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Joint optimization of 3D deployment and trajectory of FBSs to reduce power consumption under backhaul constraints

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***Abstract*—Flying Base Station (FBS) is an evolving technology, providing wireless services to ground and aerial users. With the help of this system, the service required by users can be provide with very high speed and low cost. Since pre-created structures are not require in these systems, this feature helps provide facilities in many scopes and difficult conditions. FBSs can carry a variety of equipment, so they can play a role in a variety of wireless communication networks. Meanwhile, the limited power of this equipment has led to the importance of optimizing the power consumption in this equipment. In this paper, we discuss the joint optimization of three-dimensional deployment and FBS trajectory under Backhaul constraints. We formulate the p-median model to optimize the deployment of the FBS and examined the effect of the number of candidate points and the coverage factor of the users in optimizing the minimum number of FBS required. In this paper, the height of FBSs is optimized to reduce transmission power consumptions, and finally, the 3D position of the FBS is present. Due to the high mobility of users and the need to relocate FBSs, we use the transportation model method to optimize the FBSs trajectory to reduce their power consumptions. In this model, a method is propose to calculate the optimal transit path for the FBS trajectory between two-time slots. Numerical results show that the proposed method can simultaneously minimize the number of FBSs and their power consumptions and determine an optimal path for their trajectory.**

***Index Terms*—Flying base Station, Drone trajectory, Energy efficiency, IoT, Fuzzy C-means, UAV placement, Transportation model, 3D deployment**

I. Introduction

UAVs have many advantages due to their special design. Since these systems can move continuously in three-dimensional space and are quickly deployed anywhere, they can provide high quality and extensive service in many fields such as rescue, monitoring, multimedia services, etc. This high accessibility has led to the use of drones in the fifth generation (5G) wireless communications and IoT networks. UAVs, which today have found their place in the industry more than ever, are used to increase users' access to the network with the minimum required quality of service.

In many 5G network scenarios, ground-based stations can be used. Although these stations can cover a wide area with a higher power, the static deployment of these stations, however, is very time-consuming. These devices are deployed at a very low speed and high cost at a specific point, providing real-time communication and awareness of the environment during casualties, immensely helping rescue missions [1]. Unlike ground-based stations, FBSs can be quickly deployed in an area and provide full coverage by moving throughout that area. Therefore, UAVs have attracted the attention of many researchers recently, since these types of equipment can not only support the base stations and temporarily reduce pressure during emergencies but can also connect with an available mobile network and provide greater services [2]. On the other hand, this feature of UAVs has caused its deployment and trajectory in space require careful optimization. In other words, planning the deployment and trajectory of UAVs requires optimization algorithms, which are generally mathematical or random optimization [3]. However, the issue of optimizing the deployment and trajectory of UAVs along with constraints such as energy constraints, service quality and backhaul constraints is generally an np-hard issue.

Alongside 5G mobile network scenarios, IoT scenarios can also be considered. The expansion of the range of sensors and reduction in their price along with wireless networks has increased the scope of IoT applications. However, there are still data collection problems at the edge of the cell [4] that drones can help well in solving this problem. Drones can increase the quality of service and reduce interference by changing their locations, and increase the percentage of users covered by the network [5]. Another issue that needs to be addressed is the time duration of optimal placement or trajectory generation calculations. Even though optimizing the static deployment of FBSs will take less time and energy; however, dynamic FBSs can fly closer to ground users and provide more services to improve the quality of the communication channel. [6] Although in considering the type of environment, the trajectory of drones can be predetermined or produced, for example, if we talk about urban environments, they can be

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determined with the help of satellite images and pre-prepared data according to the height of buildings and other obstacles; However, a war environment can change rapidly; In these cases, the drones must pass through unknown environments. In such environments, drones must have a route design program based on environmental information and some details in their memory. This is done to ensure that missions are completed [7].

II. Related Works

Numerous studies have been conducted on the use and application of drones in wireless communications. This research falls into several categories, one of which is the optimal deployment and routing of drones under various limitations. in [8] A new framework for the prediction of deployment of drones as a temporary base station to integrate it with ground-based mobile systems and help it against downlink traffic overhead is proposed. Their theory proposed an innovative machine learning method, based on the weighted maximum expectation (WEM) algorithm, is proposed to estimate user distribution and downlink traffic demand, and a contract theory framework is used to ensure structured information exchange.In [9] The bee colony algorithm is used to minimize the number of UAVs under constraints placed by the quality of service. The maximum coverage radius of the UAV is calculated according to the minimum required power to serve more users, and a three-dimensional position and frequency band of each UAV is calculated to increase the signal strength and reduce interference. In [10] a non-orthogonal multiple access(NOMA) based approach is presented to improve connectivity opportunities and spectrum efficiency (SE) in fifth-generation wireless communications and beyond. In this article, several drones relay information to half of the ground users. The drones are deployed using a clustering method and a location-based user pairing scheme to optimize communication and enhance energy efficiency under service quality constraints.In [11], the authors examine a UAV-equipped cellular communication system in which a very low-altitude UAV provides services to the ground user. The problem of optimizing UAV 3D positions is more realistically modeled taking 3D space constraints and ground barrier constraints into considerations. The purpose of this article is to increase the security of wireless communications with the help of drones.The goal of [12] is to maximize the total number of covered user equipment when the quality-of-service requirements are met. In this process, the deployment of UAVs is optimized to provide the satisfactory services required by users in 3D. In this paper, the air-to-ground loss model is considered and drone base stations are deployed first horizontally using a genetic algorithm and then vertically to maximize user coverage keeping in consideration the data distribution rate. In [13] the minimum achievable system throughput which provides services to all ground users has been maximized through a multidimensional deployment method. Taking co-channel interface in consideration. In this approach, first, the two-dimensional position and then the height and transmission capacity of the drones are optimized separately. In [14] UAVs are deployed to create a link between IoT devices and ground-based stations to increase signal strength. In this network, UAVs are responsible for facilitating the data transfer of IoT devices. This paper presents a distributed user clustering algorithm to cluster IoT devices as multiple user clusters. This paper also formulates an optimization model to minimize system energy consumption, where the deployment and transmission of UAV power are jointly optimized. in [15] we present an innovative evolutionary algorithm to determine the optimal number and position of UAVs in the structure of the Internet of Things. The mathematical model presented in this paper reduces the problem space and obtains the optimal position of the drones to provide IoT service for data collection from them. An innovative mechanism for calculating candidate points according to user density is also provided.In [16]we presented an optimal UAV deployment method based on fuzzy clustering. To reach optimal placement of UAVs as BS such that it covers 100% of users, a mathematical model in the form of optimal placement problem (OP) is presented to minimize the total distance between users and UAVs under Beckham constraints. In [17], a method for optimal deployment of drones in the most suitable place for task offloading with TDMA protocol is presented. Specifically, in this paper, the number of processing loads in the MDs-UAV system is modeled according to the processing capacity of each drone. In this paper, it is proved that the problem of UAV deployment and processing load transfer is an NP-hard problem, so a greedy method is proposed to optimize the algorithm. In [18], the issue of dynamic deployment of drones to optimize the energy efficiency of UAV-equipped networks in which UAVs are responsible for providing communication and lighting to users is investigated. In this study, UAV deployment, user communication and energy efficiency are optimally optimized using a combined algorithm of machine learning framework of repetitive gate units (GRU) with convolutional neural networks (CNN). The authors in [19] have investigated the connection problems of aerial users (client drones) when they only receive services from aerial-based stations. In particular, in this paper, the issue of three-dimensional deployment of aerial-based stations equipped with directional antennas is investigated. The purpose of this article is to maximize the number of aerial users covered by the spectrum sharing policy with terrestrial networks. [20] examines the deployment of UAVs which have the task of providing services to users who generate large amounts of information. This paper formulates an issue to maximize the total access rate of all users subject to a minimum rate limit for each user.

In [21], the problem of optimizing the route of several flight stations is modeled to maximize the data rate of mobile phone users. The formulation limits the strength of the ABS, including propulsion and signal transmission power, the backhaul link capacity limit, and the collision avoidance limit. The modeled problem is solved using an innovative algorithm based on a sequential convex approximation approach. [22] During emergency situations to provide a multi-UAVs enabled wireless communication system, UAV deployment, and movement should be energy efficient too, and the authors of [22] have shed light on this topic. To maximize the energy efficiency of the ground-users not only the positions of the UAVs and the users association are considered but the transmit power of the ground user is jointly optimized. In this article, if a drone is lost, other drones with the least energy optimize their location and movement to replace that drone. Joint global and local path planning optimization for crowd air monitoring is done by combining the improved particle swarm optimization(PSO) algorithm, artificial potential algorithm, path exploration mode switching strategy and energy-based task scheduling mechanism. The purpose of [23] is to use drones equipped with a surveillance system to overcome the shortcomings of fixed position surveillance equipment such as CCTV. [24] in an efficient route planning method is investigated that can minimize the completion time of the cellular-connected UAV's mission under the required QoS. An iterative path optimization algorithm based on geometric programming is proposed to design the UAV path under real-time connection constraints. Cognitive radiography has proved to improved spectral performance. However, transmit power and channel fading of a secondary network limits its secure performance. To solve this problem, exploiting the high flexibility of a UAV and the possibility of establishing the line-of-sight link,s a communication network based on unmanned aerial vehicle devices is presented in [25], in which the average secrecy rate is strongly optimized and the path of movement and transfer of the UAV is maximized. A UAV-assisted multi-carrier wireless communication for IoT scenarios is presented. as an aerial-based station, the drone transmits orthogonal frequency division (OFDM) signals to the IoT nodes, meanwhile the IoT nodes decode the information and store the signal energy. They transfer information using the stored energy to the drone. [26] proposed UDM route optimization and resource allocation scheme, by collectively optimizing UAV trajectory, subcarrier, power, and subplot allocation, the minimum achievable rate in the uplink among all IoT nodes is maximized, subject to the achievable sum rate of all IoT nodes in the downlink.

In [27], For information transmission and energy collection, subcarriers of an Orthogonal Frequency Division Multiplexing (OFDM) drone network are divided into two groups. The goal of this plan is to maximize the average rate achievable for all users by jointly optimizing the UAV route, user scheduling, sub-carriers, and power allocation. Furthermore, a drone optimization plan and a joint communication plan based on Simultaneous Wireless Information and Power Transfer (SWIPT) according to the average energy harvested for users is also proposed. [28] provides a functional SAG-IoRT framework for drones as a relay for loading data from smart devices to low-Earth orbit satellites. Given a large number of smart devices, the purpose of this paper is to jointly optimize the connection timing of smart devices, power control, and UAV path To maximize system capacity. This paper formulates the problem in the form of a nonlinear optimized complex integer problem. [29] examines the use of several UAVs to provide a joint service for several vehicles traveling on a highway with limited or no service infrastructure. In this paper, with the help of optimization of the routes of UAVs and allocating radio resources for a certain period, the number of UAVs deployed, under the minimum QoS limits required in terms of data volume and the effect of vehicle movement, is minimized. In [30], a wireless sensor network equipped with a drone is considered in which the drone is used to collect data from sensor nodes. By jointly optimizing the UAV communication schedule and the 3D path, the minimum amount of data collection from all sensor nodes that have a defined reliability limit, are maximized. In [31] we consider a sporting event in a rural area. Our goal is to use the 5G mobile network to provide the amount of data needed by the participants and attendees in this event. In this paper, we propose an efficient method for determining the minimum number of drones required and their optimal position. There is also an efficient method called MergeCells for presenting candidate points and scoring points.

In this paper, a mathematical model for optimizing the location and three-dimensional (3D) trajectory of several flying-based stations is presented. The purpose of this article is to minimize power consumption for data transmission with FBS movement. First, the deployment optimization problem is modeled based on the p-median method in the form of a binary linear optimization problem. This helps us to select the points as the optimal point from the candidate points for the 2D location of the drones so that the total distance of the drones from the users is minimized. Subsequently, we optimized the altitude of the FBS according to its distance to the farthest user. With this innovation, we optimize power used in data transmission. In the next step, based on the transportation model, a mathematical model is proposed to optimize the trajectory of FBSs for moving between two-time slots. The proposed model ensures that the path traveled by FBSs for moving from deployment points at time t to new deployment points at time $t + 1$ will be minimal. In summary, in this paper, we first present points as candidate points using the fuzzy clustering method. Then we obtain the minimum points required to serve the workers under backhaul constraints using the p-median method and then provide the optimal trajectory using the transportation model method.

The rest of the paper is organized as follows. In section III, the system model is presented and the p-median problem and transportation model are formulated mathematically. In Section IV, the numerical results are shown, the effect of the number of cluster heads and α on the positioning problem is investigated and the transportation model problem is evaluated. Finally, the conclusion is discussed in Section V.

III. System Model

UAV trajectory means finding the beginning and endpoint of a transit route. The closer these points are to each other, the more curved paths can be created, and the farther apart these points are, the more the path will be discontinuous. Although we can save on power if we can cover all of the desired environments by encountering the least number of points. To find the station points, we first use the FCM algorithm to create the candidate points. In clustering algorithms, we seek to categorize and find dense points as the center of the cluster, but in many of these algorithms, such as FCM, the presence of noise or outgoing data can cause the cluster center to shift to heavier clusters [32]. Therefore, after finding candidate points, we use the p-median algorithm to find the best points. By best points, we mean the points where the sum of the distances of the client users from those points is minimum.

Today, many species of animals are endangered, these animals are under close surveillance in protected areas. Imagine a protected area with no ground base station to protect the environment and prevent degradation. Endangered species in the area are equipped with IoT sensors to monitor the situation. We plan to relay the information of these nodes to the monitoring centers with the help of FBSs.

A. Mathematical Model of P-median Problem

In this model, we intend to model the p-median problem in the form of binary linear optimization to obtain the least total sum of user distances from FBSs.

$$min \sum_{i \in I} \sum_{j \in J} d_{ij} X_{ij} \tag{1}$$

In Equation (1) the objective function of the problem is specified. In this relation, i represents the i-th user from the I-user and j represents the j-th station from the J-station. d_{ij} means the distance of the i-th user from the j-th station. We intend to minimize the sum of d_{ij} if the i-th user is receiving service from the j-th station. X_{ij} binary indicates whether the i-th user is receiving service from the j-th station or not. This objective function is minimized under the constraints specified in equation (2) to (7)

$$\sum_{i=1}^{D} MB_i = W \tag{2}$$

$$X_{ij} \leq MB_i, \qquad \forall i \in I, \forall j \in J \tag{3}$$

MB_i in Equation (2) represents the binary selection or unelection of the i-th candidate point. Therefore, the number of selected points must be equal to the minimum number of required stations specified by W. The value of W indicates the minimum station required, this minimum value is calculated in non-consecutive iterations using the bi-section algorithm and indicates the minimum station required to serve users. In this regard, Equation (3) states that user i can receive service from station j if the candidate point j is selected as a station.

$$\sum_{i=1}^{D} X_{ij} \leq 1 \qquad \forall j \in J \tag{4}$$

$$X_{ij} = 0 \qquad \forall i \in I, j \in J, d_{ij} > R \tag{5}$$

Constraint (4) shows that a user can receive FBS service at a maximum of one station, and constraint (5) states that the client user must be within the FBS service area of a particular station.

$$\sum_{j=1}^{U} BWU_j X_{ij} \leq BW \qquad \forall i \in I \tag{6}$$

In Equation (6) WBU_j represents the bandwidth required by the user j and BW represents the maximum bandwidth of the UAV. Constraint (6) states that the total bandwidth required by users at a station should not exceed the maximum UAV bandwidth

$$\sum_{j=1}^{U} \sum_{i=1}^{D} X_{ij} \geq U * \alpha \tag{7}$$

Constraint (7) indicates that the number of connections specified between users and stations must be greater than the number of users which shows by U multiplied by α. This equation guarantees service to at least α percentage of users.

B. Mathematical Representation of Transportation Model

The purpose of the transportation model problem is to minimize the cost of moving from one point to another. In this article, we are going to move some FBSs from locations (x_n, y_n) at time T to locations (x_m, y_m) at time $T+1$ with the lowest cost.

$$min \sum_{m \in M} \sum_{n \in N} S_{mn} dist_{mn} \tag{8}$$

In equation (8), the objective function of the problem is specified. In this equation, set N represents points at time T and set M represents points at time $T+1$. $dist_{nm}$ represents the distance between the point m and n. We intend to minimize the sum $dist_{nm}$ if the drone goes from point n to m. S_{nm} is a binary indication of whether the drone goes from point n at time T to point m at time $t+1$.

$$\sum_{m \in M} S_{mn} \leq 1 \qquad \forall n \in N \tag{9}$$

$$\sum_{n \in N} S_{mn} \leq 1 \qquad \forall m \in M \tag{10}$$

Constraint (9) states that each FBS at time t can only go to one point at time $t+1$, and constraint (10) shows that each point at time $t+1$ can only hold one FBS.

$$\sum_{m=1}^{M} \sum_{n=1}^{N} S_{nm} = P \tag{11}$$

Constraint (11) indicates that the number of paths specified between points at time t to points at time $t+1$ must be equal to points at time $t+1$. This limit prevents the number of routes from reaching zero when minimizing.

IV. Numerical Results

For simulation, we consider a 10x12 km area where 4,000 animals are equipped with IoT sensors. These users are distributed at the center of 20 random points with the poisson distribution. Lora SX1272 module is used for communication, which due to its NLoS link conditions, has a working range of 2km. FBSs are equipped with a directional antenna with a beam angle of 90°, which creates a circle with a coverage radius of 1.4km. Each IoT node, depending on the animal, can send 24 to 60 KB of data, and FBS can relay up to 8 MB of data to the monitoring center at any time via the backhaul link.

A. Positioning of FBSs

To solve the problem with the help of the p-median algorithm, we need a lower bound and an upper bound. To get the lower bound, we go to the backhaul constraint. Given that each user has an average of 42 KB of bandwidth, a total of 168 MB of user bandwidth will be needed. Since each drone is allocated 8 MB of bandwidth, at least 21 FBS will be needed if users are uniformly distributed. As a result, we set the lower bound value to 21. In order to cover the whole environment evenly, 30 FBS should be placed in the form of a simple mesh with a distance of 2 km in the environment. This distance is equivalent to the length of the side of the largest square enclosed within the FBS antenna coverage circle. However, due to the Poisson distribution of users and the limitations of the backup arrangement of the drones like this, limitations of the problems are not satisfied, therefore, more points will be needed to calculate the deployment of FBSs; However, this number can also be considered as an upper bound problem.

1) Effect of Number of Cluster Heads on Number of FBSs: In the first step, we investigate the effect of the number of clusters on the minimum number of UAVs. In this study, an α coefficient of 1 is considered, which means 100% coverage of users. The number of clusters in the FCM algorithm indicates the number of candidate points presented to the positioning algorithm. The lower the number, the faster the problem is will be solved, but the problem may not reach a possible answer, so getting an acceptable number from the number of candidate points means achieving a possible answer in a short time. The mathematical model of the problem is solved with the help of CPLEX. In this execution, the maximum allowed time to solve the problem is 20 minutes and the minimum gap of the answer to the problem is 0.005. The results show that the number of candidate points less than 80 have no answer to this issue and due to the limited execution time and the enlargement of the problem space, passing 120 candidate points brought no progress in minimizing the number of UAVs. Figure 1 shows the number of FBSs required according to the number of cluster heads. Therefore, the number of candidate points for solving the problem is considered 120.

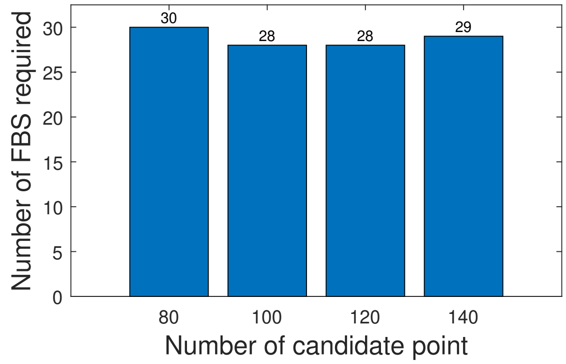

Fig. 1: Number of FBSs required for different candidate point number

2) Effect of α on Number of FBSs: Backhaul constraint will require more FBS to cover the users in cluster centers. As a result, a small number of users which are away from the cluster centers may not be covered. The alpha parameter specifies the minimum percentage of user coverage, which is very important in the positioning process, so we solved the problem with 120 candidate points for alpha 0.96 to 1. The results show that reducing the alpha up to 98% had a high effect, but after that reducing the alpha did not have a high effect on reducing the number of UAVs. Due to the high mobility of users and possible high coverage in another time slot, we use 98% alpha to compare the algorithm. Figure 2 shows the effect of α on the number of FBSs required.

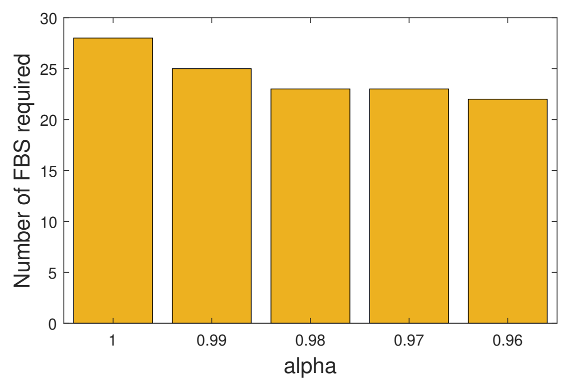

Fig. 2: Number of drones required for different α

3) Altitude Optimization: For maximum transmission power optimization, we reduce the altitude of each FBS as much as possible. In the p-median model, all users and FBSs are clustered and it is specified from which FBSs each user is receiving the service. On the other hand, reducing the altitude of each FBS means reducing the range of its coverage. For this purpose, we lower the height of each FBS as long as it is able to serve the farthest user under its coverage. Calculations show that the height of a drone can be reduced by more than 450 meters. Figure 3 shows FBSs altitude after optimization.

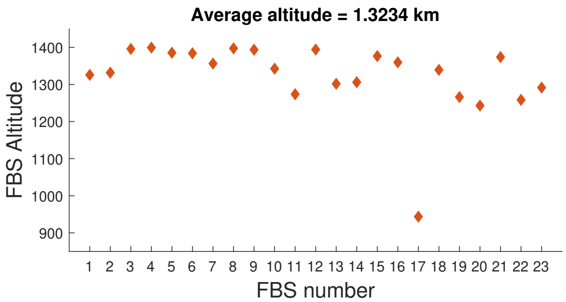

Fig. 3: FBSs altitude after altitude optimization

To compare the FCM algorithm, we obtain the problem points for a set of similar users, once using the FCM method and once using the simple mesh method, and then solve the positioning problem. In both methods, the number of candidate points is equal to 120 and α is 0.98. Figure 4 shows the location of user candidate points and the selected points in the algorithm. The results of this simulation show that the FCM algorithm needs 23 FBS and the simple mesh algorithm needs 24 FBS to satisfy the problem constraints, and the FCM algorithm performs better than the simple mesh algorithm.

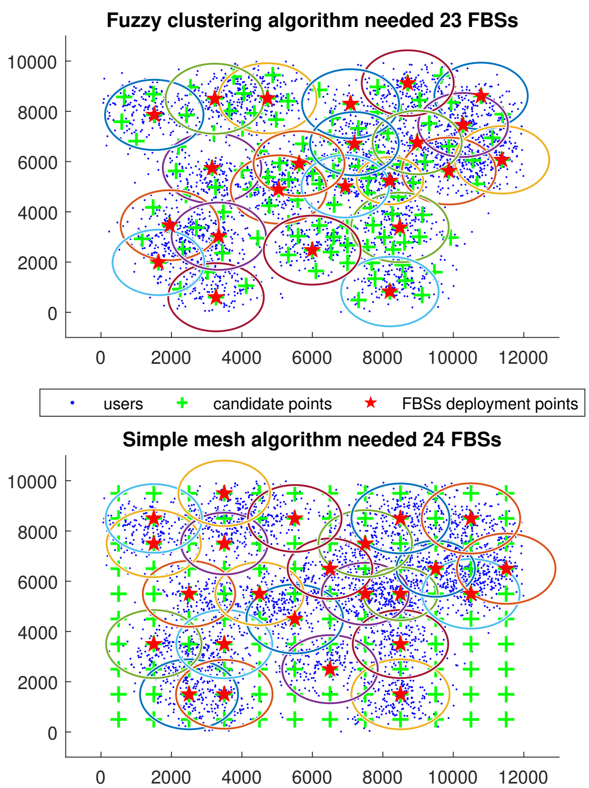

Fig. 4: FBSs location in FCM and simple mesh scenario

Given the backhaul limit, which indicates the need for at least 21 FBS even when 98% of users are covered, satisfying the problem constraints with the help of 23 candidate points is an optimal answer to the problem due to the Poisson distribution of users because Poisson distribution causes the need to overlap FBSs in cluster centers and bring them closer to cluster heads to increase, and the limited radius of coverage per FBS will necessitate the use of another FBS in areas away from cluster centers.

B. Trajectory of FBSs

Due to the high mobility of the users and their continuous movement, we need to move the drones between two different time slots. For this purpose, we mathematically modeled the transportation model problem. This algorithm guarantees an optimal global answer. For better understanding and evaluation of the performance of the algorithm, we obtained the users' position in two-time slots, t and $t+1$, and with the help of the FCM algorithm, we calculated the optimal position of the drones at these two times. We solved the transportation model problem to move drones from points M at time t to points N at time $t+1$. For comparison, we used a greedy algorithm to calculate the trajectory. In this method, the points are first sorted at time t and $t+1$, then the algorithm greedily selects the point closest to it to move. Figure 5 shows the performance of these two algorithms together.

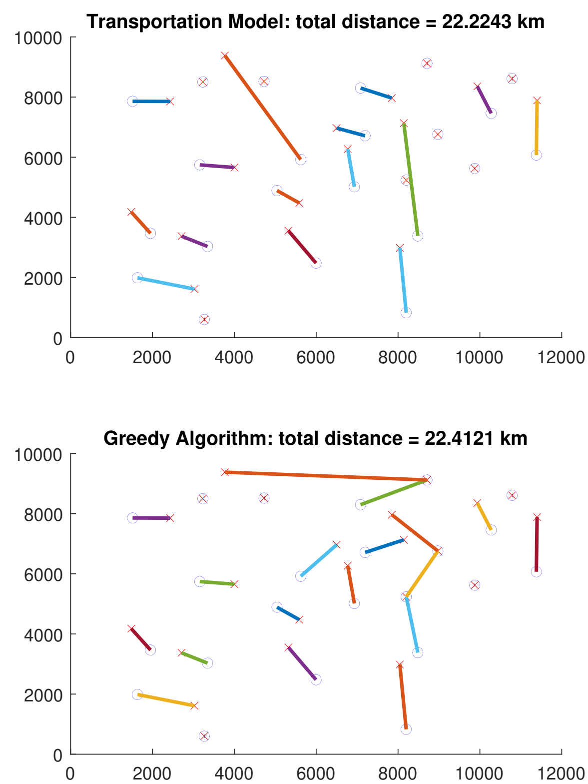

Fig. 5: FBSs trajectory using transportation model vs. greedy algorithm

V. Conclusion

The numerical results show the performance of the proposed algorithm for optimal deployment and trajectory. The study found that the FCM versus simple mesh algorithm required fewer FBSs to cover given users in an area. Although, the number of candidate points required by the p-median algorithm must be optimally selected. The small number of points will reduce the possibility of selecting the optimal point and will increase the number of FBS required. Also, due to the time constraint of the algorithm and the enlargement of the problem space, increasing this number can increase the required FBSs. In another study, it was found that reducing the alpha coefficient nonlinearly would reduce the number of FBSs required. The results of the implementation of the FBSs altitude optimization algorithm show that it is possible to reduce the FBS height up to 450m in proportion to the location of the covered users, which will significantly reduce the transmission power. The results of the implementation of the transportation model algorithm show that this algorithm provides an optimal and minimum path for FBSs trajectory, which can reduce the power consumption while moving between time slots.

References

[1] T. Zhang, J. Lei, Y. Liu, C. Feng, and A. Nallanathan, "Trajectory optimization for uav emergency communication with limited user equipment energy: A safe-dqn approach," *IEEE Transactions on Green Communications and Networking*, pp. 1–1, 2021.

[2] Y. Li, H. Zhang, K. Long, C. Jiang, and M. Guizani, "Joint resource allocation and trajectory optimization with qos in uav-based noma wireless networks," *IEEE Transactions on Wireless Communications*, pp. 1–1, 2021.

[3] X. Zhou, F. Gao, X. Fang, and Z. Lan, "Improved bat algorithm for uav path planning in three-dimensional space," *IEEE Access*, vol. 9, pp. 20 100–20 116, 2021.

[4] A. Meng, X. Gao, Y. Zhao, and Z. Yang, "3d trajectory optimization for energy-constrained uav-enabled iot system in probabilistic los channel," *IEEE Internet of Things Journal*, pp. 1–1, 2021.

[5] M. Zahedi, M. J. Sobouti, A. Mohajerzadeh, A. Rezaee, and S. Seno, "Fuzzy based efficient drone base stations (dbss) placement in the 5g cellular network," *Iranian Journal of Fuzzy Systems*, vol. 17, pp. 29–38, 2020.

[6] X. Jing, J. Sun, and C. Masouros, "Energy aware trajectory optimization for aerial base stations," *IEEE Transactions on Communications*, vol. 69, no. 5, pp. 3352–3366, 2021.

[7] A.-C. Hildebrandt, M. Klischat, D. Wahrmann, R. Wittmann, F. Sygulla, P. Seiwald, D. Rixen, and T. Buschmann, "Real-time path planning in unknown environments for bipedal robots," *IEEE Robotics and Automation Letters*, vol. 2, no. 4, pp. 1856–1863, 2017.

[8] Q. Zhang, W. Saad, M. Bennis, X. Lu, M. Debbah, and W. Zuo, "Predictive deployment of uav base stations in wireless networks: Machine learning meets contract theory," *IEEE Transactions on Wireless Communications*, vol. 20, no. 1, pp. 637–652, 2021.

[9] C. Zhang, L. Zhang, L. Zhu, T. Zhang, Z. Xiao, and X.-G. Xia, "3d deployment of multiple uav-mounted base stations for uav communications," *IEEE Transactions on Communications*, vol. 69, no. 4, pp. 2473–2488, 2021.

[10] J. Wang, M. Liu, J. Sun, G. Gui, H. Gacanin, H. Sari, and F. Adachi, "Multiple unmanned-aerial-vehicles deployment and user pairing for nonorthogonal multiple access schemes," *IEEE Internet of Things Journal*, vol. 8, no. 3, pp. 1883–1895, 2021.

[11] D. Wang and Y. Yang, "Joint obstacle avoidance and 3d deployment for securing uav-enabled cellular communications," *IEEE Access*, vol. 8, pp. 67 813–67 821, 2020.

[12] X. Zhong, Y. Huo, X. Dong, and Z. Liang, "Qos-compliant 3-d deployment optimization strategy for uav base stations," *IEEE Systems Journal*, vol. 15, no. 2, pp. 1795–1803, 2021.

[13] I. Valiulahi and C. Masouros, "Multi-uav deployment for throughput maximization in the presence of co-channel interference," *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3605–3618, 2021.

[14] S. Fu, Y. Tang, N. Zhang, L. Zhao, S. Wu, and X. Jian, "Joint unmanned aerial vehicle (uav) deployment and power control for internet of things networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4367–4378, 2020.

[15] M. J. Sobouti, Z. Rahimi, A. H. Mohajerzadeh, S. A. Hosseini Seno, R. Ghanbari, J. M. Marquez-Barja, and H. Ahmadi, "Efficient deployment of small cell base stations mounted on unmanned aerial vehicles for the internet of things infrastructure," *IEEE Sensors Journal*, vol. 20, no. 13, pp. 7460–7471, 2020.

[16] A. Alaghehband, M. Ziyainezhad, M. J. Sobouti, S. A. H. Seno, and A. H. Mohajerzadeh, "Efficient fuzzy based uav positioning in iot environment data collection," in *2020 10th International Conference on Computer and Knowledge Engineering (ICCKE)*, 2020, pp. 585–591.

[17] Y. Chen and Z. Zheng, "Joint deployment and task computation of uavs in uav-assisted edge computing network," in *2020 21st Asia-Pacific Network Operations and Management Symposium (APNOMS)*, 2020, pp. 413–416.

[18] Y. Wang, M. Chen, Z. Yang, T. Luo, and W. Saad, "Deep learning for optimal deployment of uavs with visible light communications," *IEEE Transactions on Wireless Communications*, vol. 19, no. 11, pp. 7049–7063, 2020.

[19] N. Cherif, W. Jaafar, H. Yanikomeroglu, and A. Yongacoglu, "On the optimal 3d placement of a uav base station for maximal coverage of uav users," in *GLOBECOM 2020-2020 IEEE Global Communications Conference*. IEEE, 2020, pp. 1–6.

[20] Z. Xiao, H. Dong, L. Bai, D. O. Wu, and X.-G. Xia, "Unmanned aerial vehicle base station (uav-bs) deployment with millimeter-wave beamforming," *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1336–1349, 2020.

[21] B. Khamidehi and E. S. Sousa, "Trajectory design for the aerial base stations to improve cellular network performance," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 1, pp. 945–956, 2021.

[22] L. Li, X. Wen, Z. Lu, W. Jing, and H. Zhang, "Energy-efficient multi-uavs deployment and movement for emergency response," *IEEE Communications Letters*, vol. 25, no. 5, pp. 1625–1629, 2021.

[23] Y. Tang, Y. Miao, A. Barnawi, B. Alzahrani, R. Alotaibi, and K. Hwang, "A joint global and local path planning optimization for uav task scheduling towards crowd air monitoring," *Computer Networks*, vol. 193, p. 107913, 2021.

[24] D. Yang, Q. Dan, L. Xiao, C. Liu, and L. Cuthbert, "An efficient trajectory planning for cellular-connected uav under the connectivity constraint," *China Communications*, vol. 18, no. 2, pp. 136–151, 2021.

[25] Y. Zhou, F. Zhou, H. Zhou, D. W. K. Ng, and R. Q. Hu, "Robust trajectory and transmit power optimization for secure uav-enabled cognitive radio networks," *IEEE Transactions on Communications*, vol. 68, no. 7, pp. 4022–4034, 2020.

[26] Z. Na, M. Zhang, J. Wang, and Z. Gao, "Uav-assisted wireless powered internet of things: Joint trajectory optimization and resource allocation," *Ad Hoc Networks*, vol. 98, p. 102052, 2020.

[27] Z. Na, J. Wang, C. Liu, M. Guan, and Z. Gao, "Join trajectory optimization and communication design for uav-enabled ofdm networks," *Ad Hoc Networks*, vol. 98, p. 102031, 2020.

[28] Y. Wang, Z. Li, Y. Chen, M. Liu, X. Lyu, X. Hou, and J. Wang, "Joint resource allocation and uav trajectory optimization for space–air–ground internet of remote things networks," *IEEE Systems Journal*, pp. 1–11, 2020.

[29] M. Samir, S. Sharafeddine, C. Assi, T. M. Nguyen, and A. Ghrayeb, "Trajectory planning and resource allocation of multiple uavs for data delivery in vehicular networks," *IEEE Networking Letters*, vol. 1, no. 3, pp. 107–110, 2019.

[30] C. You and R. Zhang, "3d trajectory optimization in rician fading for uav-enabled data harvesting," *IEEE Transactions on Wireless Communications*, vol. 18, no. 6, pp. 3192–3207, 2019.

[31] Z. Rahimi, M. J. Sobouti, R. Ghanbari, S. A. H. Seno, A. H. Mohajerzadeh, H. Ahmadi, and H. Yanikomeroglu, "An efficient 3d positioning approach to minimize required uavs for iot network coverage," *IEEE Internet of Things Journal*, pp. 1–1, 2021.

[32] S. Askari, “Fuzzy c-means clustering algorithm for data with unequal cluster sizes and contaminated with noise and outliers: Review and development,” *Expert Systems with Applications*, vol. 165, p. 113856, 2021.