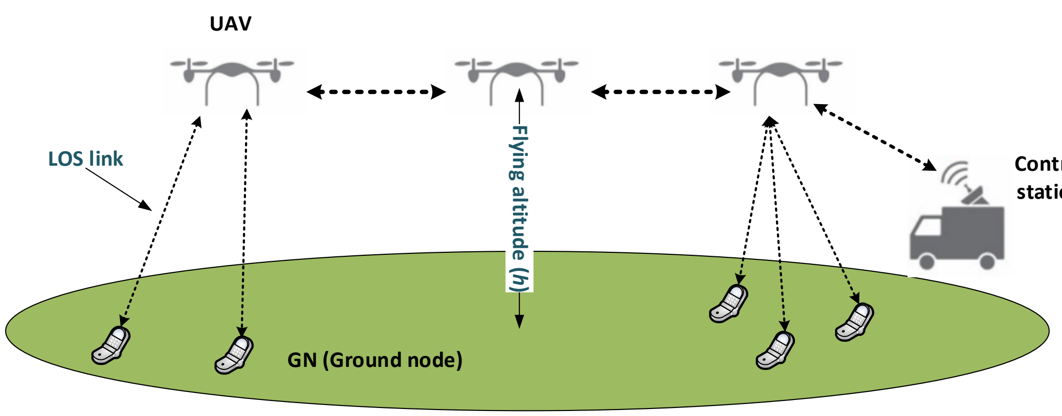

Figure 1. System model overview.

130 ## 4. Problem Definition

131 Consider the network model presented in Section 3. The goal is to ensure that all GNs are covered
132 and that the data rate requirements are met as much as possible when UAVs are used as relay nodes.
133 We assume that there is a cost associated with each used UAV. Thus, minimizing the number of UAVs,
134 is desirable. On the other hand, GNs may have different data rate requirements. The satisfaction
135 of data rate as GN requirements is closely dependent on the channel conditions (e.g., SNR), which
136 also depends on the communication distance, which results from the number and placement of the
137 serving UAV in the network. We intend to deploy as few connected UAVs as possible in suitable
138 locations to enable communication between GNs, while satisfying multiple independent data rate
139 requirements. In some instances, the QoS demands are competitive, i.e., one cannot satisfy them

simultaneously. This gives rise to the need of finding solutions that try to balance them. This problem can be modelled meta-heuristically as a multi-objective optimization problem to find the trade-off among non-dominated solutions. In the rest of this section, we define Multi-Objective Optimization Problem (MOP) and present the formulation of our UAV placement optimization problem as a MOP.

4.1. Multi-Objective Optimization Problem (MOP)

A MOP can be stated as follows [16]:

$$\begin{aligned} minimize\ \mathbf{F}(\varepsilon) &= (f_1(\varepsilon), ...f_m(\varepsilon)) \\ subject\ to\ \varepsilon &\in \Omega \end{aligned} \tag{4}$$

Where Ω is the *decision (variable) space*, $\Re^m$ is the *objective space*, and $\mathbf{F} : \Omega \rightarrow \Re^m$ consist of m real-values objective functions. If Ω is a closed and connected region in $\Re^m$ and all the objectives are continuous of ε, we call Equation (4) a continuous MOP.

4.1.1. Domination

Let $k = (k_1, ..., k_m)$, $l = (l_1, ..., l_m) \in \Re^m$ be two vectors, k is said to *dominate* l if $k_i \leq l_i$ for all $i = 1, ..., m$ and $k \neq l$ [1].

4.1.2. Pareto front

A point $\varepsilon^* \in \Omega$ is called *(Globally) Pareto optimal* if there is no $\varepsilon \in \Omega$ such that $\mathbf{F}(\varepsilon)$ dominates $\mathbf{F}(\varepsilon^*)$. The set of all the Pareto optimal points, denoted by PS, is called the *Pareto set*. The set of all Pareto objective vectors, $PF = \{\mathbf{F}(\varepsilon) \in \Re^m | \varepsilon \in PS\}$, is called the *Pareto front*.

4.2. Formulation of UAV Placement Optimization as a MOP

In this section we formulate the problem in $\mathbf{R}^2$ objective space. We seek to minimize the number of deployed UAVs and simultaneously minimize the difference between the data rate required by the GNs to transmit data and the data rates that results from the MOP solution.

4.2.1. Minimize the number of UAVs

We start by identifying a set of potential UAV placement points Q, by finding a sub-area $a' \subset \mathcal{A}$ which corresponds to the area inside the convex hull (convex envelope) [17] formed by the GNs in $\mathcal{A}$ as shown in Figure 2. We compute the convex hull to reduce the search space of the UAVs placement points in the target area. We intend to cover all GNs in a'. Therefore, we discretize a' in a grid layout according to Equation (5).

[1] This definition of domination is for minimization. All the inequalities should be reversed if the goal is to maximize the objectives in Equation (4). "Dominate" means "be better than."

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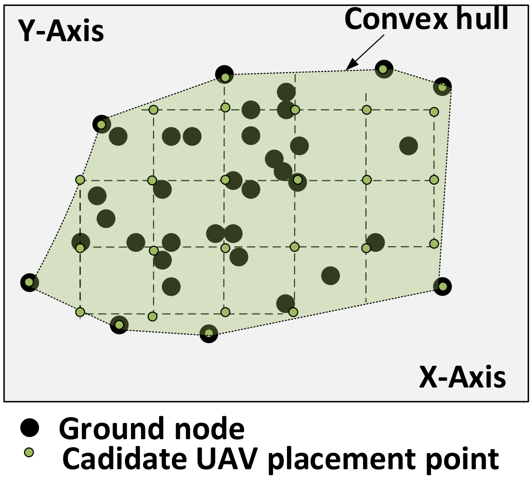

Figure 2. Convex hull formed by the GNs.

$$\alpha\mathcal{D}; \alpha \in [0,1] \tag{5}$$

165 where α adjusts the distance between two neighboring UAVs. Let $q_j \in Q$ be the jth potential UAV
166 placement point. We define $\delta^u_{q_j}$ as a binary variable to indicate which points are currently being used
167 by an UAV as presented bellow.
168

169
$$\delta^u_{q_j} = \begin{cases} 1 & \text{if UAV } u \text{ is located at } q_j \\ 0 & \text{Otherwise} \end{cases}$$

170 We also define ζ^u_v as a binary variable to indicate which GNs are being serviced by each deployed
171 UAV. It is assumed that a GN will be connected to the closest deployed UAV.
172

173
$$\zeta^u_v = \begin{cases} 1 & \text{if } v \text{ is connected to UAV } u \\ 0 & \text{Otherwise} \end{cases}$$

174 Our objective is to select points in Q such that

$$min \sum_{q_j \in Q} \sum_{u \in U} \delta^u_{q_j} \tag{6}$$

subject to:

$$\sum_{q_j \in Q} \delta^u_{q_j} \leq 1, \forall u \in \mathbf{U} \tag{7}$$

$$\sum_{v \in \mathbf{V}} \zeta^u_v \geq 1, \forall v \in \mathbf{V} \tag{8}$$

175 Constraint (7) indicates that each UAV u cannot be placed in more than one point at the same
176 time. Constraint (8) ensures that a GN is at communication range of at least one UAV. The cardinality
177 of the set Q defines the maximum number of UAVs that can be used for each formed convex hull. In
178 order to ensure connectivity among UAVs, we have considered using the Algorithm 1, which verifies
179 if each UAV has a path to the selected destination, which may be used as control station. UAVs are

assumed to have two main attributes: serving, when the UAV is used to serve GNs and to connect the network, and bridging when it is solely being used to connect the serving UAVs.

Algorithm 1 Construction of connected UAV network.

```
Input: u_dest, adjacency matrix
Result: Connected UAV network
For each u ∈ U
  IF u is serving and u is not bridging
    q^curr = q^u; /*q^curr ∈ Q is the current point toward destination*/
    Until not reachable(u,u_dest)
      6.1 Find the closest point q' ∈ Q to q^{u_dest} which is whitin distance D from q^curr
      6.2 If q' is not in use
          6.2.1 q^curr = q'
          6.2.2 Find u' ∈ U which is not serving or bridging
          6.2.3 Set: u' to bridging
          6.2.4 q^{u'} = q^curr
          6.2.5 Update adjacency matrix
```

4.2.2. Minimizing the degree of dissatisfaction of the required data rate

Consider a set of transmission modes $\mathcal{B}$ comprising the possible bit rates b_i. We denote the transmission modes in use by an UAV and requested by a GN as b_i^u and b_i^v, respectively. We define the degree of dissatisfaction as follows:

$$\gamma^v = \begin{cases} \dfrac{|b_i^u - b_i^v|}{b_i^v} & \text{if } (b_i^u - b_i^v) < 0 \\ 0 & \text{Otherwise} \end{cases} \tag{9}$$

We consider that the use of a b_i depends on the SNR. Usually, GNs experiencing a relatively low SNR will have their receiver interface tuned to a robust (with lower BER when compared with other modes under the same channel conditions) transmission mode with lower data rate. On the other hand, if SNR is relatively high, the receiver may be tuned to a transmission mode which offers higher data rate. In this work, we try to minimize the maximum dissatisfaction value as follows:

$$min\ (max_{v \in \mathbf{V}}\ \gamma^v) \tag{10}$$

5. UAV placement based on NSGA-II

In this section we present terminologies used by NSGA-II [18] and the main genetic algorithm elements (individual or chromosome, fitness, selection, population and genetic operators). The term solutions and individuals are interchangeably used along the remaining part of this paper.

NSGA-II is an elitist MOEA which comprises two main procedures. One is the Pareto ranking procedure, which aims at sorting the population into different non-domination levels (i_{rank}) in ascending order. The lowest ranking level contains the best solution. In order to identify solutions of the first non-dominated front in a population of size N, each solution is compared with every other solution in the population to find if it is dominated. After all members of the first non-dominated front are found, they are discounted temporally so that the next non-dominated front could be found by repeating this first procedure. The other procedure is the diversity preservation which is used to maintain a good spread of solutions in the obtained set of solutions. Members in each non-dominated front are assigned a value called *crowding distance* ($i_{distance}$). This value gives an estimate of the density

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of solutions surrounding a particular solution in the population. A solution with a smaller value of this distance measure is, in some sense, more crowded by other solutions. The *crowded-comparison operator*, denoted as $\prec_n$, is used to distinguish the best solution during selection process. It assumes that every individual i in the population has two attributes, i_{rank} and $i_{distance}$. The partial order $\prec_n$ is defined as:

$$\begin{aligned} i \prec_n j \text{ if } (i_{rank} < j_{rank}) \\ \text{or } ((i_{rank} = j_{rank}) \text{ and } (i_{distance} > j_{distance})) \end{aligned} \tag{11}$$

That is, between two solutions with differing non-domination ranks, we prefer the solution with the lower (better) rank. Otherwise, if both solutions belong to the same front, then we prefer the solution that is located in a less crowded region.

Algorithm 2 shows the main loop of NSGA-II proposed by the authors in [18], where the call of the routines *fast-non-dominated-sort* (R_t) and *crowding-distance-assignment* $(\mathcal{F}_i)$ corresponds to the first and second procedure described above, respectively. R_t is of size $2N$ formed by combining parent S_t and offspring Z_t populations. $\mathcal{F}_i$ refers to the i^{th} front or level. The detailed explanation of the aforementioned procedures is also available in [18]. We describe the main loop of NSGA-II as follows:

Algorithm 2 NSGA-II main loop.

$R_t = S_t \cup Z_t$
$\mathcal{F}$=fast-non-dominated-sort(R_t)
$S_{t+1} = \emptyset$ **and** $i = 1$
Until $|S_{t+1}| + \mathcal{F}_i \leq N$

  4.1. crowding-distance-assignment($\mathcal{F}_i$)
  4.2. $S_{t+1} = S_{t+1} + \mathcal{F}_i$
  4.3. $i = i + 1$

Sort$(\mathcal{F}_i, \prec_n)$
$S_{t+1} = S_{t+1} \cup \mathcal{F}_i[1 : (N - |S_{t+1}|)]$
Z_{t+1}=make-new-pop(S_{t+1})
$t = t + 1$

Step 1. Combine parent and offspring population;
Step 2. $\mathcal{F} = (\mathcal{F}_1, \mathcal{F}_2, ...)$, sort R_t according to non-domination procedure;
Step 3. Initialize an empty set for the parent population $P_{t+1} = \emptyset$ and set a counter i to 1;
Step 4. Until the parent population is filled;

4.1. Calculate crowding-distance in $\mathcal{F}_i$;
4.2. Include i^{th} non-dominated front in the parent pop;
4.3. Check the next front for inclusion. Best solutions are in $\mathcal{F}_1$. If the size of $\mathcal{F}_1$ is smaller than N, we choose all the members of the set $\mathcal{F}_1$ for the new population S_{t+1}. The remaining members of the population S_{t+1} are chosen from subsequent non-dominated front in the ascending order of their ranking, $(\mathcal{F}_2, \mathcal{F}_3, ...)$. Say that the set $\mathcal{F}_l$ is the last non-dominated set beyond which no other set can be accommodated. In general, the count of solutions in all sets from $\mathcal{F}_1$ to $\mathcal{F}_l$ would be larger than the population size. In order to choose exactly N population members, we sort the solutions of the front $\mathcal{F}_l$ using the crowded-comparison operator $(\prec_n)$ in descending order and choose the best solution needed to fill all population slots;

Step 5. Sort in descending order using $\prec_n$;
Step 6. Choose the first $(N - |S_{t+1}|)$ elements of $\mathcal{F}_i$;
Step 7. Use selection, crossover and mutation to create a new population Z_{t+1};
Step 8. Increment the generation counter.

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5.1. Individual

An individual encodes a candidate solution to the problem. Our proposed individual stores the UAVs positions $q_j^u \in Q$ inside the discretized convex hull area a' for each deployed or serving UAV. The length of the individual (see Figure 3) represents the number of deployed UAVs or points used in Q. If it is detected that some GNs are not covered, then the corresponding individual is considered as invalid, i.e., cannot be used in any step of NSGA-II algorithm. Algorithm 1 ensures that all individuals are valid during the creation of initial population.

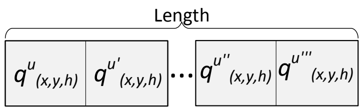

Figure 3. Individual.

5.2. Initial population

The initial population is a set of N randomly generated valid individuals.

5.3. Objective or fitness function

A fitness function decodes the solution represented by a chromosome and let us know how far we are from the optimal/ideal solution if it is known. In MOEA there will be a fitness function for each objective space. Equations (6) and (10) compute the fitness for the number of UAVs and degree of dissatisfaction, respectively. Values scored from both objective functions are used by NSGA-II to set the i^{th} front.

5.4. Selection

The goal of selection procedure is to pick the best individuals to the next generation. We use binary tournament selection based on crowded-comparison operator $\prec_n$ as described in Section 5.

5.5. Genetic Operators

Genetic operators are responsible for generating new solutions to populate the next generations. In the next sections we present how they are performed.

5.5.1. Crossover

Two parents are chosen to exchange their genes with a probability p_c. We rely on 2D representation of each parent (see Figure 4) to show how crossover is conducted. In this procedure, we find the midpoint in a' and draw a separation or cutting line to divide the area in two parts in each of the parents. The cutting line may be drawn diagonally in 45/-45 degrees or horizontally or vertically. Next, we remove all UAVs that are within $\frac{1}{2}\mathcal{D}$ distance radius along the cutting line within a'. If the separation line is either diagonally or vertically drawn, the leftmost part of one parent is joined with the rightmost part of the other to form an offspring. On the other hand, if it is horizontally drawn, the uppermost and bottommost will be joined instead. There may be some uncovered GNs in the vicinity of the separation line, since we have removed some UAVs, which makes the resulting offspring an invalid individual. In this case, we repair the offspring by repeatedly choosing a random uncovered GN and place an UAV in a closest available point $q^u_{(x,y,h)}$ until all GNs are covered and connectivity among UAVs is verified by the Algorithm 1. UAVs which are not serving or bridging any GNs are removed.

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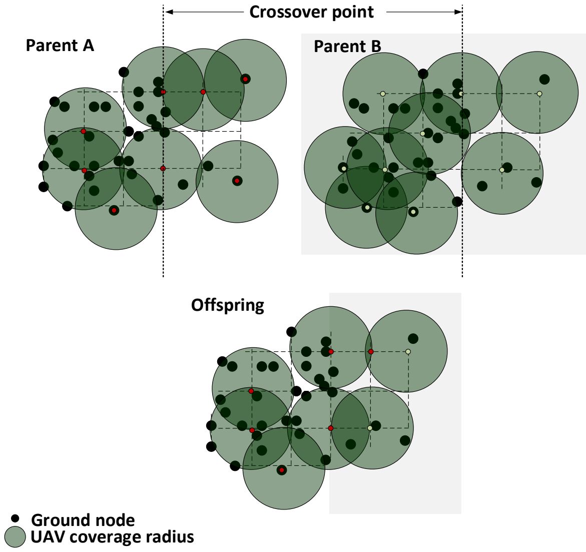
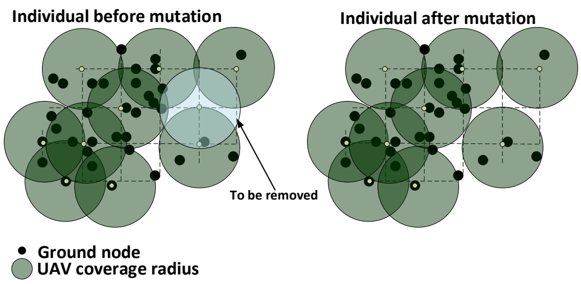


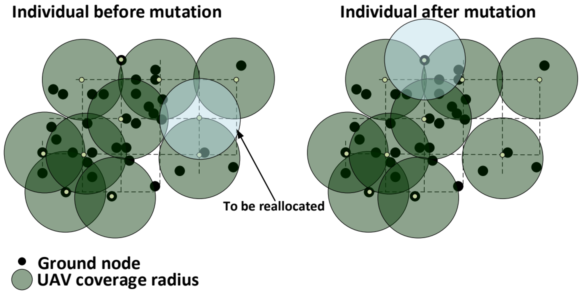
Figure 4. Crossover procedure

5.5.2. Mutation

For each individual an UAV is randomly chosen based on a probability p_m. Next, either it is temporally removed from the network or reallocated to a new available placement point with 50% chance for each procedure to be performed. If the above procedures fail to produce a valid individual, then the UAV is put back in its initial position. Figures 5a and 5b show the removal and reallocation procedures, respectively.



(a) Removal of UAV



(b) Reallocation of UAV

Figure 5. UAV removal and reallocation procedures during mutation

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6. Simulation results

In this section, we present simulation results of our implementation of NSGA-II. We have two objective functions. The first one aims at reducing the cost in term of the number of deployed UAVs used to service GNs, and the second one is intended to reduce the maximum dissatisfaction of GNs in term of the required data rate. We have developed the algorithm in C++ programming language. The setup of the proposed scenarios, the MOEA termination criterion and the dominated and non-dominated sets are presented in section 6.1, 6.2 and 6.3, respectively.

6.1. Scenario setup

We considered a network with 120 fixed GNs uniformly distributed in a rectangular area of size 10000 m $\times$ 10000 m. We set three different scenarios by varying the value of α. This parameter is used to discretize the area inside the convex hull formed by the GNs. Differently from our previous work [11] where UAVs were only allowed to fly at fixed altitude, here an UAV may fly at a given altitude h uniformly selected from the set $\mathcal{H}$= {40, 80, 120} m. We assume that the transmit power among the nodes is fixed at 23 dBm. Previously, in section 4, it was stated that potential UAV placement points will be identified within a convex hull formed by the GNs. The convex hull is found by the Graham scan algorithm [19] based on the GN deployment positions $q^{v}_{(x,y,0)}$. Table 1 shows all possible data rates and their corresponding minimum sensitivities. These values were used to compute the maximum achievable distance $\mathcal{D}_i$ given by equation 3. Moreover, each data rate in Table 1 is considered to be using a different transmission mode.

Table 1. Calculation of the maximum achievable distance of each transmission mode based on the minimum sensitivity of the receiver antenna.

Data Rate (Mbits/s)	Min. Sensitivity (dBm)	$\mathcal{D}_i$ (m)
6	-82	1760.93
9	-81	1569.43
12	-79	1246.64
18	-77	990.24
24	-74	701.04
36	-70	442.32
48	-66	279.08
54	-65	248.73

Our scenarios considers free space path loss for the signal attenuation. For the set of UAV candidate position Q, we chose $\mathcal{D}_i$ with the lowest minimum sensitivity and adjust it by using the parameter α to ensure that two UAVs positioned side by side can communicate with each other. As already stated, we assume that there is a wireless communication technology between UAVs that is capable of efficiently relaying all the traffic from the GNs, never causing a bottleneck. The parameters that are common in different scenario are detailed in Table 2 as follows:

Table 2. Parameters in each scenario.

Parameters	Value
Transmit Power	23 dBm
Antenna model	Omni-directional
Propagation model	Free space
Area $\mathcal{A}$, ($X_{max} \times Y_{max}$)	10000 m $\times$ 10000 m
Nr. of GNs	120
c	3×10^8 m/s
f	2.412×10^9 H_z
α	[0.15, 0.30, 0.45]
$\mathcal{D}$	1760.93 m

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We have adjusted NSGA-II parameters such as, the probability of crossover and mutation and the population size so that the algorithm does not prematurely converge or perform excessive number of computation due to either low values of the probability of crossover or high population size. NSGA-II parameters are summarized in Table 3.

Table 3. NSGA-II setup parameters.

Parameters	Value
NSGA-II Population Size	80
NSGA-II p_c	0.9
NSGA-II p_m	0.6

6.2. MOEA termination criterion

The MOEA termination adopted in this work is similar to that used in [20], in the sense that we also maintain an external archive of non-dominated solutions obtained at some predefined steps at earlier generations, and it is subject to be updated some generations later. However, instead of computing the ratio of the number of solutions in the archive that are dominated by the new ones of the current generation and the ratio of the number of solutions that are also present in the new set of non-dominated solutions, we compute the ratio of new solutions which are not present in both dominated and non-dominated sets of the archive and we use it to define our stopping criterion. We use $\epsilon = 0.05$ as cut-off value for the new solutions. However, the choice of the exact cut-off value may depend on the problem and may require some trial and error. Figure 6 shows the ratio of new solutions at every tenth generation (i.e., step=10). The ratio was significantly high in the first generation when the algorithm was evolving and decreased with the generation as new solutions were not frequent. We also observe that depending on α the NSGA-II takes different number of generation to achieve the cut-off value. In fact, the value of α affects the cardinality of Q hence increasing or decreasing the search space, i.e., the higher the cardinality of Q the higher is the number of generations to achieve the cut-off value. On the other hand, the lower the cardinality of Q the lower is the number of generation to achieve the cut-off value. These results are shown in Table 4.

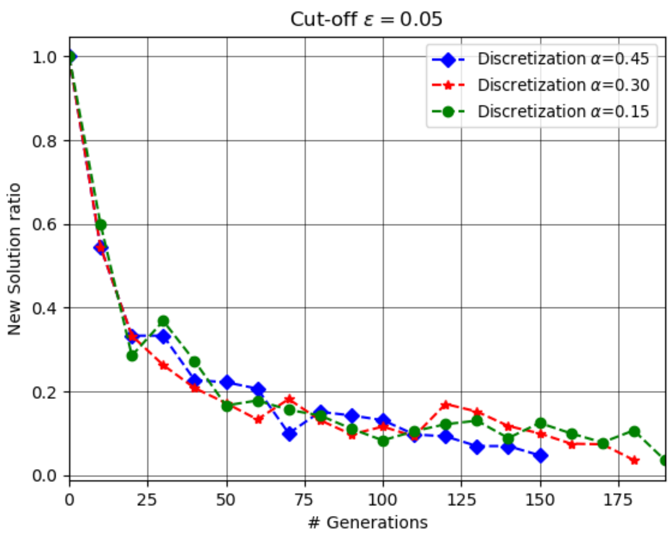

Figure 6. Ratio of new solutions

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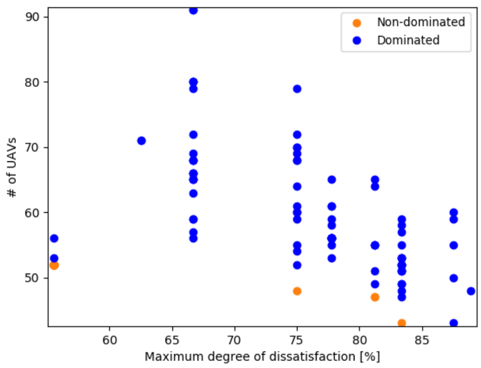
Table 4. Number od generations achieved for cut-off $\epsilon = 0.05$ for each α.

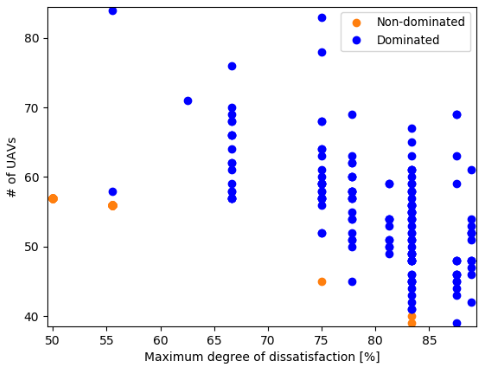
	$\alpha = 0.15$	$\alpha = 0.30$	$\alpha = 0.45$
# of generations	190	179	151

6.3. Dominated and non-dominated sets

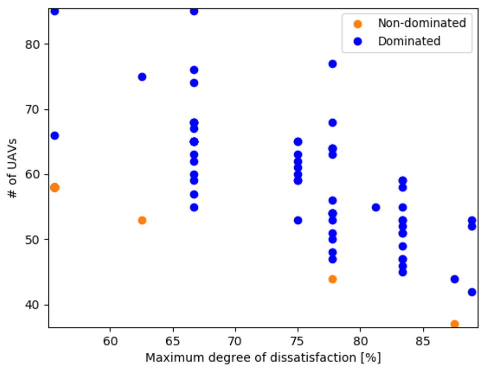
For each value of α, all dominated and non-dominated solutions are presented in Figure 7. From each Pareto front set, we can clearly see the trade-off between the number of UAVs that are flying in the area and the degree of dissatisfaction of the GNs in terms of the required data rate, i.e., when few UAVs are deployed, a high degree of the maximum dissatisfaction is observed. On the other hand, when the number of UAVs increases, the degree of the maximum dissatisfaction decreases.



(a) $\alpha = 0.15$



(b) $\alpha = 0.30$



(c) $\alpha = 0.45$

Figure 7. Trade-off between the number of UAV and the degree of dissatisfaction of the GNs

Table 5 presents the maximum and minimum number of UAVs and their respective degrees of dissatisfaction from the Pareto front set of each value of α presented in Figure 7. These results show that the proposed algorithm can optimize the UAV placement given the requirement and the positions of the GNs in the target area.

Table 5. Maximum and minimum nr. of UAVs for each scenario.

	Max. UAVs	Degree. Dissat (%)	Min. UAV	Degree. Dissat (%)
$\alpha = 0.15$	52	55.55	43	83.33
$\alpha = 0.30$	57	50	39	83.33
$\alpha = 0.45$	58	55.55	37	87.50

7. Discussion

As shown above varying α affects the objective functions, though we have computed the convex hall to reduce the search space to some extent. However, this parameter may still reduce or increase the number of candidate points to place UAVs in the target area. The choice of α depends on the requirement such as the area to be covered, the maximum transmission range, and also the number of available UAVs to cover the GNs to meet the QoS requirements.

The use of NSGA-II as an optimization tool allows us to produce a set of solutions which are better and spread as observed in our simulations results. It enables us with options to select a solution according to the requirement of the application or problem at hand. For instance, if it is not acceptable that any GN communicates beyond 75 % of degree of dissatisfaction and there are no more than 60 available UAVs , then they can easily be configured with solutions that respect these requirements from our Pareto-optimal (non-dominated) set chosen from Figure 7.

The experimental results presented in previous section are specific to the proposed scenarios and assumptions which were considered in our system model. In a realistic environment, one should take into account additional constraints such as the effect of interference, GN mobility, number of GNs to be covered, terrain conditions, etc.

- *Interference:* Nodes may be positioned within acceptable distance for the required data rate, but may fail to achieve it due to interference caused by ongoing transmission of their neighboring nodes.
- *GN mobility:* Although the mobility is not considered in this work, it is worth to mention that it would at least demand scheduling of periodic updates and computation of new solutions due to topology changes. As was previously mentioned, that is a challenging issue, namely because of the need to minimize temporary connectivity disruption due to UAV position changes.
- *Number of GNs:* UAVs have a limited capacity to efficiently service a certain number of GNs, if this capacity is exceed, additional UAVs may be needed.
- *Terrain conditions/ structure:* UAV may not fly at desired altitude due to the existence of obstacles (e.g., trees, mountains, buildings, etc.), which may require the addition of more UAVs to maintain the connectivity among the nodes.

Algorithm 1 was used to ensure the connectivity of the network and produce valid solutions. We use breadth first search (BFS) algorithm to check if there is a path to the destination. If a path is not found, it adds a new UAV to connect it as explained in Section 4.2.1. This procedure is not optimized, which may conflict with the objective of minimizing the number of UAVs. However, it may eventually reduce the degree of dissatisfaction of the GNs.

8. Conclusions

This paper presents an optimized placement scheme for UAV access points providing network connectivity to GNs with differentiated data rate requirements. The goal of the proposed algorithm is to deploy as few as possible connected UAVs to cover and simultaneously satisfy the aforementioned requirements of the GNs. In order to attain this goal, we have mathematically formulated the problem and used a MOEA named NSGA-II to run the simulations. In order to NSGA-II to work we proposed a chromosome structure, crossover scheme and mutation procedure. Simulations were performed considering Wi-Fi (802.11g) technology, where GNs would request to turn to a given transmission mode within a set of available ones. Simulation results show that the algorithm optimizes the UAV placement given the requirements and positions of the GNs, considering the trade-off between the number of UAVs and quality of the coverage.

In future work we will consider additional constrains such as limited inter-UAV link capacity. We will also consider joint topology and routing optimization.

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

Abbreviations

The following abbreviations are used in this manuscript:

BER	Bit error rate
BFS	Breadth first search
GN	Ground node
GPS	Global positioning system
IEEE	Institute of electrical and electronics engineer
MOEA	Multi-objective evolutionary algorithm
MOP	Multi-objective optimization problem
NSGA-II	Non-dominated sorting genetic algorithm II
QoS	Quality of service
PS	Pareto set
RSS	Received signal strength
SNR	Signal-to-noise-ratio
UAV	Unmanned aerial vehicles
UE	User equipment
Wi-Fi	Wireless fidelity

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Sample Availability: Samples of the compounds ...... are available from the authors.