Clustering Based UAV Base Station Positioning for Enhanced Network Capacity

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Abstract—Unmanned aerial vehicles (UAVs) are expected to be deployed in a variety of applications in future mobile networks due to several advantages they bring over the deployment of ground base stations. However, despite the recent interest in UAVs in mobile networks, some issues still remain, such as determining the placement of multiple UAVs in different scenarios. In this paper we propose a solution to determine the optimal 3D position of multiple UAVs in a capacity enhancement use-case, or in other words, when the ground network cannot cope with the user traffic demand. For this scenario, real data from the city of Milan, provided by Telecom Italia is utilized to simulate an event. Based on that, a solution based on k-means, a machine learning technique, to position multiple UAVs is proposed and it is compared with two other baseline methods. Results demonstrate that the proposed solution is able to significantly outperform other methods in terms of users covered and quality of service.

Index Terms—UAV, Clustering, Enhanced Mobile Broadband, Self Organizing Networks.

I. Introduction

Unmanned aerial vehicles (UAVs) are expected to play a fundamental role in future mobile networks, due to their mobility and adaptability, which allow them to provide network services on demand [1], [2]. Thus, UAVs are envisioned to be deployed as aerial base stations (BSs) in order to provide a wide range of services in several situations, such as in quickly restoring service in emergencies, providing connectivity to remote areas, cache in the air and capacity enhancement, to name a few [1]–[5].

In particular, in the realm of capacity enhancement, UAV BSs can be utilized as complementary solutions to ground networks, when temporary or big events happen, such as open markets, fairs or music concerts [6].. In such cases, the capacity offered by the ground network might be insufficient, leading many users to be in outage. Thus, UAVs can be a vital solution to this mobile networks use-case. However, despite the recent popularity of UAVs and all of these potential applications, integrating UAVs in mobile networks is still a challenging topic [1]. In this context, several issues still remain, such as determining the optimal deployment location of multiple UAVs, designing their optimal trajectory, minimizing the interference between aerial and ground networks, handling resource allocation, handover and backhaul of UAVs [1], [7].

In terms of UAV positioning, several recent works have proposed alternatives for tackling the issue. In [5] the authors optimize the number and position of multiple UAV BSs in the presence of a ground network in order to achieve a particular quality of service (QoS) target. In contrast, in [8], the authors develop a mathematical solution to find the optimal position of a single UAV in order to minimize its energy consumption. Sun et al., in [9] propose two different methods to position multiple UAV BSs and achieve user coverage maximization, one based on a mathematical approach and another based on k-means. However, the solutions proposed assume a very simple network scenario and also that the UAVs cannot have overlapping coverage regions, in order to limit inter-UAV interference. On the other hand, other approaches utilize machine learning methods to position multiple UAVs. In [10], for example, the authors utilize reinforcement learning to position a single UAV in a scenario where the ground network is operable in order to enhance the QoS of the network. Similarly, [2] also proposes a reinforcement learning approach to solve the positioning problem of UAV BSs. This time, however, a multiple UAV solution is proposed and the authors consider an emergency scenario, in which the previous ground network was totally destroyed. Lastly, [11] proposes a Gaussian mixture model to determine the optimal deployment of multiple UAVs considering a minimum power consumption.

However, as it can be seen in the literature, solutions such as [5], [8], [9] rely on a mathematical approach, which, in general, work in an offline manner, which can be quite limiting [12]. On the other hand, other approaches utilize machine learning methods, such as [2], [10], [11], however, these solutions require a lot of complexity and memory, which hinders the effect of these solutions.

As such, in this paper we propose a low complexity solution to determine the optimal 3D placement of multiple UAVs in a scenario of network capacity enhancement, such as an event happening in an urban area, in what is known as a pop-up network. In order to tackle this problem, a two-step solution is proposed, in which the 3D placement problem is divided into two parts. First,

This work was supported by EPSRC Global Challenges Research Fund the DARE Project: Grant EP/P028764/1, and by the Republic of Turkey Ministry of National Education: Grant MoNE-1416/YLSY.

we propose the utilization of k-means clustering to find the optimal 2D placement of multiple UAVs. After that, the optimal heights of the aerial BSs are found such that each UAV can cover all users in its cluster. In addition, since the proposed solution relies only on data, rather than specific constraints, and also because the algorithm is capable of learning in an online manner, the proposed method is applicable in several different scenarios, such as in emergency situations, for example.

Based on that, a simulation scenario is built, in which an urban area is considered and user traffic demands are generated. To simulate real network conditions, real traffic data provided by Telecom Italia, for the city of Milan, Italy is utilized [13]. It is assumed that the original ground network can cover part of the demand, but the additional capacity needs to be provided by the UAVs. The proposed solution is compared with other two baseline methods, which consist of deploying the UAVs in a symmetric and in a uniformly random manner. Results show that the proposed method is more robust and capable optimizing online the 3D position of multiple UAVs, outperforming the other baselines in terms of users covered.

The remainder of this paper is as follows. Section II presents the system model, Section III introduces the proposed solution, Section IV shows the simulation results, while Section V concludes the paper.

II. System Model

A. Environment

In this work, we consider an urban scenario with a fixed terrestrial infrastructure which provides cellular connectivity. Due to an increase demand in capacity, the network is strained (overloaded) and therefore the quality of service (QoS) experienced by its users is degraded.

We propose a strategy for mitigating this degradation by deploying UAVs equipped with small cells (SCs), such that additional capacity can be offered.

B. UAV Small Cell

1) Radio access network (RAN): The UAV is carrying a SC with a directional antenna, and therefore it has a coverage footprint [2]. This is illustrated in Fig. 1, where θ is the directivity angle, h_{d} is the UAV height and R is the radius of coverage.

The SINR at the user equipment (UE) is obtained using the same model as in [14], which considers free space path loss between the user and the UAV plus an additional factor which depends on whether or not there is line of sight (LOS) in the link between the UE and the UAV. Following [14], $L_{i,j}$, the path loss in dB, for the link between user i and UAV j is obtained as [2]

$$L_{i,j} = 20\log_{10}\left(\frac{4\pi f_{\mathrm{c}} d_{i,j}}{c}\right) + \xi, \tag{1}$$

where f_{c} is the carrier frequency, $d_{i,j}$ is the link distance, c is the light speed and ξ is a LOS dependent loss.

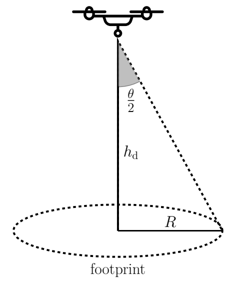

Fig. 1. Directivity angle of the SC carried by the UAV [2].

Next, the SINR for the link, $\gamma_{i,j}$, is obtained via [2]

$$\gamma_{i,j} = \frac{P_{i,j}}{N + \sum\limits_{k=1,k\neq j}^{n_{\mathrm{d}}} P_{i,k}}, \tag{2}$$

where N is the additive white Gaussian noise (AWGN) power and

$$P_{i,j} = P_{\mathrm{t},j} - L_{i,j} \tag{3}$$

is the received signal strength at user i, where $P_{\mathrm{t},j}$ is the transmit power of UAV j[1].

Furthermore, we measure the throughput using Shannon's capacity formula, as in [2], such that the throughput for the link in question is determined via [15]

$$T_{i,j} = B\log_2(1+\gamma_{i,j}), \tag{4}$$

where B is the communication bandwidth.

Moreover, since the BS carried by the UAV is compliant with cellular network standards, it utilizes orthogonal frequency-division multiplex (OFDM) for scheduling RAN resources, and therefore it has a limited number of resource blocks (RBs) to provide connectivity to users.

2) Backhaul: The backhaul connectivity for the UAV SCs is essential for the proper operation of the proposed solution to function properly. With that in mind, we propose that this should be done via a microwave link between the UAVs and the terrestrial BSs. In order to keep the interference to a minimum, this connection would be in the form of an out of band backhaul [2], thus requiring an additional spectrum, and leveraging OFDM to avoid interference between the connectivity of multiple UAVs.

C. User Allocation

User allocation is performed by the users ranking the available BSs by received SINR and choosing the one which provides the highest value. An UE is allocated to its highest ranked BS that has available RAN resources and which can provide a minimum signal level[2]. If there is no BS which meets the criteria, the user is not allocated and is considered out of coverage (in outage).

[1]Note that all the powers are measured in dB.

[2]In our simulations, we consider that this minimum signal strength is 3 dB below the required by the user.

III. Proposed Solution

With this scenario in mind, we propose a strategy to find a position to deploy the UAVs in order to provide the necessary enhanced capacity in the crowded scenario.

First, N_{UAV}, the number of UAVs to be deployed, must be determined. We propose to find it by computing the necessary increase in capacity and providing that capacity with the UAVs, such that

$$N_{\mathrm{UAV}} = \frac{T_{\mathrm{D}} - T_{\mathrm{E}}}{T_{\mathrm{UAV}}}, \tag{5}$$

where T_{D} is the demanded capacity by the users, T_{E} is the existing network capacity, and T_{UAV} is the throughput that each UAV can provide, in terms of RAN.

Next, our solution consists of first finding the best (x, y) position to deploy the UAVs using unsupervised learning and then determining the altitude for the UAVs that provides the best QoS both in terms of throughput as well as number of users served. The first task is accomplished by obtaining the position of the users using a localization technique, such as the one presented in [16], and then performing k-means clustering using the users' (x, y) position as features in order to determine cluster centers. Then, the UAVs are positioned at the cluster centers and their altitude is determined such that QoS metrics are optimized. From Fig. 1, we can easily determine R, the footprint coverage radius, as a function of the flight altitude and the antenna directivity, such that

$$R = h_{\mathrm{d}} \tan\left(\frac{\theta}{2}\right). \tag{6}$$

Due to the nature of the UAV base station with the well defined footprint, it is possible to regulate the UAV altitude depending on the desired area to be served. Moreover, due to the expensive nature of spectrum licenses, we assume that all the UAVs share the same spectrum, thus causing interference on each other. Thus, interference and coverage area create a trade-off in terms of altitude. In other words, the higher an UAV is positioned the greater its footprint, however at the same time more interference is generated on neighboring UAVs. This can be viewed as an overlap in coverage footprints.

In order to study this trade-off effectively taking into account the user distribution, we introduce $\alpha \in [0, 1)$, a parameter that can regulate the amount of footprint overlap. Therefore, the flight altitude of the UAV is obtained as a function of α and can be tuned online according to the QoS performance, such that

$$h_{\mathrm{d}} = 2\alpha R_{\mathrm{x}} / \tan\left(\frac{\theta}{2}\right), \tag{7}$$

where R_{x} is a radius that depends on the adopted strategy. For the proposed solution, it is equal to the distance of the furthest user in the cluster to the cluster center. From (7) it is possible to observe that when $\alpha = 0.5$ all the users in each cluster are in the coverage range of an UAV positioned at the cluster center, while when α increases the UAVs serve larger areas, possibly serving more users (and increasing the interference into neighboring UAVs), and lastly when α decreases the UAVs serve smaller areas, but interfere less among themselves.

IV. Simulation Results

A. Benchmark and Metrics

To compare the performance of the proposed solution, we developed two different benchmark UAV deployment methods. First, a symmetric deployment, where UAVs are deployed symmetrically, such that the distance between consecutive UAVs are the same on both x and y axes, is developed. The altitude of the UAVs are calculated through (7), by setting R_{x} as the largest radius which causes no overlap between the footprints of neighboring UAVs. Moreover, due to the symmetric nature of the deployment, the altitude is kept the same for each UAV.

Second, a random deployment, where the UAVs are uniformly distributed across the region of interest, is developed. There is no regular pattern for the distance between the UAVs, and thus the proximity of the UAVs can be small for some, while others are located far away from each other. Similar to the symmetric distribution case, the altitude of the UAVs are determined via (7). Here, the same R_{x} value that was calculated for the symmetric distribution is adopted since we do not have any reference distance value for the random deployment method.

To evaluate the performance of the developed methods, we introduce two different metrics. First, we measure the user perceived SINR, which is calculated using (2). This becomes an utilitarian metric demonstrating the signal quality that is received by the users, which subsequently effects the throughput as in (4). Given the stringent peak data rate requirements for the enhanced mobile broadband (eMBB) scenario in 5G new radio (NR) [17], improving user experienced throughput is a vital task. Second, the number of users in outage is also counted in order to investigate the link failure performance of the developed methods. In this regard, a certain threshold value, T_{S}, is selected for SINR values, such that users are counted in outage if their SINR values are below T_{S}, or covered when the SINR is equal or greater than T_{S}. Further, we calculate the percentage of users in outage using $n_{\mathrm{o,p}} = n_{\mathrm{o}}/n_{\mathrm{u}} \times 100$, where n_{o} and n_{u} are the number of users in outage and total number of users, respectively.

B. Simulated Environment

1) Data Set: As also explained in [18], the call detail record (CDR) data set utilized in this simulation is provided by Telecom Italia for the city of Milan, Italy [13]. In this dataset, the city of Milan was divided into 10,000 square-shaped grids, in which each grid has a side of 235 m. Then, call, text message, and internet activity levels, which reflect the amount of user-network interactions, were logged for each grid for a period of 2 months. Furthermore,

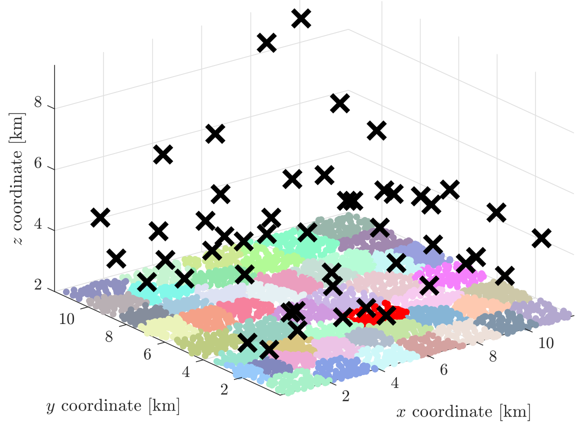

Fig. 2. Distribution of the UAVs using the proposed methods when $\alpha = 1$. Dots (●) in different colour represent the users in different clusters that the k-means algorithm found, while black crosses (✖) represent the UAVs.

the resolution of the data set is 10 minutes, meaning that the activity levels were aggregated into 10-minute time slots. However, the provided data is unitless, and thus reflects merely a relative user activity level.

2) User Positioning: Since the data set does not provide much information, pre-processing and further assumptions are needed to make it more meaningful. First, we consider the user activity level in a grid as the throughput demand from the users located in that grid. After that, call, text message, and internet activities are combined in order to estimate a total throughput demand from each grid. As the data set is from 2013, and to reflect the increase in data demand since then, the total throughput demands are multiplied with a coefficient, κ. Later, it is assumed that the ground network is capable of serving part of the demand per grid, $C_{\mathrm{e,g}}$, before the deployment of the UAVs, which is deducted from the overall throughput demand in order to find out users not covered by the ground network. A certain throughput demand per user, C_{u}, is also assumed, so that the number of users per grid can be obtained (by dividing the total grid demand by C_{u}). Lastly, the resulting number of users is uniformly distributed across a given grid.

C. Results

We have performed numerical simulations to evaluate the proposed approach using parameters from Table I. Moreover, Fig. 2 shows the obtained positions when $\alpha = 1$.

Fig. 3 demonstrates the perceived user SINR performances of the developed methods when $\alpha = 0.1$. The first point we can infer from these results is that the symmetric and random deployments performed very close to each other. The reason for this is that the altitude of the UAVs

TABLE I
Simulation parameters

Parameters	Value
UE height	2 m
UAV SC EIRP	0 dBW
UAV SC antenna directivity angle	60°
Carrier frequency, f_{c}	1 GHz
Bandwidth per RB	180 kHz
Number of RBs per UAV	100
SINR threshold, T_{S}	-3 dB
Data demand increase coefficient, κ	10
Terrestrial throughput supply per grid, $C_{\mathrm{e,g}}$	20 Mbps
Number of grids considered	2500
Area of the region of interest	50 × 50 grids
Dimension of each grid	235 m
User throughput demand, C_{u}	50 Mbps

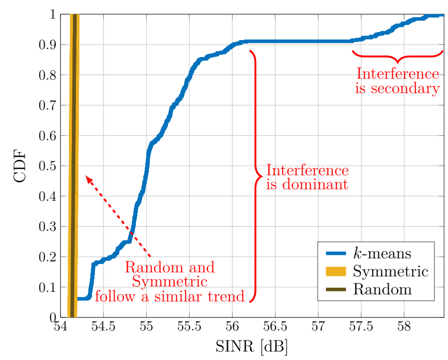

Fig. 3. Received user SINR performances of the developed methods when $\alpha = 0.1$.

are comparatively less when $\alpha = 0.1$, so are the coverage areas. Therefore, there is a very small room for interference to be effective, resulting in kind of interference-free communication for the users. This subsequently makes the path loss only dominant factor affecting the link quality between the UAVs and their associated users, and thus there are small variations observed on the received SINR. In other words, considering (2), the SINR is dependent on received signal strength and the interference, where N is constant. Hence, when the interference becomes secondary, the only parameter having an effect on the SINR is the received signal strength. From (1), it is obvious that the path loss is merely distance-dependent, since the other parameters, such as f_{c}, are kept constant. Having all these said, it is quite intuitive that when d gets smaller with decreasing α, the interference becomes secondary and the path loss causes only small variations.

On the other hand, compared to the symmetric and random distributions, the proposed k-means based UAV distribution method resulted in broader range of SINRs. We observe two separable regions in this case: a region where the interference is dominant and secondary, respectively. One can question why the dominant interference region occurred in this case while it did not exist for the symmetric and random deployments. The altitudes of the UAVs in the symmetric and random cases are

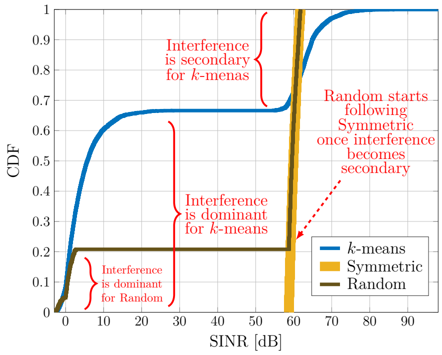

Fig. 4. Received user SINR performances of the developed methods when $\alpha = 0.5$.

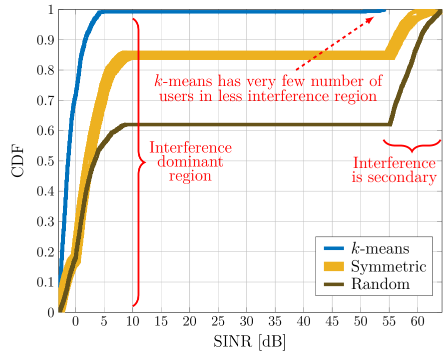

Fig. 5. Received user SINR performances of the developed methods when $\alpha = 1.0$.

identical, whereas they are different from each other in the proposed deployment method. Accordingly, while there is a clear separation between the footprints of the UAVs in the symmetric and random cases, they are more likely to be overlapping in the proposed method. Therefore, the users, who are located in the overlapping areas, experience interference and constitute the interference is dominant region in Fig. 3. The users in non-overlapping regions, on the other hand, receive better signal quality and constitute the interference is secondary region in Fig. 3.

When $\alpha = 0.1$, regardless of the deployment method, the scale of the SINR is quite high (around 54 to 58 dB) as seen in Fig. 3, since the interference is less effective and the distance between the UAVs and associated users are comparatively less. Nevertheless, Fig. 6 reveals the number of users in outage for three different deployment scenarios. It is worth highlighting that the outage performances are quite poor for all deployment methods, since they resulted in between around 87% and 98% of outage. These results are obviously unacceptable owing to the fact that the vast majority of the users are out of the service. The under-performance of the methods arises from the lower values of α, which subsequently results in reduced footprints for the UAVs. Moreover, the proposed deployment method outperformed the other two benchmarking methods, because it minimizes the Euclidean distance between the users and UAVs, making the UAVs more inclined towards more densely populated areas.

The results in Figs. 3 and 6 can be summarized as follows: when the coverage areas of the UAVs are smaller, so is the interference between them. This also makes the associated users closer to the UAVs. Therefore, the takeaway from these results is that the smaller altitudes of the UAVs—manipulated by α parameter—improves the received SINR values for the user at the expense of connecting much less users. Furthermore, the distinct altitudes of the UAVs for the proposed method render it to be more vulnerable to interference.

Fig. 4 demonstrates the SINR performances of the proposed method and two benchmark methods when $\alpha = 0.5$. We first observe that the received SINR values were scaled down compared to the $\alpha = 0.1$ case. Second, the dominant interference region for the proposed method expanded due to the fact that the footprint for each UAV is enlarged with increasing α value. When the footprint for each single UAV increases, the overlapping areas among UAV footprints also expand, which in turn leaves more users in the dominant interference regions. The symmetric deployment case, on the other hand, is still immune to the interference given that no overlapping region occurs, since $\alpha = 0.5$ yields that the footprints of the UAVs are just tangent to each other. For the random case, however, some small portion of the dominant interference region occurs, as it is likely that there are overlapping areas due to the uniform distribution, making some users experience considerable level of interference.

As seen in Fig. 6, the number of outage users also scaled down compared to the $\alpha = 0.1$ case, since the footprints of the UAVs are now increased, which results in more users to be connected. We also observe that the proposed method significantly outperformed the symmetric and random distribution methods. As aforementioned, this happens because the proposed method uses k-means algorithm, which employs the Euclidean distance as a cost function, to determine the locations of the UAVs. Therefore, the proposed method focuses on reducing the overall Euclidean distance between the UAVs and the users, which makes them position close to the more number of users.

Lastly, Fig. 5 shows the received user SINR results for the three UAV deployment methods while $\alpha = 1$. The region, where interference is dominant, for the proposed method is observed to be expanded dramatically, since around 99% of the users were found to be in this region. In addition, in this case, the dominant interference region also occurred for both symmetric and random deployment methods. The reason for this, again, is the increased footprints for the UAVs that causes the overlapping areas becomes greater, which subsequently increases the number of users experiencing considerable amount of interference. Another interesting point that is worth discussing is

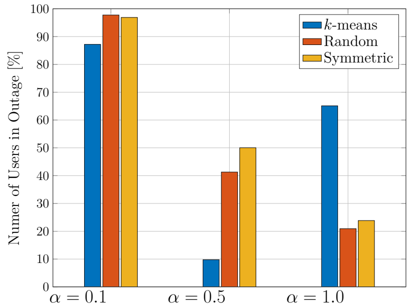

Fig. 6. Number of users in outage for various α values.

that the random deployment method outperformed the proposed and symmetric methods in terms of SINR. This arises from the fact that it is prone to result in less overlapping areas at some locations due to the nature of the uniform deployment, whereas the overlapping areas are the same for all the UAVs in the symmetric case. In other words, while the overlapping areas are large for the UAVs located close to each other, it is comparatively less for the UAVs that are separated by a considerable distance.

From the results in Fig. 6, the number of the users in outage decreased for the symmetric and random deployments compared to the cases where $\alpha = 0.1$ and $\alpha = 0.5$. Once again, the reason for this is the increased footprints of the UAVs, where the UAVs are able to serve more users. Nonetheless, this behaviour did not happen for the proposed method, where interference is much more severe making more users fall below T_{S}. Thus, from the results obtained it can be seen that the proposed k-means solution can be utilized in the deployment of UAVs. In addition, because the proposed solution depend only on data, it can be easily adapted to different applications, such as in emergency scenarios, for example.

V. Conclusion

In this work, we proposed a k-means algorithm based UAV positioning method, where (x, y) coordinates of the users were considered as features. Then, the UAVs were deployed at the centroid positions for each cluster. The obtained results reveal that the proposed UAV positioning method is mostly good at reducing the number of users in outage due to the nature of the k-means algorithm, where the Euclidean distance was employed as a cost function. However, in terms of the user perceived SINR values, the proposed method is more vulnerable to interference owing to the differences in the altitudes of the UAVs. α parameters was observed to have an crucial impacts of the performances of the developed methods; the greater α is the larger footprint for the UAVs, which in turn increases the number of connected users whereas scaling down the user SINR values. Future works can include the user positioning and limited backhaul capacity conditions, where relay UAVs and/or ground BSs would be needed.

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