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Fuzzy based efficient drone base stations (DBSs) placement in the 5G cellular network

M. H. Zahedi[1], M. J Sobouti[2], A. H. Mohajerzadeh[3], A. A. Rezaee[4] and S. A. Hosseini Seno[5]

[1]*Department of E-Learning, K.N.Toosi, Iran*

[2,3,5]*Department of Computer Engineering, Ferdowsi University of Mashhad, Mashhad, Iran*

[4]*Department of Computer Engineering and Information Technology, Payame Noor University, PO BOX 19395-3697 Tehran, Iran*

zahedi@kntu.ac.ir, javad.sobouti@mail.um.ac.ir, mohajerzadeh@um.ac.ir, A_rezaee@pnu.ac.ir, hosseini@um.ac.ir

Abstract

Currently, cellular networks are one of the essential communication methods for people. Providing proper coverage for the users and also offering high-quality services to them are two of the most important issues of concern in cellular networks. The fifth-generation cellular communication networks can provide higher data transmission rates, which lead to a higher quality of service but this higher rate has let to reduced antenna coverage in these networks. Besides this, natural and unnatural events in the environment can also affect the coverage of users in the cellular network. One way to resolve this issue is using drones as cellular antennas. The most important factor in providing good coverage and high-quality service for users is the optimal placement of antennas. In this article, the problem of finding the appropriate locations of drone base stations (DBSs) is modeled as a P-median optimization problem, where P is the number of required antennas to cover the users. We have used a fuzzy clustering algorithm to define a set of specified candidate points that are required to select the locations of DBSs in the P-median model. The optimal value of P was obtained using the bisection algorithm. Finally, the optimal positions of DBSs have been determined by solving the optimization problem. According to the results, in the case of a proper selection of fuzzy clustering parameters, better results will be obtained in comparison to the results of other approaches.

Keywords: Fuzzy clustering algorithm, 5G, UAV, cellular networks, quality of service, drone base stations.

1 Introduction

Wireless communications have significantly gained importance in todays world and proven their impact on different layers of society. Given a good reception by society, wireless communications turned out to be one of the most profiting industries in the world and consequently, its growth rate and competitiveness increased remarkably. The rate of data transfer in communication networks has also increased very rapidly. The data transfer rate in the first-generation networks was only 1.2 kilobits per second, which rose up to about 6.9 kilobits per second in the second-generation networks. In the third-generation networks, this value increased to 394 kilobits per second and then to more than 2 megabits per second. in the fourth-generation networks, this rate is about 100 megabits per second. The data transfer rate of the fifth-generation networks will reach 1 gigabit per second. It has not been a long time since the 4th generation (4G) hit the market and the scientific communities are already discussing the next generation, i.e., 5G and many research centers are studying this topic. Although it is necessary to increase the speed and also the data transfer frequency in the fifth generation, coverage is similarly also one of the most critical issues in the new generation networks. Increasing frequency will reduce the coverage area. As a result, more antennas are needed since the users cannot tolerate disconnections or disturbances in the network or its coverage.

Besides, scientific and technological advancements in computer science have brought the application of unmanned aerial vehicles (UAVs) into the spotlight. Unmanned aerial vehicles technology has significantly improved over the last

Corresponding Author: A. A. Rezaee

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few years [4], [12] and UAVs have been used in numerous applications. One of the most important applications of drones in computer and communication networks is to use them as aerial antennas to create better network coverage for the users. Using drones as mobile antennas have been proposed as a solution for providing fast and high-quality service during uncalled-for natural or unnatural events such as earthquakes, hazardous weather conditions and problems in BTSs. Using drones can also be useful in cases where installation of antennas on the ground is not economical or even impossible due to geographical conditions, e.g., include mountains and during temporary periods of high network traffic [15], [2]. The advantage of using drones as aerial antennas is that they do not need any predetermined infrastructures and can be placed in any location. Another benefit of using drones is the possibility of better LOS communication since they are placed at higher altitudes, which also reduces fading and shadowing disturbances.

Furthermore, drones can move, and it is possible to change their locations to enhance the quality of service and reduce disturbances as the conditions change. This ability can also increase the percentage of covered users by the network whenever necessary. It is also possible to assign higher bandwidths to users by expanding the coverage and number of DBSs. Despite all of these advantages, using drones also have some challenges such as determining the correct placement of drones, designing path, resource allocation, energy consumption, multiple access schemes, the optimum number of UAVs, and so on.

2 Related works

The problem of optimal placement of drones has drawn a lot of attention since the correct drones deployment increases the reliability of air-to-ground links. Using a heuristic algorithm, the minimum number of drones required and their optimal three-dimensional placement for covering users have been calculated in [16]. In this study, drones change their altitude according to user density of the area to reduce the interference with other antennas; therefore, the users get their coverage area. In other words, the drones decrease their altitudes in populous and denser regions, while they work at higher elevations over less densely populated regions. The reference [15] has presented an optimal three-dimensional deployment method, considering back haul, in two user-centric and network-centric frameworks. The network robustness has also been examined after selecting the location of the drones and determining the coverage area. An algorithm is proposed in [2] for finding the optimal two-dimensional placement of DBSs to maximize the number of covered users while their required transmit power is minimized. Reference [6]h as determined the three-dimensional placement of DBSs to achieve the maximum number of covered users.

A proactive drone-cell deployment framework was proposed in [23] to relieve the overload induced by flash crowd traffic in 5G networks. In this method, the authors approached the drone-cells placement problem as a clustering problem, where the users covered by each drone are considered as one cluster. Putting the drone at the center of the cluster minimizes the total sum of squared distances between the drone cell and the cluster members. In the end, a constraint bisecting k-means method was proposed to solve the drone placement problem. Furthermore, flash crowd traffic models for three sample social activities, including a stadium, a parade, and a gathering were investigated in this framework.

Reference [20] has investigated the problem of deploying multiple drones by developing a technique for mapping the drones to the areas with high traffic demand. This technique has been developed using a neural network-based cost function. Using the circle packaging theory, the researchers in [18] have developed a method to find the optimal three-dimensional placement of UAVs equipped with directional antennas. The 3D locations of UAVs obtained in this method maximize the total coverage area. Reference [8] has proposed a proactive deployment method for cache-enabled drones to optimize the quality-of-experience for users (QoE). In this method, a model predicts the popular contents. The drones then cache these contents that result in the reduction of the data packet transmission delay. In reference [17], the optimized locations of UAVs are found using brute force search to be able to deal with disasters and improve public safety communications. Optimal cell boundaries and optimal locations of multiple non-interfering UAVs have been obtained in [19] with the purpose of minimizing UAVs total transmission power. Paper [1] has presented an analytical model to determine the optimal altitude of a UAV for maximizing coverage area. The authors in [6] have also discussed finding the optimal three-dimensional location of a drone cell to maximize the number of users satisfying their SNRs (signal-to-noise ratio).

There are also some works in 5G cellular and computer networks based on fuzzy logic. In [22] writers introduce an algorithm for targeting handover to reduce the amount of ping pong handovers and the failure ratio based on a fuzzy logic-based threshold. In [21] a fuzzy logic-based call admission control scheme with preemption in C-RAN is proposed. In [3] writers used Fuzzy Logic which can operate with imprecision data for handover in cellular networks. The context-triggered actions are carried out based on simple IF-THEN rules. Article [14] proposes the Fuzzy-Based Multi-Interface System (FBMIS), in order to improve the communication performance where each node is equipped with two interfaces: MANET or cellular network. In [24] a Fuzzy Logic-based mobility controller is proposed to aid sensor Mobile Nodes to decide whether they have to trigger the hand off procedure and perform the hand off to a new connection position or not. Design of an integrated intelligent system for IoT device selection and placement in opportunistic networks is presented in [10] using Fuzzy Logic and Genetic Algorithm. Writers in [11] implemented and compared two fuzzy-based systems to select IoT device in opportunistic networks where each system contains certain IoT device properties such as energy, storage, security, etc. Even though there are some works in computer and cellular networks, using fuzzy in DBS placement is the first of our knowledge.

In this paper, we present a mathematical model based on the P-median problem for optimal placement of drones as mobile antennas. The P-median problem is a location-allocation problem in which we select P points from the initial candidate points in a way that the average distance of all users from these points is minimized. We then implement this model using different sets of candidate points based on fuzzy clustering. We compare the results with each other and with the results obtained based on fuzzy clustering method. The key ideas in the research are as follows:

- To the best of our knowledge, our proposed algorithm uses fuzzy decision system in DBS placement where there is no other research in the literature.
- Solving the optimal placement of DBSs in space based on the location problem.
- Determining the candidate points for the location problem using fuzzy clustering.
- Presenting a linear binary optimization model for solving the problem.
- Considering both coverage and bandwidth parameters simultaneously as inputs for the optimization problem.
- Choosing the appropriate number of DBSs using the bisection algorithm.

We continue in section 3 by presenting the mathematical model and our proposed method to solve the problem. In section 4, we present the results of implantation of the model and the comparison of results obtained by using different sets of candidate points. Finally, the conclusions are drawn in section 5.

3 A mathematical model of the problem

The problem of finding the appropriate locations for installing antennas falls into the category of location-allocation problems. One of the most well-established location-allocation problems is the P-median problem. In the P-median optimization model, we should select P points from a number of candidate points, which are the centers for providing wireless services, in a way that the average distance between the users of service and their nearest center are minimized. Since we are also looking to minimize the total/average distance between users and antennas in this paper, we perform the optimization modeling of this problem in the framework of a P-median model.

3.1 Proposed method

In the optimization model of the problem, we assume that the coordinates of users and candidate points for placing the antennas are given. It is also assumed that the bandwidth of each antenna and bandwidth required by each user are known. The goal in this problem is finding the locations of P antennas in a way that the total/average distance between users respectively and the selected antenna is minimized, and at least α percent of users are covered.
To formulate this problem, we first introduce the parameters and decision variables. The parameters used in this model are BW and BWU_j the bandwidth of DBS and bandwidth of user i, respectively. I and J are sets of candidate points and users and d_ij is the distance of user j from antenna i. Also R, P and D are covering radius of each antenna, the number of deploying antennas and number of candidate points respectively and parameter U is the number of total users. The decision variables of the mathematical model are X_ij and MB_i which orderly are binary variables that determine if antenna i covers user j and if the model select candidate point i to place a DBS.
The DBS placement problem is modeled as follows:

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

$$\text{s.t.} \qquad X_{ij} \leq MB_i, \qquad \forall i \in I, \forall j \in J \tag{2}$$

$$\sum_{i=1}^{D} X_{ij} \leq 1, \qquad \forall j \in J \tag{3}$$

$$\sum_{j=1}^{U} BWU_j X_{ij} \leq BW, \qquad \forall i \in I \tag{4}$$

$$\sum_{i=1}^{D} MB_i = P \tag{5}$$

$$\sum_{j=1}^{U} \sum_{i=1}^{D} X_{ij} \geq \alpha U \tag{6}$$

Relation (1) is the objective function in this problem. We want to minimize this function, which is the sum of distances between the antennas and their users. If the model decides that antenna i is responsible for providing wireless services for user j, the value of $X_i j$ will be 1, and this value will be substituted in the objective function.
Constraints (2) indicates that candidate point i can only provide services for user j only if that point is selected for the installation of an antenna. In other words, if point i is not selected for placement of an antenna, MB_i will be zero and constraint (2) does not allow user j to get services from point i.
Constraints (3) says that each user can receive wireless services from at most one antenna. Since $X_i j$ variables are binary variables, constraint (3) allows only one or none of them to be 1. It is evident that when a user is out of the coverage area of an antenna, that user is not allowed to receive services from that antenna. Therefore, the decision variable $X_i j$ will be zero for the users out of the coverage area of an antenna.
(4) states the bandwidth limit of each antenna. Actually, the bandwidth of the users receiving services from antenna i should not be higher than the bandwidth of that antenna.
Constraints (5) allows the installation of only P antennas. We discuss how to determine the appropriate value of P considering cost and quality of service.
Constraints (6) indicates that the ratio of covered users to the total number of users should be larger than α. Applying this constraint assures the coverage of at least α percent of users.

After modeling the problem, the following questions arise:

- What are the candidate points for installing antennas and how should they be determined? As can be seen in the description of model parameters in Table 1, the set of candidate points (I) for placement of antennas is one of the models inputs in this type of modeling.
- What is the appropriate value of P? In this type of modeling, the number of antennas for covering users should also be predetermined.

3.2 Determining the candidate points for placement of antennas based on fuzzy clustering

In the P-median model, the points in which the antennas can potentially be installed must be specified. By choosing this model and nominating a finite number of points in the plane, we can simplify the original optimization problem. Now instead of selecting P points from an infinite number of points in the plane, we should choose P points from a finite number of specified positions.
Here, we continue by describing the strategy for determination of candidate points based on fuzzy clustering method.

Clustering is an unsupervised method to categorize objects in some sense which is common in machine learning, pattern recognition, vision analysis, data mining, etc. Clusters are groups of data with the most similarities in the desired criterion. Some of the clustering algorithms are based on the distance of objects and the clusters center like k-means, k-medoids, etc. [13]. Fuzzy c-means (FCM) is a clustering method based on the fuzzy logic that determines the degree of objects membership belong to a cluster. Jim Bezdek proposed this method in 1981 as a generalized instance of prior clustering methods [5]. In FCM the following objective function which is shown in equation (7) is minimized.

$$J_m = \sum_{i=1}^{D} \sum_{j=1}^{N} \mu_{ij}^m \left\| x_i - c_j \right\|^2 \tag{7}$$

Where D represents for the number of data points, N is the number of clusters, x_i and c_j are the i-th object and the center of cluster j respectively. Also, μ_{ij} is the membership degree of x_i in the j-th cluster and m is fuzzy partition matrix exponent parameter to control the degree of fuzzy overlap and must be greater than 1. Indeed FCM makes fuzzy boundaries and the size of overlap refers to how many objects are shared between clusters.

To cluster data with FCM first membership values are determined randomly then cluster centers are calculated by the formula (8) based on μ_{ij} and after that μ_{ij} updates according to equation (9) [9]

$$c_j = \frac{\sum_{i=1}^{D} \mu_{ij}^m x_{ij}}{\sum_{i=1}^{D} \mu_{ij}^m} \tag{8}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N} \left(\frac{\|x_i - c_i\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \tag{9}$$

Steps of FCM are shown in the fig.2 flowchart.

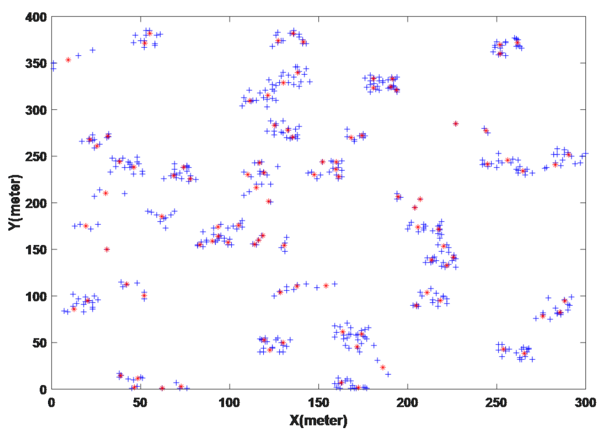


Figure 1: Users positions and clusters centers based on fuzzy c-means

The value of m exponential parameter- is a key decision for placing the center of clusters and the overlap between each. If $m = 1$, FCM acts like k-means algorithm while for other values of $m > 1$ the overlap of clusters increases and centers become close to each other. This parameters value depends on the problem and data distribution which is empirically investigated in [7]. Therefore, centers of clusters according to users positions is shown in fig.1.

3.3 The appropriate value of P

Before we can solve the mathematical model, we actually need to know the appropriate value of P. Here we propose the following algorithm for finding the proper amount of P:
First, we find P_{max}, which is the value of P for which the problem is surely feasible. Then, we search the P_{max} space using the binary search algorithm. This means that we actually solve the mathematical model with in the order of P_{max}.
The most straightforward choice for P_{max} is the number of users because if users distribution have low density and they place far from each other we need utmost U antenna for cover them which U is the number of users and, one antenna is covering just one user.
The flowchart in Figure 3 shows the order and stages of implementing the proposed method and then solving the optimization model of the problem.

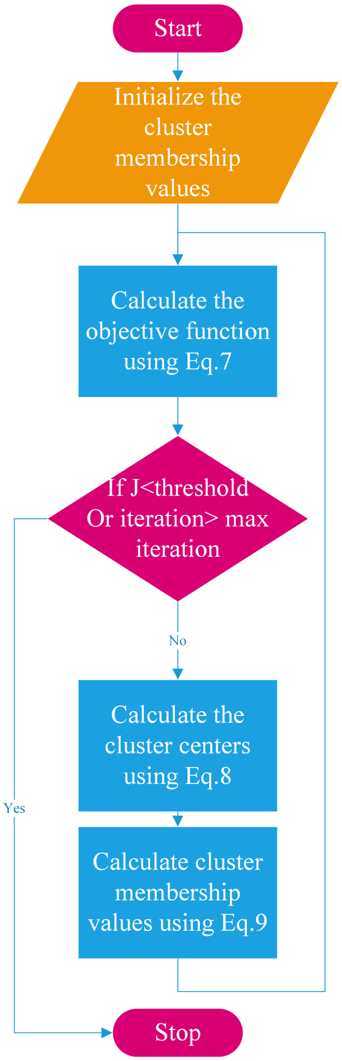


Figure 2: Fuzzy c-means flowchart

4 Numerical results

In this section, we discuss the implementation results of the optimization model for the placement of antennas in a sample problem, using the proposed methods. We also compare our proposed model with results of Genetic Algorithms (GA). In our simulations, we considered an area of 300×400 square meters with 513 points that are distributed according to real data. In this optimization problem, we would like to find the minimum number of DBSs required for covering at least 90 percent of users (parameter α), while taking the constraints of service quality into account. The bandwidth and coverage radius of all DBSs are assumed to be 50 Megabits per second and 50 meters respectively. The optimization problem is solved with Cplex as a linear programming solver. Moreover we ran each method containing GA more than 10 times for each state to have a good average result.

Figure 4a and 4b show the placements of DBSs obtained by solving the optimization problem for two sets of candidate points. These two sets were determined by two different types of fuzzy clustering. The number of clusters is 150, and the exponent parameter value is 1.5. The number of clusters in Figure is equal to 100.

Here, we compare different sets of candidate points as the inputs of the optimization model in terms of different types of fuzzy clustering with Genetic Algorithm. Figure 5 shows a comparison between the numbers of DBSs required in five different cases of fuzzy clustering and Genetic Algorithm. In Figure 5, we can see the effect of varying exponent parameter of the fuzzy c-mean algorithm including 1.2, 1.5, 2, 2.5, and 3. This Figure also shows the effect of the number of clusters on the number of DBSs. Numbers of clusters used in this simulation are 100, 125, 150, 175, and 200.

As can be seen in this Figure 5, solving the optimization problem, with the fuzzy clustering parameter of 1.5,

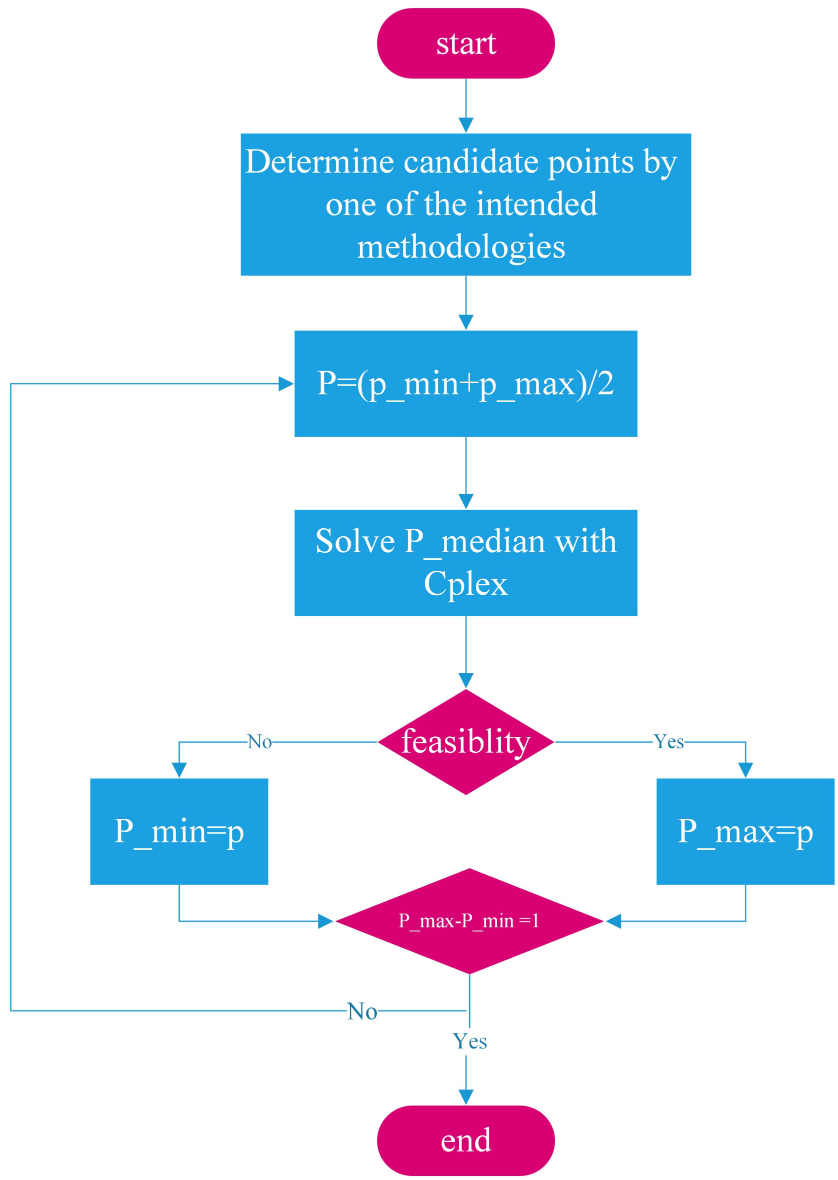
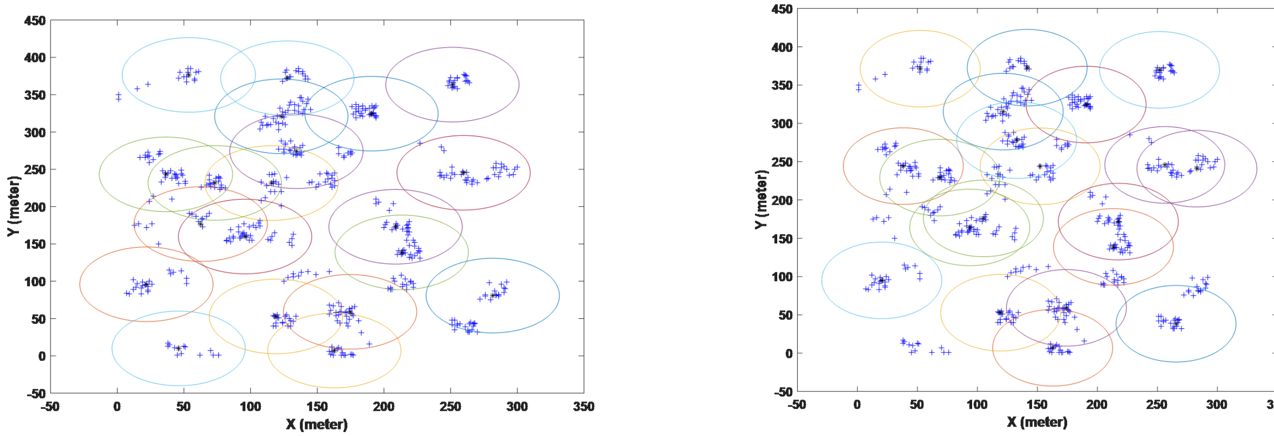


Figure 3: Flowchart of implementing the proposed method

generally results in a lower number of DBSs for the different number of candidate points in comparison with other cases of exponent parameters or GA. It is evident that in other cases, for example when the parameter is 1.2 or 2, numbers of DBSs required for covering users is not much more either.

In Figure 6, we can see the comparison between different cases of clustering in terms of covered bandwidth of users. According to this Figure, using the fuzzy c-means algorithm with the exponent parameter of 1.5 with 150 clusters results the maximum covered bandwidth of users. This value is the maximum possible bandwidth coverage of each antenna. Except for the group of 200 clusters, the covered bandwidth obtained for the exponent parameter 3 is the lowest in comparison with other cases. This could be due to the high overlap of antennas in this case. Using the exponent parameter 1.5 in clustering will lead to the maximum covered bandwidth of the users while requiring the lowest or equal number of DBSs in comparison with other cases.

Figure 7 shows a comparison between different cases in terms of covered users. In all clustering cases, more than 90 percent of users should be covered due to constraints (6). However, since the main goal of our model is to reduce the number of DBSs, in some cases this constraint is not fulfilled. For example, in the case of using the fuzzy c-means algorithm with the exponent parameter of 3, the constraint is satisfied only with 200 clusters using 28 DBSs. However, it still covers less bandwidth due to fig.6. For the exponent parameter of 1.2, 1.5, or 2 and the number of DBSs of 20 or 21, the network will not cover less than 90 percent of users. Although GA always could cover enough user, the number



(a) 150 clusters (b) 100 clusters

Figure 4: Optimal DBS placement using FCM with exponent parameter = 1.5 and a) 150 and b) 100 clusters

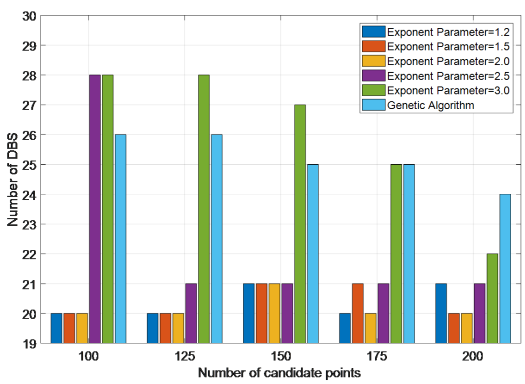


Figure 5: Number of DBSs required in each case

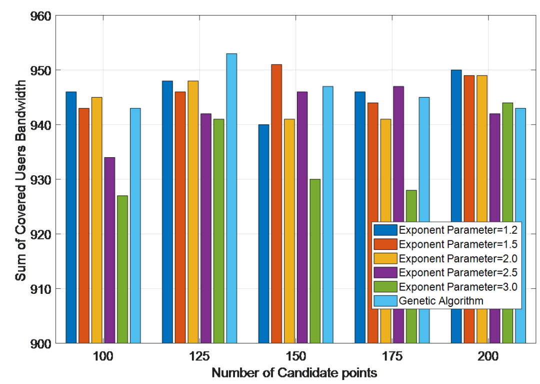


Figure 6: Sum of covered bandwidth

of required DBSs is more than the best result of the proposed method.

Figure 8 shows a comparison between the values of the objective function in different cases of fuzzy clustering and Genetic Algorithm. This comparison also shows that the results of using the exponent parameter 1.2 are significantly better than other cases. That is because the final DBS locations found by solving the optimization problem are quite near to the coordinates of users (the most optimal points). However in some cases, if the candidate points are determined using the exponent parameter of 1.5 the distance between the users and their associated drones is less. Thus, the objective function will be minimized. By the way, GA results the least objective function using 200 candidate points because of having enough points to select which have less distance from users.

It is clear that choosing the right exponent parameter and the proper number of clusters is very important in solving this optimization problem. Comparing the different cases of fuzzy clustering shows that using the exponent parameter of 1.5 and the cluster number of 150 not only leads to a less number of DBSs required for covering the same number of users but also provides more bandwidth. If we look to reduce the number of drones, we can use other values of the exponent parameter, such as 1.2 or 2, in determining the candidate points for the P-median optimization problem. But if it is more important to minimize the objective function value, the exponent parameter of 1.5 generally results in lower values for the objective function. Among different cases of using the exponent parameter of 1.5, the objective function value is minimum for the cluster number of 175.

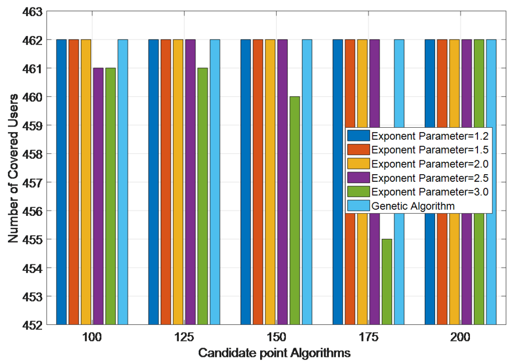


Figure 7: Number of covered users using each case of FCM in the optimization model

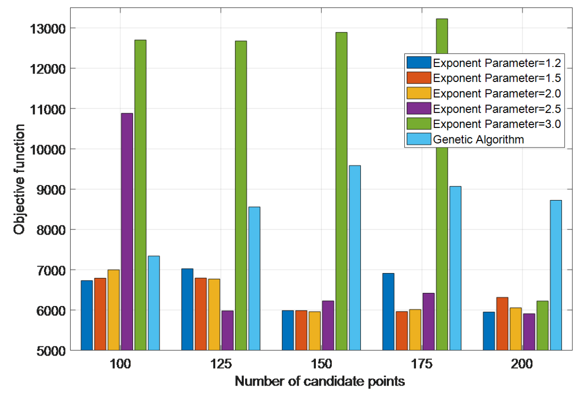


Figure 8: Value of objective function using each case

5 Conclusions

In this study, a mathematical optimization model based on the P-median model was presented to determine the placement of DBSs in the intended space. Since it is not possible to solve this problem directly in a reasonable period of time, we used the bisection algorithm to find the value of P. Besides, we suggested the use of fuzzy clustering method to find the candidate points. Different cases of fuzzy clustering were investigated. According to the results obtained by simulating and solving the optimization problem, we realized that fuzzy clustering could be one of the most functional methods for defining the candidate placement points to be used in antenna placement optimization problems. Our investigations showed that the fuzzy c-means algorithm with the exponent parameter of 1.5 and the cluster number of 150 generally had a better performance than other cases of fuzzy clustering, as it resulted in a lower number of DBSs and higher covered bandwidth. The value of the objective function was also lower in this case. But the most important purpose of solving this problem was minimizing the number of DBSs, which was obtained by using the exponent parameter of 1.5 and the cluster number of 150 in the fuzzy c-means algorithm.

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