Efficient Drone Positioning Scheme for Capacity Enhancements in Cellular Network

Aunas Manzoor, Choong Seon Hong

Department of Computer Science and Engineering,

Kyung Hee University, Yongin, 446-701 Korea

Email: {aunasmanzoor,cshong}@khu.ac.kr

Abstract

Recently, the use of drones as flying base station to assist the terrestrial cellular networks for capacity enhancements has been studied. In this paper, the drones are used to offload the cellular traffic from the ground base-stations in the geographical locations where user density is significantly high. To do this, an efficient drone positioning scheme is introduced where the drones are positioned at optimal locations in an area. The problem is formulated to optimize the drone location and the coverage area to serve the maximum number of cellular users. Simulation results are drawn to analyze the effect of user density on the coverage area of drones in a cell.

I. INTRODUCTION

Due to the enormous technological developments in the next generation cellular networks, the quality of service (QoS) requirements of the consumers have been revolutionized. To this end, 5G has introduced a number of key technologies to meet such QoS requirements including LTE-U [1], NOMA [2], and 5G-NR [3]. Another leading trend in the future mobile networks is the involvement of unmanned aerial vehicles (drones) or flying drones in the communication networks. The use of drones has gained attention in different research domains including military applications, traffic control, navigation systems and parcel delivery systems. In particular, the applications of drones are studied widely to enhance the network capacity of cellular networks where the drones are used as flying base-stations [4].

Such variety in the use of drones allows to function them as different network nodes during the different times of the day according to the user requirements. For instance, the morning traffic crowds can be relieved by using the drones as road side unit (RSU) to streamline the traffic. After that the role of drones can be switched to the base-station(BS) for downlink and uplink communication during office and school hours. Then drones can be used to collect and process data from wearable devices and sensors used in parks and sports activities. Afterwards, the local markets, food centers and shopping malls may get the data services provided by the drones. Finally, in the night time, the drone fog nodes can fetch the relevant video and social content at the edge of the network.

The flying drones are best suitable for the aforementioned roles at different times of the day by exploiting their key features of flexibility, control, automation and ease of deployment at the right place and time. In spite of such key benefits, the use of drones in future mobile networks pertain the challenges of energy efficiency and suitable deployment at the desired locations [5].

In view of the aforementioned challenges of energy efficiency and suitable deployment of drones according to the user distribution, we propose an energy efficient drone deployment scheme to maximize the network rate of the ground users by optimizing the suitable location and coverage area of each drone. To do this, we formulate the optimization problem for the efficient deployment of drones at the appropriate position. Considering the limited on-board energy of the drones, the number of users which can be associated with each drone are limited. By incorporating such limits, the coverage area of each drone is adjusted accordingly. This means that the drone deployed in a relatively denser user distribution area will have a shorter coverage area to serve the same number of users as compared to the drone deployed in a less denser area. As a result, the drone position and the coverage area of each drone are optimized to maximize the number of served users while minimizing the energy cost. To solve this problem, we used the exhaustive search method where all the possible solutions are explored to get the optimal solution.

The remaining of the paper is organized as follows. Section II discusses the system model consisting of the wireless model for the communication between drones and cellular users.
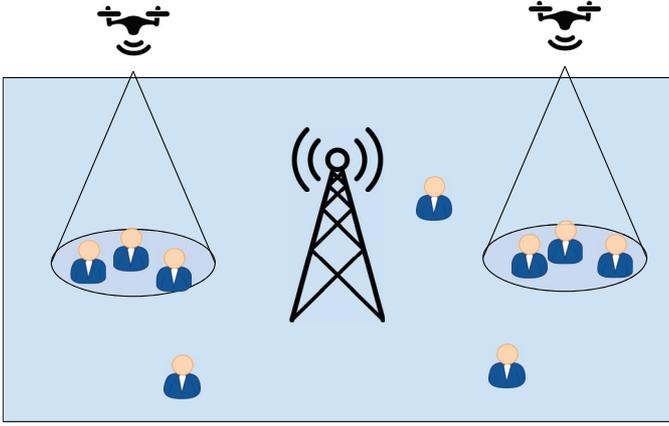
Fig. 1.   System model of drone positioning in a cellular network.

In Section III, we formulate the optimization problem and demonstrate the solution. Section IV presents the numerical results and Section V concludes the paper.

II. SYSTEM MODEL

We consider a cellular network consisting of set of drones denoted by $\mathcal{U} = \{1, 2, \ldots, U\}$ deployed in a geographical area to serve a set of cellular users denoted by $\mathcal{N} = \{1, 2, \ldots, N\}$. Note that the number of drones U required to serve the cellular users in the network is optimized according to the density of users in the network. The 3D geographical locations of drone $u \in \mathcal{U}$ and cellular user $n \in \mathcal{N}$ are denoted by $\{x_u, y_u, h_u\}$ and $\{x_n, y_n, 0\}$, respectively. The geographical area is divided into a set of certain grid points denoted by $\mathcal{L} = \{1, 2, \ldots, L\}$, where drones are deployed. As the density of cellular users vary throughout the day, we divide the day into set of 24 hours denoted by $\mathcal{T} = \{1, 2, \ldots, 24\}$. The user density $\kappa_l(t)$ in each geographical area $l \in \mathcal{L}$ at the time period $t \in \mathcal{T}$ is modeled with Poisson point process.

The Euclidean distance between drone u and cellular user n is denoted by d_{un} and is given as follows:

$$d_{un} = \sqrt{(x_u - x_n)^2 + (y_u - y_n)^2 + (h_u)^2}. \qquad (1)$$

There are the possibilities of line-of-sight (LoS) and non-line-of-sight (n-LoS) communication link between the drones and celluar users. Such possibilities are modeled with the corresponding LoS and n-LoS probabilities denoted by $\mathrm{Pr}^{\mathrm{LoS}}$ and $\mathrm{Pr}^{\mathrm{n\text{-}LoS}}$, respectively [6].

The composite expected path-loss between a drone and cellular user is given as follows:

$$\delta_{un} = \mathrm{Pr}^{\mathrm{LoS}}\delta^{\mathrm{LoS}} + (1 - \mathrm{Pr}^{\mathrm{LoS}})\delta^{\mathrm{n\text{-}LoS}}. \qquad (2)$$

where δ^{LoS} and $\delta^{\mathrm{n\text{-}LoS}}$ denote the corresponding LoS and n-LoS path-losses respectively. The corresponding SINR received at the cellular user from the drone u is given as follows:

$$\gamma_{un} = \frac{P_{un}h_{un}}{N_0}, \qquad (3)$$

where h_{un} denotes the channel gain which is computed as $h_{un} = \alpha^{-\lambda_{un}/10}$. The downlink achievable rate of the cellular user is given as follows:

$$R_{un} = W\log(1 + \gamma_{un}), \qquad (4)$$

where W denote the bandwidth of the communication channel and x_{un} denote the association of a cellular user n with the drone u.

III. PROBLEM FORMULATION

Given the defined system model, our goal is to maximize the rate of the cellular network while ensuring the constraints of limited association and coverage area. To achieve this goal, we formulate the following optimization problem:

$$\max_{\boldsymbol{x},\boldsymbol{r}} \sum_{u \in \boldsymbol{U}} \left(\varsigma \sum_{n \in \mathcal{N}} x_{un}R_{un} - \zeta r_u \right), \qquad (5)$$

$$\text{s.t.} \quad \sum_{n \in \mathcal{N}} x_{un} \le C_u, \quad \forall u \in \mathcal{U}, \qquad (5a)$$

$$\sum_{u \in \mathcal{U}} x_{un} \le 1, \quad \forall n \in \mathcal{N}, \qquad (5b)$$

$$r_u \in [0, D], \quad \forall u \in \mathcal{U}, \qquad (5c)$$

$$x_{un} \in \{0, 1\}, \quad \forall u \in \mathcal{U}, n \in \mathcal{N}. \qquad (5d)$$

The objective function in (5) represents the total profit of the mobile operator which depends on the number of served cellular users x_{un} and the cost of covering the area of radius r_u by each each drone, where ς and ζ are the normalization variables. The constraint (5a) denote that the number of users associated with each drone are under the association threshold C_u of drone u. The constraint (5b) denote the unique association of a cellular user with only one drone. Constraints (5c) and (5d) denote the bounds of the decision variables.

To solve this problem, we use the exhaustive search method where all the possible solutions are explored to find the optimal solution.

IV. NUMERICAL RESULTS

In this section, we present the simulation results for the proposed drone positioning scheme. Using the Python programming language, we built the network topology consisting
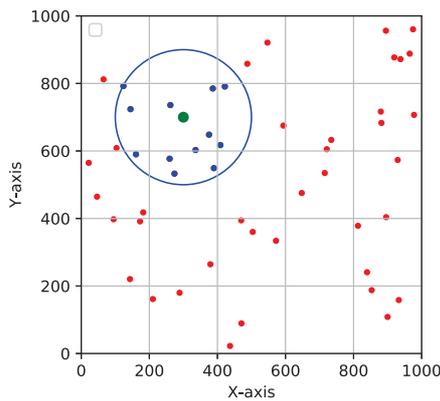
Fig. 2.   Network topology

Fig. 3.   Plot of WiFi throughput vs. the Wi-Fi duty-cycle

of up to 300 cellular users. We made the simulations for a number of runs and took average to show the results. Fig. 2 shows the snapshot of the network topology consisting of a drone deployed at the optimal position to associate the maximum number of cellular users while optimizing the coverage radius.

Fig. 3 shows the plot of drone radius against the increasing number of cellular users in the network. It can be observed from the Fig. 3 that the coverage radius of the drone is reduced with an increase in the number of users in the network. This is due to the fact that the proposed scheme deploys the drone at an optimal location where C_u number of users can be associated with less coverage radius required. Therefore the proposed scheme can achieve better rate with less energy consumption of the drone. We compared the the proposed drone positioning scheme for different drone association capacities. It can be observed that the coverage radius of the drone is increased when the capacity threshold C_u of the drones is increased. This is due to the fact that the radius of the drone becomes essential to increase in order to serve at least C_u number of users by the drone.

V.   CONCLUSION

In this paper we adapted the drone positioning scheme to deploy the drones at optimal locations in a geographical area. To do this, we have formulated the optimization problem where the network rate is maximized under the threshold of limited user associations with the drones. Simulation results have shown that the coverage radius of the drones is optimized according to the user density in the network. In the future work, we will use the multi-agent reinforcement learning to deploy multiple drones in the geographical area by developing a non-cooperative game between the drones.
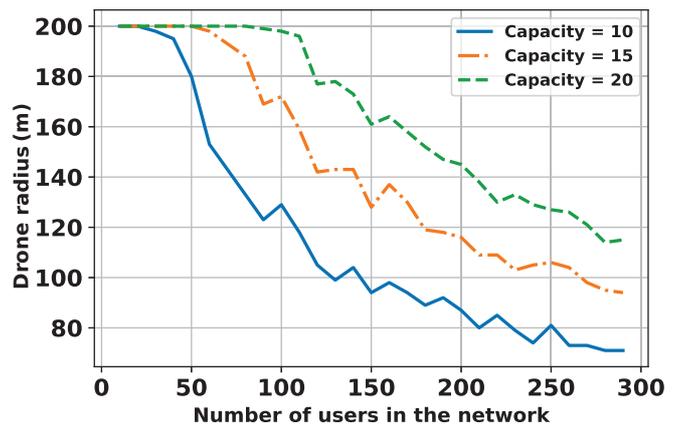
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