UAV-relay Placement with Unknown User Locations and Channel Parameters

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***Abstract*—This work investigates the problem of optimal placement of an UAV that provides communication services by acting as a flying wireless relay between a fixed base station (BS) and ground users. The proposed approach builds on the knowledge of the terrain topology where the network is deployed and aims at finding the optimal position of the UAV that maximizes the throughput in the max-min sense. Different from prior works, we do not assume any prior knowledge on user locations and the underlying wireless channel pathloss parameters. We first jointly estimate the user location and the pathloss parameters from the measurements collected by the UAV, and then use them to find the optimal relay position. When it comes to the optimal placement, an iterative algorithm is provided which iterates between the planar UAV placement and altitude optimization by exploiting the 3D city map information.**

I. Introduction

The usage of drones, a.k.a unmanned aerial vehicles (UAVs) as wireless relays to improve the coverage or capacity gaps in a wireless network has gained significant attention recently [1]–[5]. With the inherent advantage in terms of mobility, such UAV relays can be rapidly deployed to provide coverage in disaster recovery scenarios, temporary cultural, sporting events, etc. The UAV-relay placement problem consists of finding the optimal UAV position that maximizes the performance of the wireless network in which it is deployed [2]–[5].

When using model-based approaches to solve UAV-relay placement problems, prior works assume that the pathloss model parameters and user locations are perfectly known, hence the channel gains (UAV-user or UAV-BS) are merely an explicit function of the UAV's position [2]–[4]. However, in practice, this information is not available, and the pathloss model parameters are highly depend on the scenario and surroundings where the network is deployed (e.g. urban, rural, etc.). Therefore, the UAV needs to first learn the channel propagation parameters and user locations which are then used in finding the optimal UAV-relay position.

Another crucial factor in optimal UAV placement is the prediction of line-of-sight (LoS) availability of the UAV-user link. Two approaches were taken in the literature to find the LoS availability of the UAV-user link: One is based on generalized models [5], [6] while the second one relies on the maps (3D or Radio maps) [3], [4], [7]. The former category relies on a statistical model predicting LoS availability as a function of e.g. UAV height and distance to the user in order to place the UAV. While being analytically highly tractable and lending themselves to system analysis, UAV placement based on the probabilistic LoS models cannot offer performance guarantees on a specific deployment scenario. In contrast, map-based placement exploits detailed information pertaining to the terrain in order to optimally place the flying relay. The UAV placement based on the raw map data without further processing often leads to complex search problems. In [3] a UAV-relay placement problem in a single user scenario is considered by utilizing the radio map. The complexity arising from using raw map is reduced by exploiting the so-called LoS irreversibility property in cities composed of well-behaved building shapes [3]. Further more, when dealing with the 3D map data, [7] introduces a *map compression* approach that extracts the local LoS probabilities from the 3D map of the environment.

In this paper, a 3D map based approach is introduced to optimally place an UAV-relay, without any prior knowledge on the pathloss parameters and user locations. Specifically, our contributions are as follows:

- We formulate and solve a joint user location and pathloss model parameter estimation problem based on the radio signal strength measurements collected by the UAV. For this, we consider a segmented pathloss model where the shadowing distribution and pathloss parameters are different in LoS and non-line-of-sight (NLoS) propagation conditions [8]–[10].
- We derive an iterative algorithm to address the UAV-relay placement problem which leverages the 3D map of the environment via the map compression approach [7].

II. System Model

We consider a scenario where an UAV is acting as a relay between a fixed base station and users in an urban area consists of a number of city buildings. There are K static ground level users randomly scattered over the city, and $\mathbf{u}_k = [x_k, y_k]^{\mathrm{T}} \in \mathbb{R}^2$, $k \in [1, K]$ denotes the k-th user's location. User locations are unknown and need to be estimated. We assume that the 3D map of the city is known. The UAV/drone position is denoted by $\mathbf{v} = [x, y, z]^{\mathrm{T}} \in \mathbb{R}^3$, where z represents the altitude of the drone. We assume that the drone is equipped with a GPS receiver, hence $\mathbf{v}$ is known. The location of the BS is denoted by $\mathbf{x}_b = [x_b, y_b, z_b]^{\mathrm{T}} \in \mathbb{R}^3$, which is also known.

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

A. Channel Model

Classically, the channel gain between two radio nodes which are separated by distance d meters is modeled as [9], [11]

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

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 $s \in \{\text{LoS}, \text{NLoS}\}$ emphasizes the strong dependence of the propagation parameters on LoS or 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

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

where $g_s = 10 \log_{10} \gamma_s$, $\text{ß}_s = 10 \log_{10} \beta_s, \varphi(d) = 10 \log_{10}(d)$, $\eta_s = 10 \log_{10} \xi_s$, and η_s is modeled as a Gaussian random variable with $\mathcal{N}(0, \sigma_s^2)$. In this paper we assume that the UAV flies at an altitude such that it is always in LoS with respect to the BS.

III. User localization and channel learning

In this section, our goal is to jointly estimate user locations and pathloss model parameters from the channel gain measurements collected by the UAV from users. The problem of joint localization and pathloss parameter estimation has been addressed in [12] in a single segment propagation model that does not differentiate between LoS and NLoS scenarios. This work is reminiscent to [13] where the authors use Expectation-Maximization (EM) algorithm to localize the users using segmented propagation model, however, we provide a different solution. The measurement collection process and then the estimation problem are described next.

A. Measurement Collection

During the measurement phase, the UAV flies over N different locations, and in each location it collects the radio measurements form all K users. Let $g_{n,k}$ represent the measurement obtained from the k-th user when the UAV is at location n. By denoting $\theta_s = [\alpha_s, \text{ß}_s], s \in \{\text{LoS}, \text{NLoS}\}$ and using (2), $g_{n,k}$ is modeled as

$$g_{n,k} = \begin{cases} p_{n,k}(\theta_{\text{LoS}}, \mathbf{u_k}) + \eta_{n,k,\text{LoS}} & \text{if LoS} \\ p_{n,k}(\theta_{\text{NLoS}}, \mathbf{u_k}) + \eta_{n,k,\text{NLoS}}, & \text{if NLoS} \end{cases} \tag{3}$$

where

$$p_{n,k}(\theta_s, \mathbf{u_k}) = \text{ß}_s - \alpha_s \varphi(d_{n,k}),$$

$d_{n,k}$ being the distance between k-th user and the UAV in the n-th location, and $\eta_{n,k,s}$ represents the shadowing component. The mean squared error (MSE) of estimator is given by

$$\begin{aligned} \frac{1}{NK} \sum_{k=1}^{K} \sum_{n=1}^{N} \omega_{n,k} \left\| g_{n,k} - p_{n,k}(\theta_{\text{LoS}}, \mathbf{u_k}) \right\|^2 + \\ (1 - \omega_{n,k}) \left|| g_{n,k} - p_{n,k}(\theta_{\text{NLoS}}, \mathbf{u_k}) \right\|^2, \end{aligned} \tag{4}$$

where $\omega_{n,k} \in \{0, 1\}$ is a classifier binary variable (yet is unknown) which indicates if the measurement falls into LoS or NLoS category.

B. Estimation

The optimal channel parameters and user locations that minimize the MSE in (4) can be formulated as

$$\min_{\omega_{n,k}, \theta_s, \mathbf{u_k}} (4) \tag{5}$$

As the estimation error comprises the classifier binary variables $\omega_{n,k}$ and moreover $p_{n,k}(\theta_s, \mathbf{u_k})$ is a non-linear function of parameters $\mathbf{u_k}$, in general it is difficult to solve (5) which is a simultaneous classification and estimation problem. To tackle this problem, we introduce an iterative algorithm where we split the original problem into two sub-problems, and iterate between them.

1) Classification: Prior to the user localization and learning the pathloss parameters from the collected measurements, each measurement needs to be classified into LoS or NLoS segment. For this let's assume the channel parameters $\theta_s, \mathbf{u_k}$ are fixed, then the collected measurements are classified by solving

$$\min_{\omega_{n,k}} (4)$$

Since, the classifier variable $\omega_{n,k}$ only takes the binary values $\{0, 1\}$, then the optimal solution is given by

$$\omega_{n,k} = \begin{cases} 1 & |g_{n,k} - p_{n,k}(\theta_{\text{LoS}}, \mathbf{u_k})| \le |g_{n,k} - p_{n,k}(\theta_{\text{NLoS}}, \mathbf{u_k})| \\ 0 & \text{otherwise} \end{cases}$$

where $|.|$ denotes the absolute value function.

2) Learning and localization: Having classified the measurements i.e, finding $\omega_{n,k}$, we proceed to jointly estimate the pathloss parameters in each segment and localize the ground users by solving

$$\min_{\theta_s, \mathbf{u_k}} (4) \tag{6}$$

This is a non-linear least squares problem, since $p_{n,k}(\theta_s, \mathbf{u_k})$ is a non-linear function of the user's location $\mathbf{u}_k, k \in [1, K]$. To solve (6), we use Gauss-Newton method which is a standard algorithm to solve this sort of problems. In Gauss-Newton algorithm the original problem is iteratively solved by performing a local least squares (LS) estimation [14].

IV. Optimal UAV Placement

Once the user locations and the pathloss parameters are estimated, we can find the optimal UAV position in a downlink relay scenario. For the sake of simplicity, in the UAV placement we assume that the perfect channel model parameters and the user positions are used, while the impact of imperfect estimation is investigated in Section V.

A. LoS Probability Model Using Map Compression

To efficiently exploit the 3D city map while reducing the complexity of the map-based placement approaches, we employ the *(statistical) map compression* approach [7]. The map compression approach relies on converting map data to build a reliable user location dependent LoS probability model [7]. For a link between a drone located at altitude z and the k-th user, the LoS probability is modeled by:

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

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 user located at $\mathbf{u}_k$, and $\{a_k, b_k\}$ denote the model coefficients. The model coefficients are learned (e.g. logistic regression method) by using a training data set formed by a set of tentative UAV locations around the k-th user along with the true LoS status obtained from the 3D map.

Using (7), the average channel gain between the k-th user 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 $B = \frac{\beta_{\mathrm{NLoS}}}{\beta_{\mathrm{LoS}}}$, $A = \frac{\alpha_{\mathrm{NLoS}}}{\alpha_{\mathrm{LoS}}} \geq 1$, $\gamma_{s,k}$ denotes 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 user and the drone. Note that, in order to keep he notation simple, the average random shadowing is assumed absorbed into β_s in (8) i.e., $\beta_s \triangleq \beta_s exp(\sigma_s^2/2)$.

B. Communication Model

The UAV serves only one user among the K users at a time by acting as a relay. We assume that a decode-and-forward type of relay protocol is used. If the UAV is serving k-th user, the achievable throughput on the UAV-user link can be upper-bounded by

$$C_k^u = \log_2\left(1 + \frac{P_d\,\mathrm{E}\left[\gamma_k\right]}{\sigma^2}\right). \tag{9}$$

The throughput of the BS-UAV link is upper-bounded by

$$C_b = \log_2\left(1 + \frac{P_b\,\mathrm{E}[\gamma_b]}{\sigma^2}\right), \tag{10}$$

where P_d, P_b are the transmit powers of the UAV and base station, respectively. The additive white Gaussian noise power at the receivers is denoted by σ^2. γ_k stands for the channel gain between the UAV and k-th user, and γ_b is the BS-UAV channel gain. $\mathrm{E}\left[\gamma_b\right]$ is computed by averaging over the LoS component as the UAV is always connected to the BS with a LoS link at all times. The upper-bounding argument originates from the Jensen's inequality.

Since we assume decode-and-forward type of relaying, using the above bounds, the achievable throughput for the k-th user can be approximated as

$$C_k = \min(C_k^u, C_b). \tag{11}$$

C. UAV Placement Optimization

Since only one user can be served by the UAV at any time, in order to provide a performance guarantee to the connected user, we aim to find the UAV position which maximizes the minimum achievable rate of all the users. Using the approximation in (11), the placement problem can be formulated as

$$\max_{\mathbf{v}} \min_{k\in[1,K]} C_k \tag{12a}$$

$$\text{s.t. } h_{min} \leq z \leq h_{max}, \tag{12b}$$

where (12b) 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 altitude h_{max}. The problem shown in (12) is non-convex, hence hard to solve. To solve (12a), we propose an iterative algorithm by employing the block-coordinate descent to split it up into two sub-problems and then we utilize the sequential convex programming technique to solve each sub-problem. The algorithm then iterates between two phases to converge to a final solution [7]. Note that, we use the notion of the center of gravity of ground users to initialize the drone position. Moreover, the flying altitude is initialized at h_{max}. The convergence of the algorithm can be established along similar lines to the one provided in [7].

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

$$\max_{x,y} \min_{k\in[1,K]} C_k. \tag{13}$$

This problem is not convex and to solve this problem first we introduce some auxiliary variables f_k, w_k, l_k, and θ_k. We then rewrite (13) as follows

$$\max_{\mathbb{V},x,y,\mu} \mu \tag{14a}$$

$$\text{s.t. } c_k\left(f_k, w_k, l_k\right) \geq \mu\ , \forall k, \tag{14b}$$

$$c_{\mathrm{b}}\ \left(l_{\mathrm{b}}\right) \geq \mu \tag{14c}$$

$$w_k = \left(\left(z^2 + l_k\right)^{(A-1)\alpha_{\mathrm{LoS}}/2} - B\right)^{-1}\ , \forall k, \tag{14d}$$

$$f_k = \exp\left(-a_k\theta_k + b_k\right)\ , \forall k, \tag{14e}$$

$$l_k = r_k^2\ , \forall k, \tag{14f}$$

$$l_{\mathrm{b}} = (x - x_b)^2 + (y - y_b)^2 \tag{14g}$$

$$\theta_k = \arctan\left(z/\sqrt{l_k}\right)\ , \forall k \tag{14h}$$

$$f_k, w_k, l_k, \theta_k, l_{\mathrm{b}} \geq 0\ , \forall k, \tag{14i}$$

where

$$c_k\left(f_k, w_k, l_k\right) \triangleq$$

$$\log_2\left(1 + \left(\frac{1}{w_k(1+f_k)} + B\right)\frac{P_d\,\beta_{\mathrm{LoS}}}{\sigma^2\left(z^2 + l_k\right)^{\alpha_{\mathrm{NLoS}}/2}}\right), \tag{15}$$

and

$$c_{\mathrm{b}}\ \left(l_{\mathrm{b}}\right) = \log_2\left(1 + \frac{P_b\,\beta_{\mathrm{LoS}}}{\sigma^2\left(\left(z - z_{\mathrm{b}}\right)^2 + l_{\mathrm{b}}\right)^{\alpha_{\mathrm{LoS}}/2}}\right).$$

It can be shown that $c_k\left(f_k, w_k, l_k\right), c_{\mathrm{b}}\ \left(l_{\mathrm{b}}\right)$ are convex and

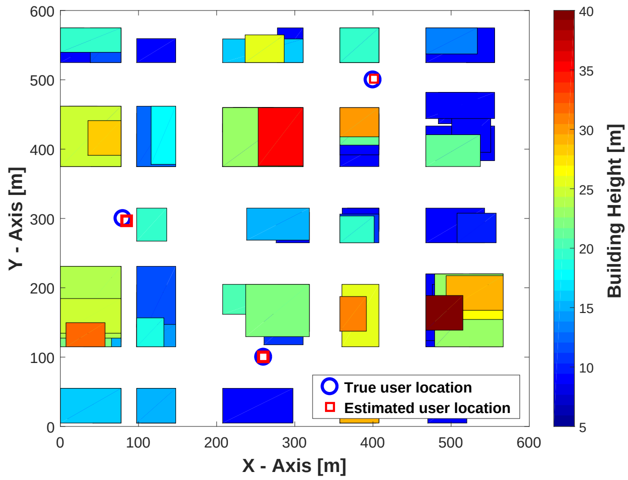


Fig. 1: Top view of the city, true users location (circles), and the estimated users' positions (squares).

also all the constraints (14d) to (14h) comprise convex functions, however (14) in general is not a convex optimization problem and it can be solved similar to the approach introduced in [7] by applying the sequential convex programming technique [15]. Due to the space limitation, we refer the reader to [7] for more details.

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

$$\max_{z} \min_{k\in[1,K]} C_k. \quad \text{s.t. (12b)} \tag{16}$$

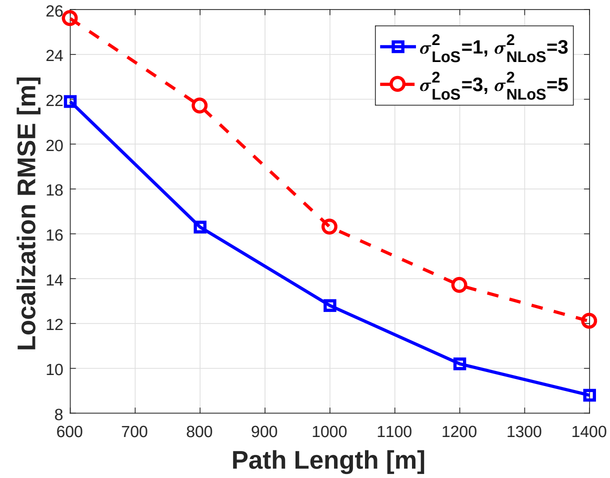
This problem is not convex and is solved in a similar manner as the last section by introducing same auxiliary variables and then applying the sequential convex programming [7].

V. Numerical Results

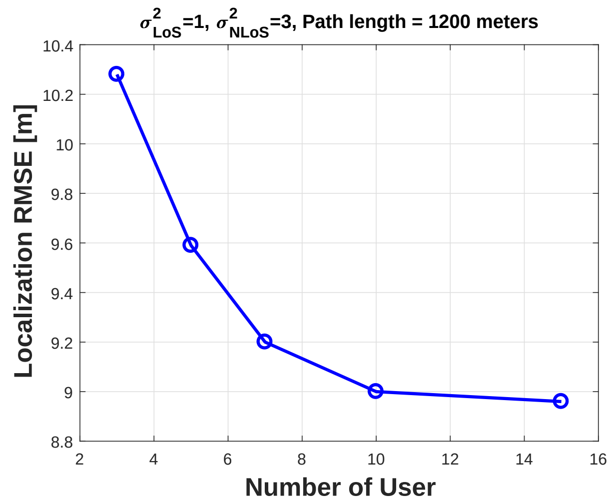
We consider a dense urban Manhattan-like area of size 600×600 square meters, consisting of a regular street grid and buildings. The buildings' heights are in the range of 5 to 40 meters and are distributed according to the Rayleigh distribution [5]. True propagation parameters (in dB) for the UAV-user link are selected as $\alpha_{\text{LoS}} = 2.27$, $\alpha_{\text{NLoS}} = 3.64$, $\beta_{\text{LoS}} = -30\,\text{dB}$, $\beta_{\text{NLoS}} = -40\,\text{dB}$ and the BS-UAV channel parameters are chosen same as the LoS link according to an urban micro scenario in [16]. The transmission power for the UAV is chosen as $P_d = 30$ dBm, and the BS's transmission power is $P_b = 36$ dBm. The noise power at the receiver is -80 dBm. The base station is located at $\mathbf{x}_b = (0, 0, 50)$ meters.

An illustration of the user localization by considering $K = 3$ ground users is presented In Fig. 1. To estimate the user locations and the pathloss parameters, the UAV follows an arbitrary trajectory of length 1200 meters, and collects measurements from all ground users every 5 meters. The variances of the shadowing component in LoS and NLoS scenarios are $\sigma^2_{\text{LoS}} = 1$ and $\sigma^2_{\text{NLoS}} = 3$, respectively. It can be seen that the proposed algorithm can localize the users with high accuracy.

In Fig. 2, we evaluate the performance of the users localization in terms of the root mean square error (RMSE). In Fig. 2a, and Fig.2b the localization error as a function of the UAV trajectory length for collecting measurements, and the number of ground users are shown, respectively. It can be seen that by increasing both path length and the number of ground nodes the performance improves since in both cases the number of collected measurements increases. Similarly, the performance of the estimated pathloss parameters versus increasing the UAV trajectory length is illustrated in Fig. 3 in terms of normalized root mean square error (NRMSE). Note that the estimation error pertaining to the NLoS segment is greater than



(a)



(b)

Fig. 2: (a) User localization error versus increasing the UAV path length for collecting measurements from ground users. (b) User localization improvement by increasing the number of ground users.

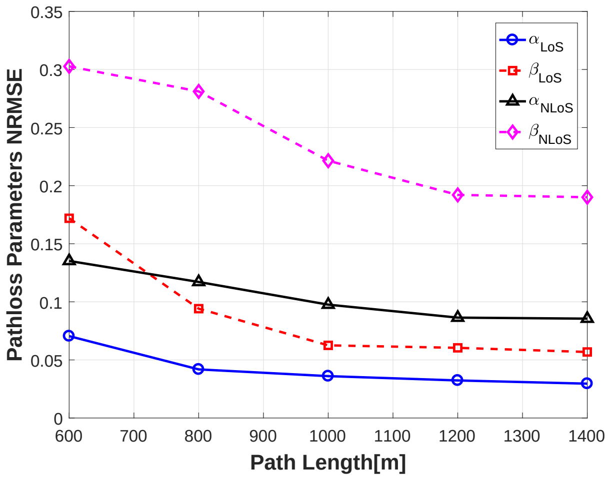


Fig. 3: Channel parameters estimation error versus increasing the UAV path length for collecting measurements from ground users.

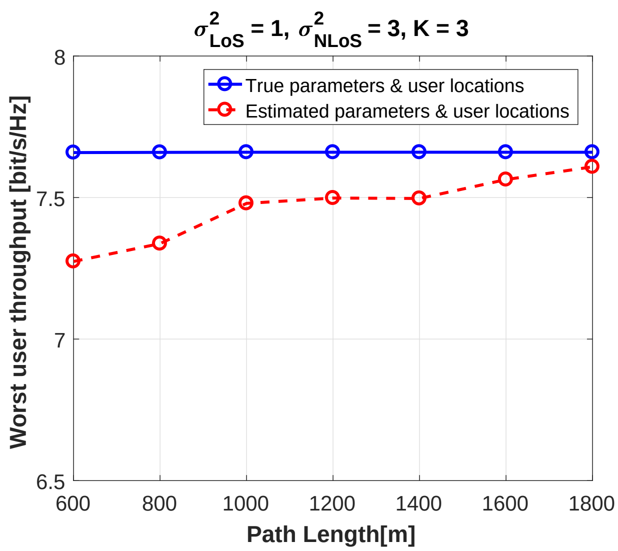


Fig. 4: Impact of the estimated users' locations and the pathloss parameters on the performance of the UAV-relay placement Algorithm.

that of LoS which stems from the higher shadowing fluctuation in the NLoS measurements.

Finally, in Fig. 4 we investigate the impact of the imperfect user location and pathloss parameters estimation in finding the UAV-relay optimal position by considering fixed $K = 3$ users. It can be seen that by improving the estimation of the user location and also channel parameters, resulting from enlarging the UAV trajectory to collect measurements, we can get the performance closer to the ideal case.

VI. Conclusion

This paper studied the problem of optimal placement of an UAV-relay in order to maximize the minimum quality of service provided to the ground users. The proposed approach does not require any prior knowledge on the user locations and the underlying wireless channel parameters. To find the optimal UAV position, we have presented an iterative algorithm that leverages the knowledge of the 3D city map via map-compression method and uses the block coordinate descent and sequential convex programming techniques.

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