

# Efficient Fuzzy based UAV Positioning in IoT Environment Data Collection

Afshin Alaghehband, Marzieh Ziyainezhad, Mohammad Javad Sobouti,  
Seyed Amin Hosseini Seno and Amir Hossein Mohajerzadeh

**Abstract**—Wireless networks can be considered one of the key features of Internet of Things (IoT), and the rise of IoT, has helped wireless networks to be improved and developed immensely. This improvement has increased QoS, data rate, transmit range, etc. The use of Unmanned Aerial Vehicles (UAVs) as Flying Base Stations (FBS) are growing in wireless networks specially in IoT environments. FBSs are a cost-effective and rapid way that can be used in areas which are difficult to access or there are no chances to build a fixed BS. The inherent characteristics of drones such as high mobility and presence of Line of Sight (LoS) in their connection has increased their efficiency when used as FBS, but one of the main challenges is the optimal placement of drones as BS in such a way that full coverage of sensors and actuators is provided to guarantee the demanded service. In this paper, the efficient placement of drones as BSs is modeled in the form of an optimization placement (OP) problem. The objective of this approach is to minimize the number of required UAVs and the distance of the drones from the cluster points while the sensor positions are accessible, keeping in mind the limitations of backhaul. We are using fuzzy-based clustering to find the candidate cluster heads. Finally the results shows that a proper parameter of fuzzy-based clustering algorithm can significantly improve the results of the optimization problem.

**Index Terms**—UAV Placement, IoT, Fuzzy C-means, 5G, Cellular Networks, Drone Base Stations

## I. INTRODUCTION

The advent of the Internet of Things and the expansion of its applications has led to the development of automation connected to the internet. One of the applications of the IoT is to monitor the quality of climate, soil, and atmospheric conditions governing the environment using data collected by the sensors. Wireless networks can be used to transmit this information and data [1].

In recent decades, many advances have been made in the wireless mobile telecommunications industry. So far, five generations of cellular networks have been introduced in the world. Each generation of cellular networks is generally associated with changes in system nature, speed, technology, frequency, data capacity, latency, and so on. In each generation, a number of standards with different capacities, new

techniques, and emerging features are introduced that make it different from the previous generation. The speed of data exchange in telecommunication networks has been growing very fast. Due to increase the speed and consequently increase the frequency of data transfer in the fifth generation, coverage is also one of the most important issues in this generation. Increasing the frequency reduces the coverage area and as a result, more Base Stations are needed. Also, due to the tendency of industries to use telecommunication networks to transmit information, the occurrence of interruptions or disruptions in coverage will cause harm to them. For this reason, service organizations seek to create the infrastructure to cover 100% of users without disruption. For this purpose, UAVs are used as Flying Base Stations (FBS). Today, the use of UAVs, also known as drones, is growing. Drones have key applications in wireless networks due to their inherent characteristics such as mobility, maneuverability, flexibility, adaptive altitude, ease of deployment, and relatively low cost [2].

In rural or mountainous areas where the installation of ground-based stations is not possible or cost-effective, UAVs can be used as FBSs. In case of unintended natural or unnatural events such as earthquakes, bad weather, terrestrial BS breakdowns, or in important and temporary events such as football games or presidential inaugurations when network traffic is temporarily increased, one of the proposed solutions for fast and high-quality service is the use of drones as BS [3]. One of the advantages of using drones is that they do not need any pre-determined infrastructure and can be located anywhere, and according to the conditions to increase the quality of service and reduce interference, their location can be changed, thereby the percentage of covered users can be increased according to the needs. UAVs can also increase the performance of existing ground wireless networks in terms of coverage, capacity, latency, and overall service quality by providing LoS communication links. However, the use of drones also has challenges, such as locating the right location, route design, resource allocation, energy consumption, multiple access, the optimal number of drones, and so on [4].

Optimal drone deployment is one of the major challenges in UAV-based communications, which depends on many factors such as deployment environment (e.g. climatic condition), location of ground users and properties of the air to ground channel, flight limitations and UAV energy. The adjustable al-

Afshin Alaghehband, Marzieh Ziyainezhad, MohammadJavad Sobouti, Seyed Amin Hosseini Seno and Amir Hossein Mohajerzadeh are with the Department of Computer Engineering, Ferdowsi University Of Mashhad, Mashhad,Iran.

The corresponding author is Amir Hossein Mohajerzadeh (email: mohajerzadeh@um.ac.ir)

titude of drones and their high mobility provide more freedom for efficient deployment. In the following, we will review the related work of UAV placements.

## II. RELATED WORKS

According to the fact that the correct positioning of the drones increases the reliability of the air-to-ground link, the issue of their proper placement has been considered. In [5], minimum number of drones and their optimal 3D location that necessary to cover users has been served using an exploratory algorithm. In this article, the drone achieves its coverage bound by altering its height according to the density of users and reducing interference with other antennas and users. In this way, in densely populated and denser areas, it reduces its height, and in areas with less population density, it serves with higher altitude. [4] presents an optimal 3D deployment method, concerning the backhaul in both user-oriented and network-oriented modes, and then, after selecting the location of the drone and its coverage area, its robustness is also examined. [3] Proposed a two-dimensional DBSs location algorithm to maximize user coverage while minimal transmission energy consumption. [6] Achieves the optimal three-dimensional location of DBSs intending to maximize the number of users covered. In [7], a proactive drone-cell implementation framework is proposed to reduce the overload due to instantaneous traffic (flash crowd) in 5G. This method assumes the issue of cell placement as a clustering problem and considers the users covered by each drone as a cluster. Locating drones in the center of each cluster allows the drone-cell to have at Least total square distance with all members of the cluster. Finally, a constraint bisecting k-means method is proposed to solve the problem of the drone placement. Traffic models have also been studied for three examples of social activity: stadium, parade, and gathering. In [8] authors examine the issue of the deployment of multiple drones. So that the method of mapping develops drones to areas with high traffic demand using the cost function based on the neural network. In [9], the authors proposed a method that finds the optimal 3D location of drones equipped with directional antennas by using the circle packing theory, so that the overall coverage of the area is maximized. Authors in [10] proposed an active deployment method for drones with cache, according to the content of the messages and for the improvement of QoE (Quality of Experience) of users. In this method, the drone tries to cache the desired contents based on a predictive model; such caching can reduce the data packet transmission delay. In [11], by using the brute force search, the optimal location of UAVs to deal with disaster and improve the security of the public communications is obtained. In [12], the optimal cell boundaries and locations for the multiple non-interfering drones have been investigated. The purpose of the authors is to minimize the transmission capacity of all the UAVs. [13] Provides an analytic model to find the optimal altitude of a drone with the aim of maximizing the coverage of the area. In [6], the authors discussed about finding the optimal 3D

location of a drone-cell in order to maximize the number of users whose SNR (Signal-to-Noise Ratio) is met. In [14], an algorithm was presented for placing drones to provide service to a group of users upon request. The goal of the paper was to maximize the number of users by providing their data rate. In [15], the authors proposed a mathematical model for the proper placement of drones as aerial BS to cover the IoT nodes and data collection. The purpose of this model is to minimize the number of drones and to select the proper locations from among the candidate points for drones to minimize the total distance of IoT nodes from UAVs and also to cover a percentage of users and provide the data rates they required.

There are also some papers in 5G and computers networks that using fuzzy logic. In [16] the authors used simple if-then rules to implement a fuzzy logic which is able to avoid ping-pong effect and has a good handover decision. In [17], a new fuzzy logic-based threshold is considered by the authors, which is used for handover decision. also a handover failure ratio is also reduced comparing to the competitive algorithms. Fuzzy-based multi-interface system (fbmis) is proposed by [18] where they equipped each node with 2 interfaces: mobile ad hoc network and traditional cellular network interface, where the presented FBMS system can switch between cellular to ad-hoc mode. In [19] authors presented an integrated intelligent system design for IoT device selection and placement in opportunistic networks using FL and GA. The system structure has also been introduced by the authors in addition to the details of the design and implementation issues. In [20], a mathematical model based on the P-median problem was proposed for the optimal placement of the drones as mobile base stations to give service to a certain percentage of users. Then, implemented this model with several different candidate points sets based on the fuzzy clustering and genetic algorithms and compares the results with each other. In order to avoid the uncertainties, in distributed RAN systems, cause by traditional CAC schemes, fuzzy logic-based called admission control scheme has been used by the researchers in [21]. In [22] authors used a combination of two locally available metrics, the RSSI and the Link Loss by a fuzzy logic-based mobility controller to perform the hand off to a new connection position or not. In [23] authors implemented and compared two fuzzy-based systems for selection of IoT devices in order to carry out a task in opportunistic networks.

In this paper, a mathematical model in form of an Optimization Placement (OP) Problem is presented to determine the proper position of drones as BSs to cover 100% of users. OP is a matter of finding the location, so that selects G points of the initial candidate points in order to minimize the average distance of all users from these points. In this problem, we have used the regular bi-section method to calculate the minimum G required. In this article, we have considered three scenarios called Random, Regular, and Different Density (DD) in which the distribution of users is different. By using the fuzzy clustering method, we obtain the initial candidate points

required for the OP problem for each scenario with different power parameters that indicate the degree of overlap of the clusters with each other. Then we compare the results of the OP problem in three considered scenarios with each other. The key idea set of this article includes:

- Solving the optimization problem of DBS placement to cover all users.
- Determining the candidate points based on the fuzzy clustering.
- Providing a binary linear optimization model to solve the problem.

In the following in Section III, the mathematical model and the proposed method of problem-solving are introduced. In Section IV, the results of the implementation and comparison between different modes are reviewed, and then the conclusion is discussed in Section V.

### III. SYSTEM MODEL

Here, we model the placement problem of FBSs. In the OP model,  $G$  is the optimal point of the set of candidate points for the drones in such a way that the total distance of the sensors being serviced is minimized to the nearest center. To obtain the set of candidate points, we use the fuzzy clustering method.

In the OP model, it is assumed that the coordinates of the sensors and candidate points for the drones are given. Also, the bandwidth of each drone and the required bandwidth of each sensor are assumed as given parameters in Table I. In this case, we try to find the proper position for  $G$  UAVs in such a way that the total distance of the sensors from the UAVs is minimized, and all sensors are covered and the limitations of the back haul are taken into account. To formulate this problem, we first introduce the parameters and decision variables. All used parameters are shown in Table I. The Table II also contains explanations of the decision variables of the mathematical model of the problem.

TABLE I: Parameters and descriptions

Parameters	Descriptions
DR	Data rate of DBS
$DRU_j$	Data rate of sensor j
I	Set of candidate points
J	Set of sensors
$d_{ij}$	Distance of sensor j from drone i
R	Covering radius of each drone
D	Number of candidate points
G	Number of deploying drones
U	Number of total users

TABLE II: Decision variables

Decision Variables	Descriptions
$X_{ij}$	1, if drone i covers sensor j
$MB_i$	1, if the model select candidate point i to place a DBS

The problem of DBS placement is modeled as follows.

$$\min_X \sum_{i \in I} \sum_{j \in J} d_{ij} X_{ij} \quad (1)$$

$$s.t. \quad X_{ij} \leq MB_i, \quad \forall i \in I, \forall j \in J \quad (2)$$

$$\sum_{i=1}^D X_{ij} \leq 1 \quad \forall j \in J \quad (3)$$

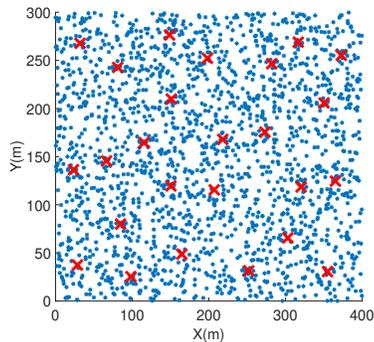
$$X_{ij} = 0 \quad \forall i \in I, j \in J, d_{ij} > R \quad (4)$$

$$\sum_{j=1}^U DRU_j X_{ij} \leq DR \quad \forall i \in I \quad (5)$$

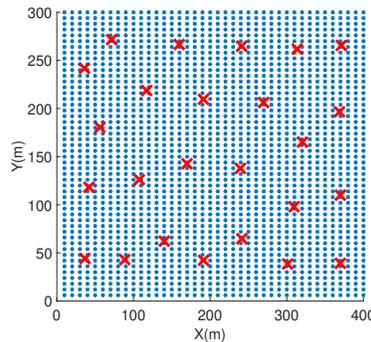
$$\sum_{i=1}^D MB_i = G \quad (6)$$

$$\sum_{j=1}^U \sum_{i=1}^D X_{ij} = U \quad (7)$$

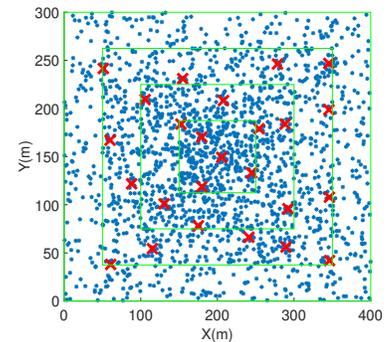
In Equation (1), which is the objective function of this problem, we seek to minimize the total distance of the sensors from the drones from which they are serviced. If the model decides to use sensor j from drone i, the value of becomes 1 and the distance from the sensor to drone j will be taken into account in the objective function. If point i is not selected to accommodate the drone, takes the value zero, and constraint (2) does not allow sensor j to be served from point i. Constraint (3) states that each sensor can be serviced by a maximum of one UAV. Since are binary variables, constraint (3) allows at most one of them to become 1. Constraint (4) does not allow sensors outside the range of a UAV to be serviced by that UAV. This is done by resetting the decision variable to zero for sensors outside the UAV radius. In constraint (5), the limited data rate of each drone is mentioned. The total data rate of the sensors serviced by the drone i should not be more than the data rate of the drone. Constraint (6) only allows the installation of G of the drone. Constraint (7) states that the sensors covered must be equal to the total number of sensors. That means all sensors must be covered. Therefore, the set of candidate points obtained from the fuzzy clustering method is given to the OP problem. The OP problem obtains the G optimal point for placing the drones. The value of G is obtain based on the bisection algorithm.



(a) Random scenario with power parameter 2.5



(b) Regular scenario with the power parameter 2.5



(c) DD scenario with power parameter 2.5

Fig. 1: Candidate points in different scenarios

### A. Obtaining the Required Candidate Points Using Fuzzy Clustering

In the case of OP, specific points where drones can be located must be identified. These points must be selected from the innumerable points, and have a limited number to obtain the required  $G$  point from them using the OP problem. Clustering means grouping points into a specific number of groups. This classification can be done based on various features, such as size, distance, material, etc. Fuzzy c-means (FCM) is a clustering method that determines the membership of different groups based on fuzzy logic. Here, we use the fuzzy clustering method of to obtain candidate point  $D$  [24], [25].

### B. The appropriate value of $G$

In the bi-section method, the problem first starts with a definite interval  $[a, b]$ . We call the midpoints “a” and “b” as “ $G$ ”. Solve the OP problem with “ $G$ ” drones. If the problem reaches the optimal solution, the value of “b” is replaced by “ $G$ ”, otherwise it is replaced by “a” and we repeat the bi-section method. Repeat the problem until the values of “a” and “b” are equal and get the minimum value of  $G$ . If the optimal solution is not found in any “ $G$ ”, there will be no optimal solution in that case. In this method, determining the value of  $b$  as the largest point of the interval is very important. Here, considering the area of the ground and the radius of the antenna cover, the value of  $b$  is considered to be 25 [15].

TABLE III: simulation assumptions

Length of agricultural land	400 m
Width of agricultural land	300 m
Number of sensors nodes	2000
Maximum number of drones	25
Bandwidth of each sensors node	192 – 115.2 bps
Bandwidth of each drone	20 kbps
Radius covered by each drone	70 m

## IV. NUMERICAL RESULTS

In this section, we review the results of the implementation of the drone optimization model using the proposed method in Section III, which focuses on three different samples of problems that include distribution of sensors in random, regular and different densities. For the simulation, we have considered an agricultural farm with dimensions of  $300 \times 400$  meters with 2000 sensors. Assume that we want to send the information collected by the sensors via drones for monitoring to a monitoring center. We assume that the resolution of each sensor is 16 bits and there are between 6 and 10 sensors in each sensor node. We also consider 20% of the data overhead, so total data rate required to send information to each sensor node is between 115.2 and 192bps. We have assumed three scenarios for the type of sensor distribution and the power parameter value in the fuzzy clustering method is equal to 1.1, 1.8 and 2.5 for each scenario. The power parameter indicates the amount of overlap of the clusters. The higher the power parameter value, the greater the overlap between the clusters. We examined each scenario with the 3 power parameters mentioned for clustering. In the first scenario, the distribution of sensors is uniformly random, in the second scenario, the sensors are arranged at regular distances from each other, and in the third scenario, the sensors are placed at different densities. In DD scenario, 4 regions with different densities for placing sensors is considered.

We considered zigbee as a communication module with a communication mode of 20 kbps. The maximum communication distance of the module in the considered model is equal to 100 meters. The selected antenna is a directional antenna with

TABLE IV: Comparison of the percentage of selected points between the three scenarios with different power parameters

	EP=1.1	EP=1.8	EP=2.5
Random	75.2%	75.2%	71.4%
Regular	74.8%	76.8%	70.4%
DD	52.8%	47.2%	0

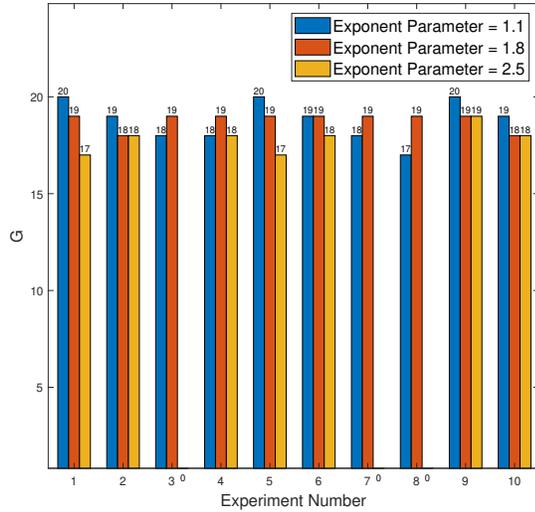


Fig. 2: Number of drones for different power parameters in the Random scenario

a beam angle of 100 degrees. According to these hypotheses, the radius coverage is approximately 70 meters. Therefore, the bandwidth of each DBS is assumed to be 20 kbps and the radius coverage of the DBS is 70 meters.

Given the number and average bandwidth required by each sensor node and the backhaul bandwidth of each drone, we need at least 19 drones to cover all sensors, but due to the different distributions of sensors and the overlap between clusters in the mentioned scenarios, we considered 25 as the maximum number of UAVs. It should be noted that using the bi-section method, the minimum number of UAVs that meet the limitations of the problem is selected. Table III shows the hypotheses of the problem.

In this optimization problem, we want to obtain the minimum number of DBSs needed to cover 100% of the sensors considering service quality constraints. Figures 1a to 1c show the candidate points obtained by the fuzzy clustering method for the three scenarios considered with the power parameter 2.5.

In each scenario, we repeat the experiment ten times with different fuzzy clustering parameters to experiment low, middle and high, power parameters. For higher power parameter, we will experience more overlap on the clusters. Figures 2 to 4 show the results of fuzzy clustering optimization in three scenarios with 1.1, 1.8 and 2.5 power parameters. As can be seen, in some iterations the problem is not solved. Especially when the power parameter is set to 2.5. In this case, due to the increased overlap between the clusters and the proximity of the drones to the denser area and the distance from the sensors that are in the less dense areas due to the limited radius of the drones as well as service quality limitations, with 25 positions as the centers of clusters, chosen by the

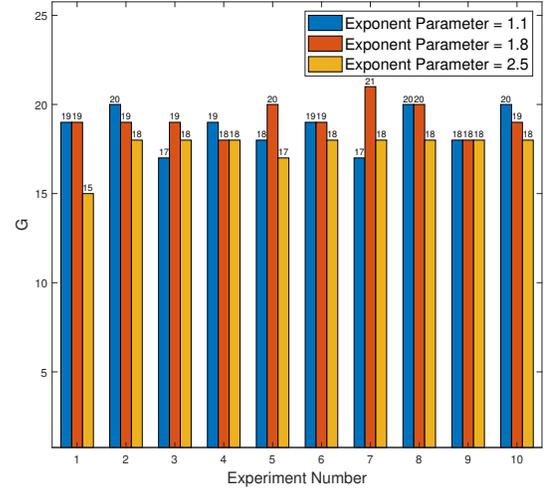


Fig. 3: Number of drones for different power parameters in the Regular scenario

fuzzy clustering method for the placement of the drones, we can not cover 100% of the sensors. Table IV shows the percentage of positions selected from the candidate points for the drones when the problem is solved. In this table, the lower the percentage obtained, the less drones will be needed. Consequently, we will have the best conditions in the DD model and selecting the appropriate power parameter.

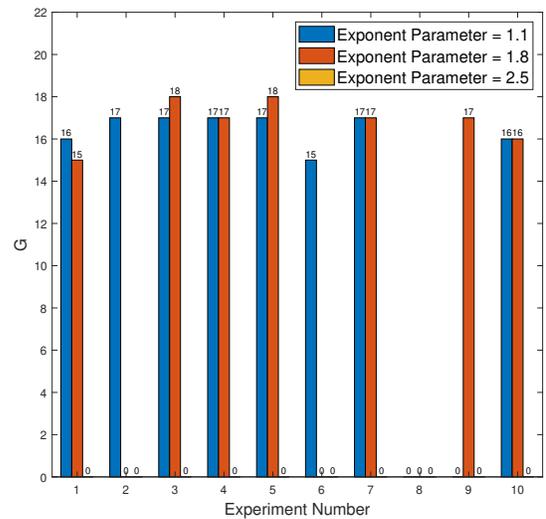


Fig. 4: Number of drones for different power parameters in the DD scenario

Figure 5 shows the comparison between the three scenarios and illustrates the importance of the shape of the distribution of sensors in the environment to determine the parameters of the problem. When the power parameter is set to 1.1 or 1.8,

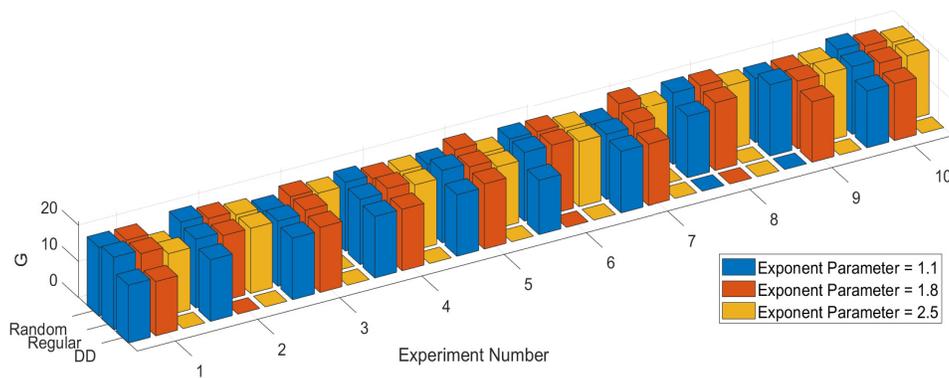


Fig. 5: Comparison of three scenarios using different power parameters

in the DD scenario, on average, fewer UAVs are required compared to random or regular scenarios. Considering the power parameter equal to 2.5, the problem in the DD scenario with 25 positions considered as the centers of clusters has not been answered, because service quality limitations. Due to the increased overlap between the clusters and the the distance of the candidate points from the sensors that are in the less dense areas, even with the selected 25 positions as centers for clusters, the coverage of 100% of sensors is not possible, because of the limited drone covering radius.

## V. CONCLUSION

In this article, a mathematical model in form of an Optimization Placement (OP) problem is presented to determine the proper positions of drones as BSs to cover 100% of users. The purpose of this problem is to find out the minimum required points that introduce minimum distance between the drone and the sensors. We used the fuzzy clustering algorithm to introduce the candidate points required by the (OP) problem and these points are minimized by the bi-section algorithm. According to the experiments, when the distribution of sensors is regular or random to cover 100% of sensors, changing the power parameter will not have a positive effect on the number of drones required, but in DD scenario, by increasing the power parameter, the cluster heads moved to denser position and drones will not cover all the sensors. Therefore, due to the coverage radius of each drone to cover all sensors, cluster overlap should be reduced to serve low-density areas. In conclusion, in order to properly place the drones when using fuzzy algorithm and OP problem, it is necessary to consider the distribution of sensors.

## REFERENCES

- [1] I. Bekmezci, O. K. Sahingoz, and Ş. Temel, "Flying ad-hoc networks (fanets): A survey," *Ad Hoc Networks*, vol. 11, no. 3, pp. 1254–1270, 2013.
- [2] S. Hayat, E. Yanmaz, and R. Muzaffar, "Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 4, pp. 2624–2661, 2016.
- [3] M. Alzenad, A. El-Keyi, F. Lagum, and H. Yanikomeroglu, "3-d placement of an unmanned aerial vehicle base station (uav-bs) for energy-efficient maximal coverage," *IEEE Wireless Communications Letters*, vol. 6, no. 4, pp. 434–437, 2017.
- [4] E. Kalantari, M. Z. Shakir, H. Yanikomeroglu, and A. Yongacoglu, "Backhaul-aware robust 3d drone placement in 5g+ wireless networks," in *2017 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE, 2017, pp. 109–114.
- [5] E. Kalantari, H. Yanikomeroglu, and A. Yongacoglu, "On the number and 3d placement of drone base stations in wireless cellular networks," in *2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)*. IEEE, 2016, pp. 1–6.
- [6] R. I. Bor-Yaliniz, A. El-Keyi, and H. Yanikomeroglu, "Efficient 3-d placement of an aerial base station in next generation cellular networks," in *2016 IEEE international conference on communications (ICC)*. IEEE, 2016, pp. 1–5.
- [7] P. Yang, X. Cao, C. Yin, Z. Xiao, X. Xi, and D. Wu, "Proactive drone-cell deployment: Overload relief for a cellular network under flash crowd traffic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 10, pp. 2877–2892, 2017.
- [8] V. Sharma, M. Bennis, and R. Kumar, "Uav-assisted heterogeneous networks for capacity enhancement," *IEEE Communications Letters*, vol. 20, no. 6, pp. 1207–1210, 2016.
- [9] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage," *IEEE Communications Letters*, vol. 20, no. 8, pp. 1647–1650, 2016.
- [10] M. Chen, M. Mozaffari, W. Saad, C. Yin, M. Debbah, and C. S. Hong, "Caching in the sky: Proactive deployment of cache-enabled unmanned aerial vehicles for optimized quality-of-experience," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 5, pp. 1046–1061, 2017.
- [11] A. Merwaday and I. Guvenc, "Uav assisted heterogeneous networks for public safety communications," in *2015 IEEE wireless communications*

- and networking conference workshops (WCNCW). IEEE, 2015, pp. 329–334.
- [12] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Optimal transport theory for power-efficient deployment of unmanned aerial vehicles,” in *2016 IEEE international conference on communications (ICC)*. IEEE, 2016, pp. 1–6.
- [13] A. Al-Hourani, S. Kandeepan, and S. Lardner, “Optimal lap altitude for maximum coverage,” *IEEE Wireless Communications Letters*, vol. 3, no. 6, pp. 569–572, 2014.
- [14] C.-C. Lai, C.-T. Chen, and L.-C. Wang, “On-demand density-aware uav base station 3d placement for arbitrarily distributed users with guaranteed data rates,” *IEEE Wireless Communications Letters*, pp. 913–916, 2019.
- [15] M. H. Zahedi, M. J. Sobouti, A. H. Mohajerzadeh, A. A. Rezaee, and S. A. Hosseini Seno, “Fuzzy based efficient drone base stations (dbss) placement in the 5g cellular network,” *Iranian Journal of Fuzzy Systems*, pp. 29–38, 2020.
- [16] L. Barolli, J. Anno, F. Xhafa, A. Durrresi, and A. Koyama, “A context-aware fuzzy-based handover system for wireless cellular network and its performance evaluation.” *J. Mobile Multimedia*, vol. 4, no. 3&4, pp. 241–258, 2008.
- [17] K. C. Silva, Z. Becvar, E. H. Cardoso, and C. R. Francês, “Self-tuning handover algorithm based on fuzzy logic in mobile networks with dense small cells,” in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 2018, pp. 1–6.
- [18] T. Inaba, S. Sakamoto, E. Kulla, S. Caballe, M. Ikeda, and L. Barolli, “An integrated system for wireless cellular and ad-hoc networks using fuzzy logic,” in *2014 International Conference on Intelligent Networking and Collaborative Systems*. IEEE, 2014, pp. 157–162.
- [19] M. Cuka, D. Elmazi, R. Obukata, K. Ozera, T. Oda, and L. Barolli, “An integrated intelligent system for iot device selection and placement in opportunistic networks using fuzzy logic and genetic algorithm,” in *2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA)*. IEEE, 2017, pp. 201–207.
- [20] 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*, pp. 1–11, 2020.
- [21] T. Sigwele, P. Pillai, A. S. Alam, and Y. F. Hu, “Fuzzy logic-based call admission control in 5g cloud radio access networks with preemption,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2017, no. 1, p. 157, 2017.
- [22] Z. Zinonos, C. Chrysostomou, and V. Vassiliou, “Wireless sensor networks mobility management using fuzzy logic,” *Ad Hoc Networks*, vol. 16, pp. 70–87, 2014.
- [23] M. Cuka, D. Elmazi, K. Bylykbashi, E. Spaho, M. Ikeda, and L. Barolli, “Implementation and performance evaluation of two fuzzy-based systems for selection of iot devices in opportunistic networks,” *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–11, 2018.
- [24] S. L. Chiu, “Fuzzy model identification based on cluster estimation,” *Journal of Intelligent & fuzzy systems*, vol. 2, no. 3, pp. 267–278, 1994.
- [25] D. J. Bora and A. K. Gupta, “Impact of exponent parameter value for the partition matrix on the performance of fuzzy c means algorithm,” *arXiv preprint arXiv:1406.4007*, 2014.