Autonomous UAV-aided Mesh Wireless Networks

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***Abstract*—Mesh networks are known to provide enhanced and robust coverage by leveraging the multi-hop relaying and self-organization capabilities. Despite these advantages, in deployment scenarios where some nodes are severely obstructed from others, overall network connectivity may still be hampered. In this work, we investigate the use of an unmanned aerial vehicle (UAV) serving as a smart relay to improve the connectivity in a wireless mesh network. It is the first contribution of its kind in the context of mesh networks where an UAV autonomously navigates itself to maximize the mesh connectivity based on the positioning algorithm that exploits the radio measurements collected in the network. We also validate the performance of the developed algorithm in a real-life experimental setup.**

I. Introduction

Unmanned aerial vehicles (UAVs) bring about unique advantages in terms of aerial 3D mobility, allowing to shorten propagation distances and their ability to promote line-of-sight (LoS) conditions for ground users. This largely explains significant attention recently given to the study of integrating UAVs in wireless networks as well as on the role of UAVs as a means to improve the communication performance. Nice summaries of a variety of such studies, ranging from cellular to Wi-Fi technologies, theoretical to experimental, UAV as a terminal to base station, etc. are provided in [1], [2].

Wireless mesh networks have proved popular in many practical scenarios due to benefits such as flexible deployment, improved coverage, network robustness to node failures, etc. Use cases of mesh networks include community maintained wireless networks, public safety systems, small cells with wireless backhaul in cellular networks [3], especially in the 5G and post 5G context, etc. [4], [5].

However, in spite of the multi-hop routing redundancy offered by mesh networks, global connectivity failure poses a challenge especially when the nodes are mobile and/or deployed in adversarial propagation conditions (hilly terrain, dense urban, etc.). In such situations the network may be locally (as opposed to globally) connected (small isolated clusters) due to limited radio range of the nodes. This problem can in principle be mitigated by the use of an *intelligently placed* UAV acting as a relay between pairs of nodes that seek to communicate with each other.

While many works focused on the problem of UAV placement or trajectory design in two-hop scenarios where UAV acts as a relay between a source and destination [6], [7], little attention has given to UAV placement in mesh networks with multi-hop routing capabilities. In contrast, the use of UAVs in scenarios such as, efficient formation of UAV swarms with mesh connectivity [8], [9], coverage extension and routing enhancement in ground ad-hoc networks [10], [11], aerial mesh network with UAV access points to enhance the coverage to ground users [12], [13] has been studied in previous works. We however point out that the problem of optimal positioning of UAV relay to enhance the performance in mesh network consisting of multiple ground nodes with multi-hop routing capabilities has not been studied.

Beyond analytical studies, a few experiments for evaluating UAV-aided mesh networks have also been conducted. The works in [14]–[16] have studied throughput and coverage using UAVs and IEEE 802.11 technologies. The evaluations are performed on indoor and outdoor performance tests, multi-sender, multi-hop network using both infrastructure and ad-hoc modes. Experimental frameworks for mesh networks consisting of flying UAVs and ground nodes are developed in [17], [18]. While [18] studied the impact of UDP packet losses, frame errors, and received signal strength indicator (RSSI) in the network with mobile UAVs, the framework developed in [17] studies the autonomous placement of UAVs, which demonstrated that UAV placement can significantly improve the network performance. However, the UAV placement algorithm is simplistic, and a network topology with only two static ground nodes is considered.

In this work, we examine both theoretical and algorithmic aspects for the autonomous placement of the UAV relay in a mesh network with the objective to maximize the network's throughput performance. We also develop an experimental platform which builds on the proposed algorithm concepts to validate our ideas. The key contributions of this work are:

- We propose and implement a UAV placement algorithm that aims to maximize the worst link throughput (max-min fairness performance) across the entire mesh network. One originality of our approach lies in (i) the exploitation of a 3D map of the environment as well as the exploitation of radio measurements from the nodes, and (ii) the devising of an analytical model for the multi-hop routing performance, which is then used in the 3D location optimization algorithm.
- We design a UAV-aided mesh network prototype with commercially available Wi-Fi modules and optimized link state routing protocol (OLSRD) protocol stack, which is a standard open-source mesh software.
- Both simulation and experimental results obtained from

This work was supported by the ERC under the European Union Horizon 2020 research and innovation program (Agreement no. 670896).

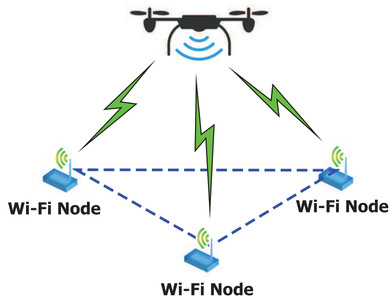


Fig. 1: UAV-aided mesh network.

an outdoor scenario demonstrate the gains stemming from the UAV placement algorithm.

II. System Model

We consider a mesh network, as shown in Fig. 1, consisting of K ground nodes in an urban area and a UAV acting as an extra flying node. The k-th ground node, $k \in [1, K]$, is located at $\mathbf{u}_k = [x_k, y_k]^{\mathrm{T}} \in \mathbb{R}^2$. The UAV does not have any data communication needs on its own. Instead, it opportunistically serves as a relay to enhance the connectivity between the ground nodes. Hence, by placing itself in an optimal manner, it can improve the overall mesh performance. In this paper, we quantify the network performance in a max-min fairness sense, i.e. trying to enhance the throughput between the worst connected pair of nodes. The position of the UAV is denoted by $\mathbf{v} = [x, y, z]^{\mathrm{T}} \in \mathbb{R}^3$. We assume that the ground nodes and the drone are equipped with GPS receivers, hence the coordinates $\mathbf{u}_k, \forall k$ and $\mathbf{v}$ are known.

A. Channel Model

The channel gain between two radio nodes which are separated by distance d meters is modeled as [19]

$$\gamma_s = \frac{\beta_s}{d^{\alpha_s}} \xi_s, \tag{1}$$

where α_s is the pathloss exponent, β_s is the average channel gain at the reference point $d = 1$ meter, ξ_s denotes the shadowing component, and finally $s \in \{\mathrm{LoS}, \mathrm{NLoS}\}$ emphasizes the strong dependence of the propagation parameters on LoS or non-line-of-sight (NLoS) scenario. Note that (1) represents the channel gain which is averaged over the small scale fading of unit variance. The channel gain in dB can be written as

$$g_s = ß_s - \alpha_s \varphi(d) + \eta_s, \tag{2}$$

where $g_s = 10 \log_{10} \gamma_s$, $ß_s = 10 \log_{10} \beta_s, \varphi(d) = 10 \log_{10}(d)$, $\eta_s = 10 \log_{10} \xi_s$, and η_s is modeled as a Gaussian random variable distributed as $\mathcal{N}(0, \sigma_s^2)$.

III. UAV Placement

The proposed autonomous UAV placement algorithm relies on the 3D map of the environment and the pathloss model parameters. In practical systems, the 3D map can be obtained by either using photogrammetry techniques or radio (including recently UAV-aided) based reconstruction approaches [20]. Pathloss parameters can be also estimated from radio measurements obtained in an off-line or on-line fashion [21].

A. Optimization Problem

The problem of finding a UAV position that maximizes the minimum achievable throughput between any pairs of the ground nodes can be formulated as

$$\max_{\mathbf{v}} \ \min_{j \neq k} C_{j,k} \tag{3a}$$

$$\text{s.t. } h_{\text{min}} \leq z \leq h_{\text{max}}, \tag{3b}$$

where $C_{j,k}$ denotes the throughput between ground node $j, k \in [1, K]$. Constraint (3b) implies that the drone always flies above all the city's buildings, where h_{min} is the height of the tallest building in the city, and below the altitude h_{max}.

In general, solving (3) is very challenging as the throughput between the nodes in our mesh network depends not only on the channel gains but also on many factors such as routing protocol metrics, multi-hop routes, etc. To tackle this difficulty, we make some approximation to the original problem. We first split the original problem into two sub-problems of clustering and placement. The ground nodes are divided into clusters such that within a cluster, nodes can communicate (directly or through the multi-hop) with certain link qualities. The details of the clustering phase are explained in Sec III-B. Once the clustering is finished, UAV treats each cluster as a single entity and placement is done according to these entities. Detailed description of the placement algorithm is given in Sec III-C. Finally, the throughput of links between UAV and the ground users are approximated by the Shannon's point-point channel capacity formula.

B. Clustering

Let's denote RSSI of the direct link between nodes j, k as

$$\ell_{j,k} = \ell_{k,j} = \min\left(g_{j,k}, g_{k,j}\right). \tag{4}$$

where $g_{j,k}$ is the RSSI from node j measured at node k.

We then consider two nodes j and k, which are connected with 1 hop link (directly), in a same cluster if

$$\ell_{j,k} \geq t, \tag{5}$$

where t is a threshold value. If nodes are connected through m-hops, then the following constraints need to be satisfied

$$\ell_{j,q_1} \geq t, \ell_{q_1,q_2} \geq t, \ell_{q_2,q_3} \geq t, \cdots, \ell_{q_{m-1},k} \geq t. \tag{6}$$

Where $q_1, q_2, \cdots, q_{m-1}$ are the index of the intermediate nodes between two nodes j and k. In other words, j and k will be considered in a same cluster if the RSSI of all the links between the intermediate nodes are greater than or equal to t. It implies that all the intermediate nodes are also in a same cluster as nodes j and k.

Note that, the number of clusters varies according to the value of t. For a small t the number of clusters equals to the number of ground nodes (K), while a large t yields one big cluster. Hence, the value of t needs to be tuned based on the experiment setup and the equipment.

As mentioned earlier, by assumption within each cluster, ground nodes can communicate with certain link qualities. Therefore, to guarantee the connectivity in the entire mesh network, we need to enhance the the connectivity between clusters. To this end, we use a UAV as an aerial relay. In the following sections, we proposed an algorithm to optimize the UAV-relay position to maximize the minimum average throughput between the members of each cluster and the UAV.

C. Placement Algorithm

To guarantee the performance of the placement algorithm for a given deployment scenario, the 3D map information pertaining to the terrain where the network is deployed is exploited. Map information enables us to differentiate between LoS and NLoS channel conditions. However, UAV placement based on the raw map data without further processing often leads to complex search problems. To tackle the complexity, a map compression approach is introduced in [21] that extract the local LoS probability from the 3D map of the environment.

For a link between the drone located at $\mathbf{v}$ and the k-th ground node, the LoS probability is modeled as

$$\rho_k = \frac{1}{1+\exp\left(-a_k\,\theta_k + b_k\right)}, \tag{7}$$

where $\theta_k = \arctan(z/r_k)$ denotes the elevation angle and r_k is the ground projected distance between the drone and the k-th ground node located at $\mathbf{u}_k$, and $\{a_k, b_k\}$ denote the model coefficients of the LoS probability for the k-th ground node which can be learned from the 3D map [21]. Using (7) and (1), the average channel gain between the k-th ground node and the drone can be written as follows:

$$\begin{aligned}\mathrm{E}\left[\gamma_k\right] &= \rho_k\gamma_{\mathrm{LoS},k} + (1-\rho_k)\gamma_{\mathrm{NLoS},k}\\ &= \left(\frac{d_k^{(A-1)\alpha_{\mathrm{LoS}}} - B}{1+\exp(-a_k\theta_k + b_k)} + B\right)\frac{\beta_{\mathrm{LoS}}}{d_k^{\alpha_{\mathrm{NLoS}}}},\end{aligned} \tag{8}$$

where $B = \frac{\beta_{\mathrm{NLoS}}}{\beta_{\mathrm{LoS}}}$, $A = \frac{\alpha_{\mathrm{NLoS}}}{\alpha_{\mathrm{LoS}}} \geq 1$, $\gamma_{s,k}$ stands for the channel gain in segment $s \in \{\mathrm{LoS}, \mathrm{NLoS}\}$, and $d_k = \sqrt{z^2 + r_k^2}$ is the distance between the k-th ground node and the UAV. Note that not to complicate the notation, the average random shadowing is assumed absorbed into β_s in (8) i.e., $\beta_s \triangleq \beta_s \exp(\sigma_s^2/2)$.

As mentioned earlier, we assume that within each cluster, ground nodes can communicate with certain link qualities. To enhance the connectivity between clusters we use a UAV as an aerial relay. To find an optimal position for the UAV, we treat each cluster as a single entity. Then, the UAV position is optimized in order to maximize the minimum average throughput between the members of each cluster (entity) and the UAV. Hence, the optimization problem in (3), using clustering and LoS probability models, can be approximated as follows

$$\max_{\mathbf{v}} \min_{i\in[1,M]} \frac{1}{N_i}\sum_{k\in G_i} C(\mathbf{v}, \mathbf{u}_k) \tag{9a}$$

$$\text{s.t.} \quad (3b), \tag{9b}$$

where M denotes the number of clusters, G_i is the set of nodes' index of the i-th cluster, and N_i is the number of ground nodes in cluster i. The maximum (upper-bound) achievable throughput on the UAV-ground node link is denoted by $C(\mathbf{v}, \mathbf{u}_k)$ which is given by

$$C(\mathbf{v}, \mathbf{u}_k) = \log_2\left(1 + \frac{P\,\mathrm{E}\left[\gamma_k\right]}{\sigma^2}\right), \tag{10}$$

where P is the transmit power, and the additive white Gaussian noise power at the receivers is denoted by σ^2, and γ_k stands for the channel gain between the UAV and the k-th ground node. The upper-bounding argument originates from the Jensen's inequality. The problem shown in (9) is neither convex nor concave, hence difficult to solve. To solve (9), similar to [21], we propose an iterative algorithm by employing the block-coordinate descent to split up the original problem (9) into two sub-problems of horizontal UAV placement, and altitude optimization. Then the sequential convex programming technique is applied to solve each sub-problem. The algorithm then iterates between two phases to converge to a final solution. Note that, to initialize the UAV position we use the notion of the center of gravity of ground nodes. Moreover, the flying altitude is initialized at $h_{\max}$. The convergence of the algorithm can be established in the same manner provided in [21].

1) Horizontal Optimal Placement: For a given drone's altitude z, the drone position in the horizontal plane can be optimized by solving

$$\max_{x,y} \min_{i\in[1,M]} \frac{1}{N_i}\sum_{k\in G_i} C(\mathbf{v}, \mathbf{u}_k). \tag{11}$$

This problem is not convex and to solve this problem first we introduce a set of auxiliary variables $\mathbb{V} = \{f_k, w_k, l_k, \theta_k\}$. We then reformulate (11) as follows

$$\max_{\mathbb{V},x,y,\mu} \ \mu \tag{12a}$$

$$\text{s.t.} \ \frac{1}{N_i}\sum_{k\in G_i} c_k\left(f_k, w_k, l_k\right) \geq \mu \ , \ i\in[1,M], \tag{12b}$$

$$w_k = \left(\left(z^2 + l_k\right)^{(A-1)\alpha_{\mathrm{LoS}}/2} - B\right)^{-1} \ , \forall k, \tag{12c}$$

$$f_k = \exp\left(-a_k\theta_k + b_k\right) \ , \forall k, \tag{12d}$$

$$l_k = r_k^2 \ , \forall k, \tag{12e}$$

$$\theta_k = \arctan\left(z/\sqrt{l_k}\right) \ , \forall k, \tag{12f}$$

$$f_k, w_k, l_k, \theta_k \geq 0, \forall k, \tag{12g}$$

where

$$c_k\left(f_k, w_k, l_k\right) \triangleq \log_2\left(1 + \left(\frac{1}{w_k(1+f_k)} + B\right)\frac{P\,\beta_{\mathrm{LoS}}}{\sigma^2\left(z^2 + l_k\right)^{\alpha_{\mathrm{NLoS}}/2}}\right). \tag{13}$$

In [21] it is shown that $c_k(f_k, w_k, l_k)$ is convex. Moreover, all the constraints (12c) to (12f) consist of convex functions, although (12) in general is not a convex optimization problem and it can be solved by applying the sequential convex programming technique which solves instead the local linear approximation of the original problem [22]. By using a linear approximation of the original problem, we have a standard convex problem which can be solved by any convex optimization tools like CVX [23]. We omit the detail here due to the limited space, more details can be found in [21].

2) Altitude Optimization : Now we continue to optimize the UAV altitude for a given horizontal UAV position (x, y). The UAV altitude is optimized as follows

$$\max_{z} \min_{i \in [1,M]} \frac{1}{N_i} \sum_{k \in G_i} C(\mathbf{v}, \mathbf{u}_k). \tag{14}$$
$$\text{s.t.} \quad (3b)$$

This problem is not convex and is solved similar to the last section by introducing the same auxiliary variables and then applying the sequential convex programming.

IV. System Design

In this section, we elaborate on the equipment, tools and the autonomous placement software used for designing our experimental platform.

A. UAV Design

Since the experiment involves autonomous placement of the UAV based on the output of the UAV placement algorithm, the interaction between the drone flight controller system and the mesh network is essential. Therefore, we needed a fully customized drone to enable us sending control commands to the drone and reading drone information like instantaneous drone location. For this, we have designed a custom-built drone by considering the required flight time and maximum payload. To build the drone, we have used an off-the-shelf Quad-Rotor carbon body frame with diameter of 65 cm, DJI propulsion system and Pixhawk 2 flight controller which is an open-source flight controller and allows us to manipulate the drone by the output of the autonomous placement algorithm which is based on the information obtained from mesh nodes. Note that, the overall weight of the drone including the communication parts is less then 2 Kg. We use a Futaba T8J radio controller (RC) which is an 8 channel radio controller and works in 2.4 GHz frequency ISM band to control and fly the drone manually (in emergency cases). Different parts of the drone are shown in Fig. 2.

B. Mesh Network

The mesh network comprises $K + 1$ nodes including K ground nodes and the UAV. All nodes are equipped with IEEE 802.11n (Wi-Fi) radio cards. Each node comprises of a MicroTick Wi-Fi card [24] connected with a commodity single board x86 based computer running Ubuntu operating system. The nodes are configured on channel 48 in the 5 GHz band.

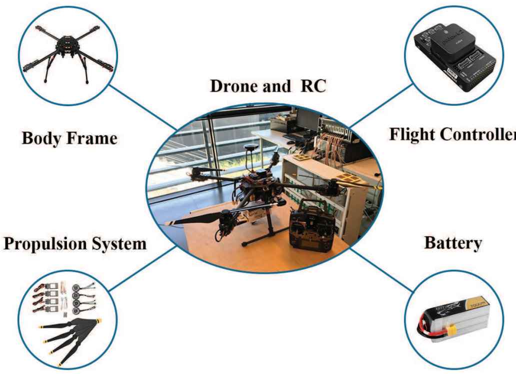


Fig. 2: Custom-built UAV.

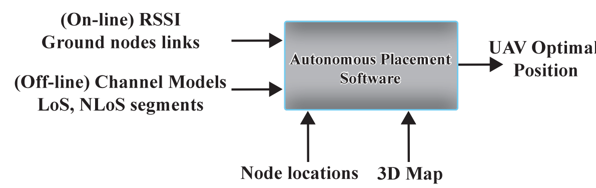


Fig. 3: The block-diagram of the UAV autonomous placement software in a mesh network.

The choice of using 5GHz band for the mesh network was to avoid the interference arising from UAV's radio controller which works in the 2.4GHz ISM band. To implement the mesh network, the optimized link state routing protocol (OLSRD) [25] is used on top of a wireless ad-hoc network established by the nodes. The maximum transmission power of each node is set to 20 dBm.

C. Autonomous Placement Software

The autonomous placement software allows the UAV to navigate to the desired position based on the output of the UAV placement algorithm explained in Section III. Note that this framework is general and it allows us to implement any placement algorithm, not necessarily the one presented in this work. The placement algorithm clusters the ground nodes and computes the optimal UAV position in accordance with the instantaneous location and RSSI of ground nodes, and the 3D map of the surrounding area. Then the optimal position is sent to the UAV's flight controller by the algorithm. The block-diagram of the autonomous placement software is depicted in Fig. 3.

As mentioned in Section III, a critical component of the UAV placement algorithm is the knowledge of radio channel parameters that vary slowly with time such as pathloss or shadowing. These channel parameters can be learned either beforehand in an offline fashion or on the fly by making radio measurements from ground nodes. Our system design is capable of implementing both types of algorithms. The placement algorithm is implanted in an on-board computer along with the OLSRD on the UAV. To obviate the expensive computation and be able to update the UAV optimal position

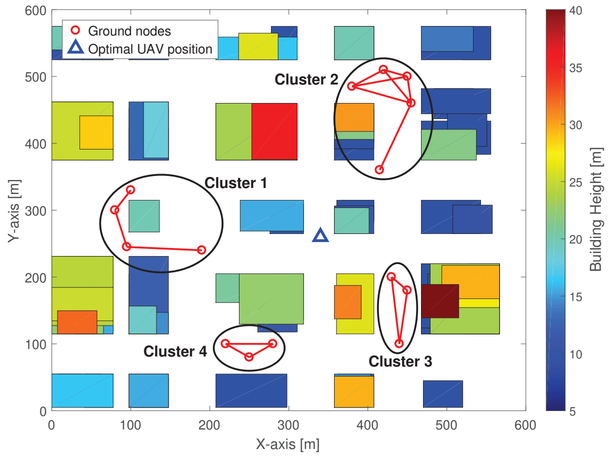


Fig. 4: An example of the optimal UAV placement and ground nodes clustering in a mesh network comprising 15 outdoor ground nodes which are randomly scattered in a city. For the ground node clustering, the threshold value is chosen as $t = -80$ dBm. The optimal UAV altitude is computed as 380 meters.

in a real-time fashion, the channel parameters are learned prior to the experiment in an offline manner and are given to the algorithm.

V. Numerical results

We consider a dense urban Manhattan-like area of size 600×600 square meters, consisting of buildings. The height of the building is Rayleigh distributed within the range of 5 to 40 meters [26]. The propagation parameters are chosen as $\alpha_{\mathrm{LoS}} = 2.5$, $\alpha_{\mathrm{NLoS}} = 3.2$, $\beta_{\mathrm{LoS}} = -30\,\mathrm{dB}$, $\beta_{\mathrm{NLoS}} = -32\,\mathrm{dB}$ according to an urban micro scenario in [27]. To conduct the simulations, the clustering threshold value is chosen as $t = -80$ dBm. The routing protocol is performed by finding a best path between a source and a destination node. To implement the routing algorithm, the achievable throughput of a path between a source node j and a destination node k by hopping through m intermediate nodes can be modeled as

$$C_r(\mathbf{u}_j, \mathbf{u}_k) = \frac{1}{2^m} \min_{i \in [2, m+2]} C_{q_{i-1}, q_i}, \tag{15}$$

where q_i, $i \in [1, m+2]$ is the index of the i-th ground node in the path (i.e. $q_1 = j$, $q_{m+2} = k$), and C_{q_{i-1},q_i} denotes the throughput of the direct link between two consecutive nodes in the path. Note that, we assume $C_{q_{i-1},q_i} = C_{q_i,q_{i-1}}$. The normalization factor 2^m stems from the fact that in a wireless mesh network, every hop between nodes, in a given path, will decrease the bandwidth by half. This happens because wireless links can either transmit or receive at a time. Finally, the best path between a source and a destination node is the one that maximizes (15). In this paper, for the sake of simulation, the best route is found by performing an exhaustive search.

Fig. 4 shows an example of the clustering algorithm for a set of 15 ground nodes which randomly are scattered in the city. The ground nodes are shown by the circles and the edge between each pair of the nodes indicates that the RSSI of that link is greater than or equal to the threshold t. The optimal position of the UAV after clustering ground nodes is indicated by a triangle marker. The optimal altitude is computed as 380 meters.

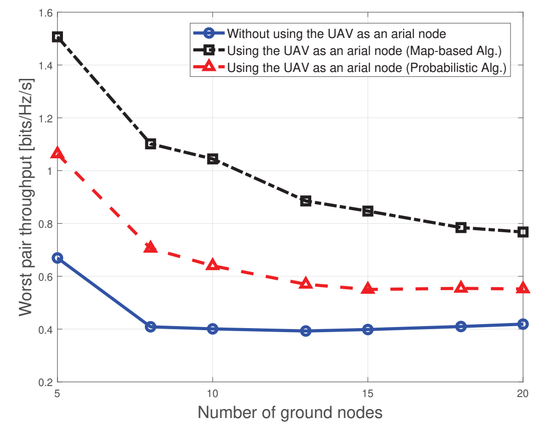


Fig. 5: Achievable throughput between the worst pair of ground nodes in the network vs. increasing the number of ground nodes for different algorithms.

In Fig. 5, the performance of the proposed algorithm is evaluated in a wireless mesh network for a different number of ground nodes in two cases of using the drone as an areal node (black dashed dotted-line marked with squares) and without using the drone (blue solid-line marked with circles). The vertical axis represents the achievable throughput between the worst pair of nodes in the network which is defined as follows

$$C_{\min} = \min_{j,k \in [1,K], j \neq k} C_r^*(\mathbf{u}_j, \mathbf{u}_k), \tag{16}$$

where $C_r^*(\mathbf{u}_j, \mathbf{u}_k)$ is the maximum achievable throughput between two ground nodes j, k by following the best route between them. We also compare our algorithm with a generalized version of the method introduced in [28] which can be used for UAV placement in wireless network (not necessarily wireless mesh network). We call this method probabilistic approach which does not exploit the 3D map information. Then, an optimal position for the UAV is found similar to the algorithm proposed in Section III-C, by considering each ground node as one cluster (i.e. K clusters), with the difference that for a link between the drone located at $\mathbf{v}$ and the k-th ground node, the LoS probability is given by

$$\rho_k = \frac{1}{1 + \exp\left(-a\,\theta_k + b\right)}, \tag{17}$$

where parameters $\{a, b\}$ are computed according to [26] and based on the characteristics of the 3D map. In other words, we use a global LoS probability model (instead of a local LoS probability). It is clear that, the map-based algorithm proposed

Parameters	LoS	NLoS
α	2.38	3.083
ß	-40.84	-45.33

TABLE I: Learned pathloss parameters from measurements.

in this paper outperforms other approaches.

VI. Experiment Results

We have carried out our experiments in EURECOM campus. We established a Wi-Fi mesh network comprises 4 outdoor ground nodes and a UAV. The ground nodes and the UAV are equipped with MicroTick Wi-Fi card, which is configured on channel 48 in the 5 GHz band, with two vertically polarized dipole antennas. The links between the ground nodes may be obstructed by the buildings depending on the nodes positions. The threshold value regarding the ground node clustering algorithm is selected as $t = -70$ dBm to guarantee a good connection between nodes within each cluster. The experimental setup is shown in Fig. 6 and Fig. 7. In Fig. 7-a the UAV position is obtained using the placement algorithm explained in Section III. Prior to applying the placement algorithm, it is required to learn the wireless channel parameters based on the measurements that are collected in the environment where the experiment is conducted.

Since the pathloss parameters highly depend on the LoS or NLoS nature of the channel, we obtain measurements in both segments. The corresponding best-fit path loss parameters are given in Table I. Note that the channel model presented here are valid for our setup and cannot be generalized to any scenarios.

In Fig. 6 we evaluate the network performance when no UAV is included in the mesh network. Fig. 6-b shows the achievable throughput between each pair of ground nodes. The ground nodes are depicted by the circles labeled with the corresponding node number, and the edge connecting the nodes indicates the worst link throughput between that pair using the color code (the more green, the better throughput). The label on each edge represents the minimum throughput of the bidirectional link between each pair. Note that the maximum achievable throughput in the mesh network is limited to 20 Mbps. As it is shown in Fig. 6-b, node 1 can communicate perfectly with node 2 while the throughput between node 1 and ground nodes 3 and 4 are poor because of the building in between.

In Fig. 7, the drone is added to the network as the fifth node. The learned parameters and the 3D map of the environments are then fed to the placement algorithm. In Fig. 7-a the output of the placement algorithm is shown. First, the ground nodes are clustered into two groups based on the instantaneous RSSI of the links between each ground nodes. Having clustered the ground nodes, the algorithm seeks to find the optimal position of the UAV by considering the 3D map and the ground nodes' locations to favor the propagation of the radio signals between

(a) (b)

Fig. 6: (a) An illustration of the mesh network setup with 4 outdoor ground nodes. (b) The network performance and the throughput (in the scale of Mbps) between each pair of ground nodes.

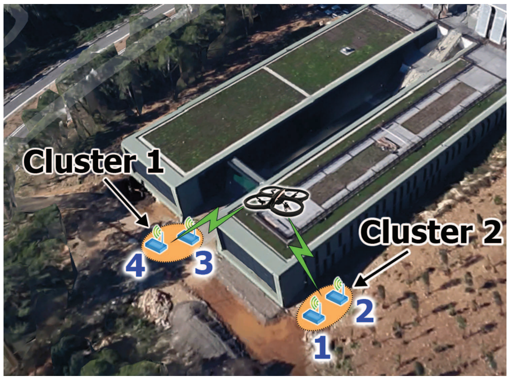
the UAV and the members of all clusters. The achievable throughput of the links between each pair of the ground nodes, when the UAV places itself in the optimal position, is depicted in Fig. 7-b. Is it clear that the overall network performance is improved by placing the drone in the optimal position since the ground nodes from different clusters can communicate together via the UAV.

Moreover, in [29], a video recording of the experiment in EURECOM campus is also captured, illustrating both the throughput advantage, and real-time self-placement and tracking capabilities of the proposed approach when ground nodes move.

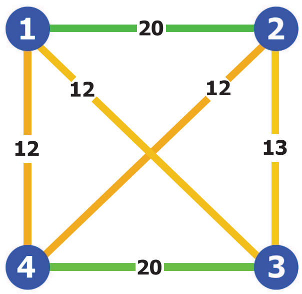
VII. Conclusion and Future Work

In this paper, we have demonstrated the performance gains obtained from intelligent UAV positioning in a wireless mesh network. The proposed placement algorithm is built on the prior knowledge of the 3D map of the environment, the ground node location information, and the underlying wireless channel parameters. We have also developed an experimental framework that allowed us to place the UAV autonomously in real-time according to the output of the placement algorithm in an outdoor experiment.

While experimenting with Wi-Fi modules that are mounted on the UAV, we have faced some interesting issues that need further investigation.



(a)



(b)

Fig. 7: (a) The output of the mesh placement algorithm in an outdoor Wi-Fi mesh network including 4 ground nodes and a UAV. (b) The network performance and the throughput evaluation (in the scale of Mbps) by employing the UAV as a flying node.

- When the UAV is configured as an access point (Wi-Fi AP mode), a point-point (ground nodes to the UAV) link throughput is around 150Mbps while the UAV propellers are not running. However, the throughput drops to 70-80 Mbps when propellers are running, even at lower speeds. This effect is maybe due to electromagnetic field interference caused by the motors or some sort of multi-path effect created by the rotating propellers. Although, in an experiment this throughput degradation was not observed when the motors were running by removing propellers. Moreover, this effect is only visible at higher throughputs. When using with mesh (Wi-Fi ad-hoc network) this effect was not noticeable as the maximum throughput was 20 Mbps. So, this phenomenon of rotating propellers is probably only affecting the higher modulation and higher coding rates, which needs to be verified with data logs from PHY/MAC layer and needs further experimentation.

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