Efficient Fuzzy-Based 3-D Flying Base Station Positioning and Trajectory for Emergency Management in 5G and Beyond Cellular Networks

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***Abstract*—The need for continuous coverage, as well as low-latency, and ultrareliable communication in 5G and beyond cellular networks encouraged the deployment of high-altitude platforms and low-altitude drones as flying base stations (FBSs) to provide last-mile communication where high cost or geographical restrictions hinder the installation of terrestrial base stations (BSs) or during the disasters where the BSs are damaged. The performance of unmanned aerial vehicle (UAV)-assisted cellular systems in terms of coverage and quality of service offered for terrestrial users depends on the number of deployed FBSs, their 3-D location as well as trajectory. While several recent works have studied the 3-D positioning in UAV-assisted 5G networks, the problem of jointly addressing coverage and user data rate has not been addressed yet. In this article, we propose a solution for joint 3-D positioning and trajectory planning of FBSs with the objectives of the total distance between users and FBSs and minimizing the sum of FBSs flight distance by developing a fuzzy candidate points selection method.**

***Index Terms*—3-D positioning, flying base station (FBS), fuzzy candidate point selection (FCPS), trajectory planning, unmanned aerial vehicle (UAV)-assisted 5G.**

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I. Introduction

New-generation cellular networks deliver higher data transmission rates, better quality of service (QoS), and more energy efficiency. Significant improvement in 5G performance in terms of ultrareliability, low latency, high throughput, and secure communication compared with the previous generations of cellular networks has paved the way for various emerging use cases, such as augmented and virtual reality, smart healthcare, smart cities, and smart transportation [1], [2]. According to an international telecommunication union study, mobile traffic would surge to 5016 exabytes per month by 2030. In addition, it was anticipated that the worldwide mobile user base will grow to 13.8 billion by 2025 and 17.1 billion by 2030 [3], [4].

A. Unmanned Aerial Vehicle (UAV)-Assisted Solutions

The drone industry has been remarkably enhanced over recent years and new applications of drones have appeared [5], [6]. In recent years, UAVs have been deployed as flying base stations (FBSs) to extend the coverage of cellular networks and enhance QoS [7]. Exploiting FBSs to provide network users with wider network coverage is a major application of UAVs in cellular networks. The main idea behind employing UAVs as FBSs is to achieve immediate and relatively reliable services while encountering unwanted happenings and situations, e.g., earthquakes, floods, and damaged or broken base transceiver stations. A key application of FBSs is to provide agile and reliable communication services during man-made and natural disasters, e.g., earthquakes and floods where the terrestrial base stations (BSs) are damaged [8], [9]. Another motivation for the installment of FBSs is where the positioning of terrestrial BSs becomes uneconomical or impractical owing to mountainous, rugged, and rocky terrain, and also when the cellular network is suffering from high traffic loads, such as sports or cultural events [10], [11]. Easy and low-cost deployment and the high chance of line-of-sight (LoS) communication are amongst the unique features offered by aerial BSs [12]. In addition, due to the mobility capability of UAVs, in the case that the network status deteriorates, UAVs can increase the QoS and decrease the impairments by changing their positions. The mobility feature may also increase the number of covered network users if required.

Furthermore, network users may be also provided with upper data rates by expanding the coverage and quantity of FBSs [13].

The implications for the FBS solution arise from the assumption that the BS should have multiple antennas and analog beamforming capabilities. Analog beamforming facilitates the use of larger arrays and enhances spectral efficiency by steering beams toward multiple users with different frequencies or time slots. The FBS can enhance coverage and capacity, particularly in mmWave bands with high path loss and LoS communication needs. It can decrease hardware complexity and power usage in FBS by using just one radio frequency chain per antenna array, rather than one per antenna element like digital beamforming. The FBS's battery life and flight time can be extended while reducing equipment cost and weight [14].

Analog beamforming may also pose limitations and challenges for the FBS solution. The lacks of spatial multiplexing support, preventing it from transmitting multiple data streams to one or multiple users simultaneously. Therefore, high-demand applications like video streaming or virtual reality can be limited by the data rate and throughput of the FBS. The user equipment (UE) with analog beam former faces another challenge: fast and accurate beam tracking. To maintain a reliable link with the UE, the FBS must constantly adjust its beam direction and width. In order to optimize its beamforming strategy, the UE must relay its channel state information back to the drone BS. The feedback process may cause slower response times and increased system load, leading to decreased performance [15].

It is worth noting that new releases of the 3rd Generation Partnership Project included basic features for new radio to support satellite communications; however, there are several issues yet to be addressed for satellite-assisted communication, such as long delay and high Doppler shifts [16]. UAV-assisted 5G communication offers several advantages compared with satellites to extend the coverage of 5G and beyond as summarized below.

1) Lower latency: Since UAVs are closer to the ground and have shorter communication lines, UAV networks have substantially less latency. This is crucial for real-time applications that demand lower latency. Due to the longer distance that signals must travel, satellites have substantially higher delays.
2) Increased Flexibility: UAV networks are more flexible since drones can be deployed and repositioned more quickly and easily than satellites as needed. Satellites are fixed in orbit once deployed.

B. Challenges of UAV-Based Networks

Since UAVs are usually battery-powered and have limited energy resources, their deployment as aerial relays or BSs requires optimal position and effective path planning strategies to achieve the expected performance in terms of coverage extension and QoS-improvement while extending the UAVs' lifetime. Besides the 3-D positioning and the trajectory of UAVs, the impact of interference caused by UAVs to neighbor BSs due to strong LoS ray and channel modeling has been investigated in developing UAV-assisted 5G networks. Numerous studies have been undertaken on the 2-D and 3-D deployment of drones and stations in various wireless networks [17], [18], [19]. In addition, several studies have been conducted on the movement of drones across wireless networks, the Internet of Things, and sensor networks [20], [21]. We will review these works in the next section in detail. We have conducted several studies on routing challenges as well, which will be addressed in future works [22], [23].

C. Contributions of This Article

In this article, we consider a disaster occurrence in the target area. As mentioned, one of the applications of FBSs in cellular networks is when disasters occur. With a disaster, first aid teams start assisting and cooperating quickly, and communication becomes one of their most essential needs, particularly when the disaster has destroyed terrestrial BSs. In such conditions, we will need a fast deployment structure to make communication available. Therefore, the target area is considered as free space for attenuation.

We introduce an efficient fuzzy-based approach for positioning and trajectory of FBSs in emergency situations to overcome QoS and network coverage challenges. Existing positioning and trajectory approaches in the FBS domain are categorized based on 2-D and 3-D operational altitudes. Most 2-D positioning works overlook the ability of UAVs to change altitude on demand and consider a small number of users and UAVs, while 3-D positioning works have considered fewer limitations in solving the problem in a reasonable time. Trajectory optimization works have focused on both 2-D and 3-D trajectories, but most have not considered user movement and have used traditional clustering algorithms that are location-aware and do not consider data rate and user-requested QoS.

Unlike the majority of earlier research, this article addresses both coverage and data rate limits concurrently. The mathematical model provided in this article determines the UAV altitudes, and we solve the problem using an accurate manner. In contrast to existing commonly used methods, we describe a fuzzy candidate point selection (FCPS) approach that takes users' locations and their desired data rate into account. In addition, we present a 3-D trajectory solution, whereas the majority of the literature examines 2-D space. To sum up, the main contributions of this article are as follows.

1) Proposing a fuzzy algorithm to find candidate points, which significantly improves the performance of the proposed positioning model.
2) Finding the minimum number of required FBSs to cover and serve users using a heuristic method.
3) Considering the positioning and trajectory of FBSs to improve not only the QoS but also minimize the number of required FBSs.

The rest of this article is organized as follows. In Section II we review the literature. Section III presents the system model of the problem. In Section IV, the mathematical models and formulation of positioning and trajectory problem are discussed. In Section V, the performance of our proposed infrastructure is evaluated. Finally, Section VI concludes this article.

II. Related Works

This article introduces an efficient fuzzy-based FBSs positioning and trajectory approach to overcome the QoS and the network coverage challenges in an emergency. This section makes an overview of the existing positioning and trajectory approaches in the FBS domain while categorizing them based on 2-D and 3-D operational altitudes.

A. Positioning

Sobouti et al. [24] presented a multi-UAV efficient 2-D placement algorithm covering IoT nodes. They exploited an algorithm to obtain the least number of possible drones. A mathematical model was also proposed to obtain suitable places, where all drones on a 2-D plane lie at the same elevation. Since the mathematical model needed candidate points to obtain a suitable place for drones, a smart mesh method was presented. Rahimi et al. [25] goal was to leverage the 5G cellular network to supply the traffic required by participants of a sporting event held in a rural region. An efficient approach to obtaining the minimum number of necessary UAVs and the best 3-D location for them was presented. In addition, they proposed an efficient technique for finding candidate points and scoring points, named MergCells. Wang and Yang [26] investigated a drone-enabled cellular network with drones flying at a very lower elevation and offering services to terrestrial users. The problem of finding the optimal 3-D locations for drones was formulated more practically, considering the restrictions of 3-D space and terrestrial obstacles. This article was aimed at improving the security of wireless networks using UAVs. Zhong et al. [27] maximized the overall number of the individuals covered while satisfying the QoS requirements. They optimized the 3-D placement of drones to address the individuals' expected services. In this work, the A2G path loss model was taken into account, and drones were initially deployed horizontally by exploiting a genetic algorithm and then vertically in order to maximize the coverage while considering the data distribution rate. Their work, similar to our proposed solution, addresses both coverage and data rate limits concurrently; however, it does not take into account the trajectory of UAVs. Our method covers both the placement and trajectory of UAVs.

The primary flaw with 2-D positioning works is that they overlooked the most significant characteristic of UAVs: the ability to change altitude on demand. In addition, most positioning works consider a small number of users to service and a few UAVs to deploy (often one or two UAVs). Moreover, to the best of our knowledge, most of the works on UAV 3-D positioning have considered a relatively small set of constraints to solve the problem in a reasonable time. As a result, the developed solutions are not practical and scalable for real scenarios. In addition, the early works of literature often have solved optimization models using heuristic or metaheuristic algorithms, which directly affect the precision of the findings and are time-intensive.

B. Trajectory

Khamidehi and Sousa [21] optimized the path traveled by multiple FBSs, maximizing the bit rate of mobile users. The formulated problem constrains the strength of FBS, taking into account the signal power, backhaul capacity, and interference. The problem exploits a new algorithm on the basis of a sequential convex approximation method. Wang et al. [28] provided relay drones with a SAG-LoRT architecture to load data from smartphones to the satellites located at low-Earth orbit. In order to maximize network capacity, this work jointly optimized the connection time of smartphones, power management, and drone trajectory. The problem was modeled as nonlinear integer programming. Zhang et al. [29] examined the drone-enabled emergency networks, where drones serve as FBSs in order to gather data from terrestrial individuals in disaster-affected regions. Owing to the failure of the terrestrial power supply caused by disasters, the accessible energy is insufficient for influenced user devices. In addition, due to post-disaster environmental circumstances, drone flight is influenced by terrestrial barriers. To tackle the problem, the authors of this work modeled the drone trajectory optimization problem with limits on user-device energy and the position of terrestrial barriers to maximize the uplink efficiency of drone networks within the flying period. As the user-device energy limitation was dynamic, they turned the problem into a constrained Markov decision-making process (CMDP) with the drone as an agent. To solve CMDP, they presented a drone path planning algorithm, based on safe deep Q-network, in which the drone learns to do the best action based on sensible policies. UAV paths for serving IoT devices were chosen based on a connected graph in [30]. To find the shortest-path energy for conservative planning to meet the nodes dynamically, their suggested technique, known as semidynamic mobile anchor guidance, employed a weighted search algorithm. Wu et al. [31] proposed a learning-based approach for optimal UAV caching and trajectory in aerial-assisted vehicular networks. They formulated a joint caching and trajectory optimization problem to maximize the overall network throughput and proposed a deep supervised learning scheme to enable real-time decision-making.

To jointly optimize the 3-D trajectory of the UAV and the phase-shift of the reconfigurable intelligent surface, Mei et al. [32] suggested the double deep Q-network and deep deterministic policy gradient-based methods. The suggested method has been demonstrated to be successful in increasing the UAV's energy efficiency while meeting ground terminals' demands for data transfer. Cai et al. [33] introduced an IRS to support NOMA-based UAV communication systems for numerous ground users. By collaboratively constructing the resource allocation plan, the UAV's 3-D trajectory, and the phase control at the IRS, they could reduce the average overall system energy consumption. Liang et al. [34] looked at a real-world energy efficiency optimization challenge in a cognitive UAV communication system. By reusing the spectrum of the ground primary user, the moving following UAV communicates data acquired to the leading UAV. For this situation, a combined UAV trajectory and resource allocation optimization approach is suggested. They aimed to increase the cognitive UAV communication systems' energy efficiency while considering speed, collision avoidance, smallest step size, and interference.

According to Qian et al. [35], a single UAV might operate as a mobile server, outsourcing computation-intensive tasks to a group of mobile users moving along a random waypoint model on the ground. Their proposed time-saving Monte Carlo tree search algorithm was able to help them reach their goal of maximizing average throughput while considering energy consumption and customer fairness. Ding et al. [36] addressed the issue of 3-D drone trajectory and spectrum allocation, taking into account the power consumption of drones and the fairness regarding terrestrial users. To this end, they initially formulated the power consumption of a drone as a function of 3-D movement. After that, the fair throughput was maximized considering the limited energy. They proposed a new algorithm based on deep reinforcement learning (DRL). The new method enables the drone to, first, regulate the speed and direction in order to improve energy efficiency and arrive at the desired endpoint while still having energy, and second, allocate a spectrum band to realize fairness. Nguyen et al. [37] developed a novel UAV-assisted IoT system that relies on the UAVs' shortest flight route to maximize the quantity of data collected from IoT devices. The best trajectory and throughput in a specific coverage region are then discovered using a DRL-based method. Following training, the UAV can independently gather all the data from user nodes with a marked increase in the total sum rate while using the least amount of resources possible. Wang et al. [38] examined a drone-aided secure network with two types of drones, where one drone travels around to transmit confidential data to a moving user, and the other supportive drone, simultaneously, sends fake noises to distract the attackers. The objective of the authors was to maximize the worst-case secrecy rate of moving users, considering the mobility of drones and users. The problem was solved by jointly optimizing the 3-D trajectory of drones and the time allocation, constrained by maximum drone speed, drone collision avoidance, drone placement error, and drone energy harvesting. To cope with nonconvexity issues arising from constraints, they divided the main problem into three subproblems and developed an iterative algorithm to obtain the suboptimal solution, exploiting the block coordinate descent method. To solve the subproblems, they leveraged mathematical tools, including integer relaxation, S-procedure, and successive convex approximation.

Previous research in path optimization has concentrated chiefly on the 2-D trajectory segment. As previously said, the primary benefit of employing UAVs is to utilize their capacity to change altitude. In addition, the majority of these researches did not account for user movement. In the real world, particularly in cellular network applications, users are always on the move, which is critical for determining the future location and trajectory of the FBSs. In addition, past research frequently makes use of traditional clustering algorithms. These clustering algorithms are location-aware and do not consider data rate and user-requested QoS. In contrast, service to users should be tailored to their location and the kind of service they demand.

III. System Model

In this article, a network of multiple FBSs is proposed to serve cellular users during a disaster. In this scenario, we assume that a disaster, such as a flood or an earthquake, has occurred in a residential area. As a result of this event, ground BSs are out of order and we are trying to provide the service users need with the help of FBSs for emergency management. Fig. 1 presents a possible situation of using FBSs in a disaster.

Fig. 1. Possible scenario of FBS service.

In such situations, not only user coverage is crucial; but also it is essential to employ the fewest feasible FBSs and deploy them in the most effective positions and altitudes to efficiently cover users. In addition, we consider orthogonal frequency reuse to prevent interference with the operation of other UAVs in the network. We present a mathematical model for efficient UAV placement as FBSs to cover 5G users. Our suggested methodology reduces the number of UAVs necessary to cover all users while maintaining the desired QoS. In addition, our approach finds the most appropriate positions to minimize the overall distance between users and FBSs, which causes the minimization of total path loss in LoS situations.

To determine the ideal FBS positions, the model requires a set of candidate points from which to pick. As people congregate in specific locations throughout the disaster, we may categorize them into groups. Each group's center will serve as a candidate point for the mathematical model used to deploy the FBSs. To locate the appropriate candidate points, we employ a fuzzy technique considering different numbers of groups. The proposed FCPS will help us to the discretization of the continuous space of the problem and get the output in a reasonable time, without losing generality. In what follows, the performance of the proposed technique to several groups of candidate points to choose the best one is evaluated.

We also plan to build an FBS infrastructure to serve the users caught in an area. After determining the optimal placements of FBSs in various snapshots, to find the optimal trajectory for FBSs, we offer a mathematical model based on the transportation problem to minimize the overall distance traveled by FBSs. We solve the mathematical model for transiting FBSs between two snapshots.

We aim to obtain the appropriate 3-D FBSs locations, as well as the optimal path for each of them within the operation period. To this end, we first decouple the problem into multiple snapshots. We solve the positioning problem in each snapshot, taking into account the data rate of network users, limited backhaul, and the range of the area covered. For this purpose, by obtaining the backhaul at different altitudes and path loss states, we have obtained the minimum backhaul available for FBSs to serve users. Taking this into account, we have chosen the minimum backhaul available at different altitudes to serve FBS users. To solve the positioning problem, we give a mathematical model to obtain the optimal FBS location, minimizing the overall distance between users and FBSs. As we assume a free space environment, minimizing the distance between users and FBSs has a direct relationship with link quality. The proposed model requires candidate points, based on which decides on an FBS location. To obtain the candidate points, we employ an FCPS algorithm, considering user places and necessary data rates. To this end, we consider an SDN-based infrastructure that is almost aware of users' positions and their data rate demanded. We also employ the bisection method to minimize the number of necessary FBSs. To this end, we initially consider a fixed number of FBSs (P), formulate the problem of obtaining an optimum position for all P FBSs and solve it accurately in each iteration of the bisection method, by exploiting a solver. Through this, we decrease a biobjective optimization problem to bisection and then solve a single-objective optimization problem in each iteration. We will discuss how to obtain optimum P, later in Section IV-C.

After obtaining the appropriate position for each FBS in each snapshot, in the next step, we have to decide upon the destination and traveling path of each FBS. We propose a mathematical model to minimize the total distance traveled by FBSs. It is worth noting that the number of necessary FBSs may change at different snapshots. To cope with this challenge, in the case that we require more FBSs in the next snapshot, more required FBSs will fly from the base to the desired destinations. On the other hand, if fewer FBSs are going to be needed, extra FBSs land on the nest to recharge. Fig. 2 shows the frame diagram of the model.

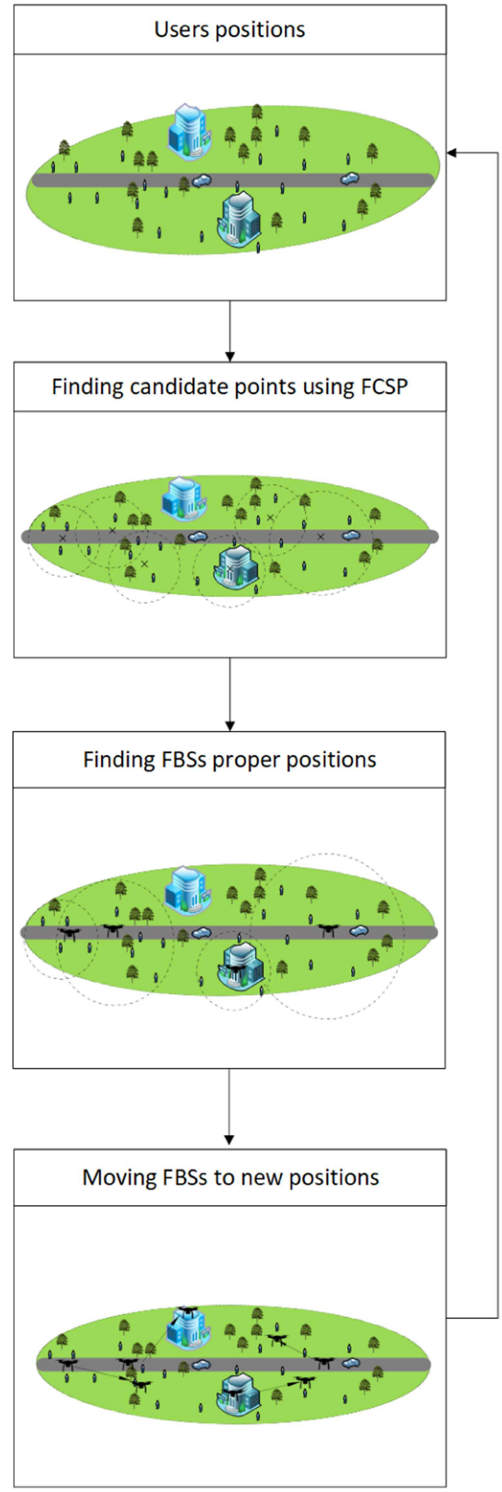

Fig. 2. Complete frame diagram of the model.

IV. Problem Formulation

In this section, the mathematical models and formulation of positioning and trajectory problem are discussed. Section IV-A discusses the mathematical model of the positioning problem. Section IV-B focuses on how to obtain candidate points through the proposed FCPS technique. Section IV-C talks about obtaining the optimal number of required FBSs for the proposed deploying mathematical model, and Section IV-D discusses the mathematical model of the trajectory problem.

A. Mathematical Model of Positioning Problem

In the positioning problem, we aim to obtain the appropriate positions of FBSs, covering users of the network. We have two options to address this non-polnomial (NP)-hard problem: heuristic or meta-heuristic methods, and mathematical programming. In a mathematical programming with small dimensions, we may utilize methods, such as branch-and-bound or cutting plane, to obtain the optimum solution within a reasonable time. To decrease the problem dimensions, we discretize the continuous space.

Obtaining P optimal locations to deploy P FBSs in discrete space is an example of a P-median problem, widely known among positioning problems [39]. In a P-median problem, we locate P facilities to minimize the demand-weighted average distance between demanding customers and the closest facility out of chosen ones. A P-median problem can be a capacitated or uncapacitated facility location problem. Because each FBS has a

TABLE I
PARAMETERS USED IN THE MATHEMATICAL MODEL

Parameters	Description
I	Candidate points set for deploying FBSs
J	Users set
B	The backhaul of each small cell (Mbps)
φ_j	Required data rate of user j (Mbps)
d_{ij}	The distance of FBS i from user j (m)
R	Coverage radius of each small cell (m)
K_i	Candidate Point i
P	The number of FBSs that should be deployed
D	The number of candidate points for FBS positioning
U	The total number of users
x_{ij}	Decision variable. If user j covers by FBS i, the variable is set to 1; otherwise, 0.

certain capacity, thus we formulate the problem as a capacitated P-median problem.

In the P-median problem, the position of candidate points for locating facilities is already known. We consider the points obtained from discretizing 3-D space as candidate points, whereas by applying a discrete setting on the 2-D space, we still encounter an NP-hard problem, we can solve it more efficiently through an intelligent discretization of 3-D space [25]. To avoid the impact of noises and measurement errors on the locations, we assume a normal distribution noise for the user position errors. Hence, in general, the distance between FBSs and users will not be impacted. We also presume that FBSs take advantage of dynamic channel allocation or dynamic frequency selection techniques to avoid interference. To formulate the positioning problem as an optimization problem, our goal is to obtain the optimal location for P FBSs so that the overall distance between users and their covering FBSs is minimized, ensuring that all users are covered. Here, we presume that the user coordinates, candidate points (K_i), the backhaul (B), and each user's data rate (φ_j) are known as described in Table I. The sets of candidate points (I) are found using FCPS and D is the number of candidate points. J is the parameter of users set, U is the number of users, and d_{ij} is the distance between FBS i from user j. Also, R is the coverage radius of each FBS.

The objective function (1) aims to minimize the overall distance between users and FBSs, for placing FBSs in optimal locations. Therefore, we need to determine, which FBS should serve which users. In other words, we need to map each user to an FBS. This is accomplished by x_{ij}, which equals to 1 if user j is served by FBS i, otherwise is 0. As mentioned earlier, we discretized the search space. Therefore, the FBSs are placed on a collection of finite candidate points. In our optimization problem, we denote the candidate points by K_i, which equals 1 if the ith candidate point is chosen for FBS positioning.

In the proposed optimization model, (2) specifies that each user may only receive service from one single FBS. Because x_{ij} is a binary variable, this constraint permits at most one FBS to take the value 1. Constraint (3) considers each small cell's limited data rate. It indicates that the overall data rate of users served by ith FBS may not exceed that of the small cell itself. Constraint (4) allows to place only P FBSs. The Section IV-C elaborates on how to determine the P, considering the demanded QoS of the network users. Constraint (5) indicates that the proportion of covered users to total users is one. This constraint ensures that all users can access the services. Constraint (6) indicates that user j may only be served by candidate point i, if that point is chosen for FBS positioning. It is obvious that if candidate point i is not chosen, it cannot serve any of the users. Constraint (7) prevents users who are outside the coverage area of a single small cell from receiving service provided by that cell. In addition, (3) and (5) ensure that each FBS provides service at maximum data rate capacity

$$\min_x \sum_{i\in I}\sum_{j\in J} d_{ij}x_{ij} \tag{1}$$

s.t.

$$\sum_{i=1}^{D} x_{ij} \le 1 \qquad \forall j \in J \tag{2}$$

$$\sum_{j=1}^{U} \varphi_j x_{ij} \le B \qquad \forall i \in I \tag{3}$$

$$\sum_{i=1}^{D} K_i = P \tag{4}$$

$$\sum_{j=1}^{U}\sum_{i=1}^{D} x_{ij} = U. \tag{5}$$

$$x_{ij} \le K_i \qquad \forall i \in I \quad \forall j \in J \tag{6}$$

$$x_{ij} = 0 \qquad \forall i \in I, j \in J, d_{ij} > R. \tag{7}$$

Equations (7) and (5) do not exist in original P-median problem. As these limitations are similar to those of the covering problem, our model thus consists of two NP-hard problems, i.e., P-median and covering. As a result, determining the optimal location belongs to NP-hard. Since we may not find the optimal point in a polynomial time regarding NP-hard problems, we can utilize heuristic and metaheuristic algorithms to achieve a reasonable problem solution. Another technique we can employ is to decrease the problem size to a small-sized one to obtain the optimum solution. Because the quantity of candidate points influences the problem's complexity, we strive to decrease the size of our NP-hard problem by intelligently determining the collection of candidate points and then solving it to achieve an exact solution.

After formulating our problem, we need to address the best set of candidate points to place FBSs. The candidate points set (I) must be given to the proposed mathematical model for deploying the FBSs. Also, we need to determine the optimum value regarding the number of required FBSs (P).

B. Fuzzy Candidate Points Selection

In the proposed mathematical model the points where the FBSs may potentially be located has to be determined. With this model and designating a limited number of points in the 3-D plane, we may simplify the main optimization problem. Accordingly, we select P points from a limited number of determined locations rather than choosing them from an unlimited number of points. Now we carry on the discussion with the elaboration of the approach to determining the candidate points through the FCPS technique.

Fuzzy C-means (FCM) is a technique based on fuzzy logic, which specifies the degree of an object's membership belonging to a cluster. In 1981, Bezdek [40] developed this technique as a generalization of previous clustering techniques. The following objective function is minimized in FCM:

$$J_m = \sum_{i=1}^{D} \sum_{j=1}^{N} \mu_{ij}^{m} \left\| x_i - c_j \right\|^2 \tag{8}$$

where D and N denote the number of data points and clusters, respectively. x_i is ith object and c_j is the center of cluster j. In addition, μ_{ij} indicates the membership degree of x_i in the jth cluster, and m is the fuzzy partition matrix exponent parameter to adjust the fuzzy overlap degree and has to be higher than one. FCM makes fuzzy boundaries and overlap size refers to how many objects are shared among clusters.

To cluster the data by FCM, at first, membership values are specified randomly and then cluster centers are obtained by the formula (9) based on μ_{ij} and then μ_{ij} is updated using formula (10) [41].

$$c_j = \frac{\sum_{i=1}^{D} \mu_{ij}^{m} x_{ij}}{\sum_{i=1}^{D} \mu_{ij}^{m}} \tag{9}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N} \left(\frac{\|x_i - c_i\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \tag{10}$$

The parameter m is a critical exponential parameter in deciding where to place the centers of clusters and how much overlap exists between them. If m equals one, FCM behaves like the k-means method, otherwise when m is greater than one the cluster overlaps grows and centers get close together. The value of the parameter is determined by problem and data distribution, as described in [42].

The FCM's drawback is that it clusters users based on their locations; however, the clustering itself is not satisfactory in the FBS positioning and the user coverage problems. the required data rate, like the users' locations, is also a significant factor in determining the FBSs' locations. Leaving the clustering alone, we tweaked the fuzzy technique to find the candidate points that are more precise and relevant to the FBS positioning problem in 5G networks and beyond. To this end, for each data rate of 1 Mbps demanded by each user, we consider another user in the same location. For example, if the demanded data rate of a user equals 10 Mbps, we assume that there are 10 users in the same position, each demanding 1 Mbps data rate. In this approach, by expanding the user density in the locations, where the demanded user data rate is larger, the shortage of FCM can be compensated and the data rate impact can also emerge in the candidate point selection. Consequently, the candidate point selection technique will operate more effectively.

The primary objective of this article is to solve the FBS 3-D positioning and trajectory problems. To address the 3-D positioning problem, the candidate points, as the inputs of the proposed mathematical model have to be 3-D too. Hence, after obtaining the candidate points using the proposed method, which determines candidate points based on the features of drones employed in the problem, these points need to be converted into 3-D candidate points. To this end, the elevation parameter is applied to the 2-D candidate points' positions. This parameter can be obtained discretely, considering particular distances (determined based on the problem) between the FBS's lowest and highest elevation.

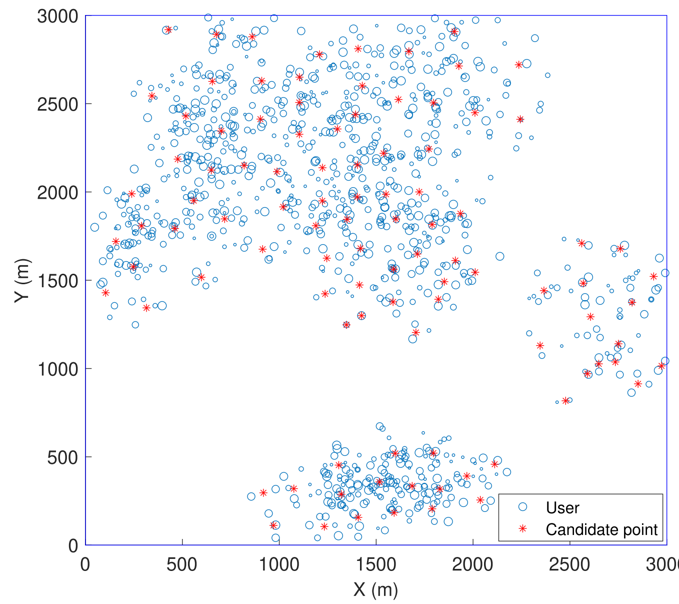

Fig. 3. Users positions and selected candidate point.

Fig. 3 depicts the location of users and 2-D candidate points. In addition, the radius of the user circle specifies the necessary data rate for each user. The higher the required data rate is, the larger the circle gets.

C. Finding Optimal P

Before solving the mathematical model, we require an appropriate P. This article's proposal for determining the optimum P is as follows. First, the maximum number of FBSs ($P_{\max}$) that can be placed in the area is known, because of the restricted number of FBSs employed. Second, the range of $[1, P_{\max}]$ is explored using the bisection algorithm with the computation complexity of $\log_2^{P_{\max}}$. Finally, we may narrow the search space down to $[P_{\min}, P_{\max}]$, where $P_{\min}$ comes from the following:

$$P_{\min} = \frac{N * \psi}{B} \tag{11}$$

where $P_{\min}$ is the lower bound for the number of FBSs needed, N is the number of users, ψ is the mean of users' demanded data rate, and B is the backhaul limitation. Suppose we assume that all users are concentrated on one point. According to the backhaul limit of the FBSs, the minimum number of FBSs required to cover the desired data rate of users is equal to the product of the number of users in their average requested data rate divided by the amount of backhaul limit [24].

We compute $P_{\min}$ after obtaining 3-D candidate points. Given the $P_{\max}$, we solve the problem of deploying $P = \frac{P_{\min}+P_{\max}}{2}$ FBSs, according to the mathematical model, by utilizing Cplex, which is a commercially available solver software [43]. If we can satisfy all constraints and provide at least one FBS to each user, the problem has a feasible solution with P FBSs. Otherwise, the answer space of the problem will be empty, and we consider it infeasible. We update $P_{\max} = P$ if the mathematical model has both a feasible solution and also all users are covered, otherwise update $P_{\min} = P$, and then again solve the problem by letting $P = \frac{P_{\min}+P_{\max}}{2}$. We carry on this procedure as long as $P_{\max}$ is greater than $P_{\min}$.

D. Mathematical Model of Trajectory Problem

We aim to obtain the optimal path for each FBS in the trajectory phase. To this end, we have to obtain the optimal destination for each FBS in each snapshot. We present a mathematical model based on the transportation problem to obtain the appropriate destination for each FBS. The goal of the mathematical model is to minimize the total distance of moving from one location to another. In this article, we intend to move some FBSs from the location (x_n, y_n) at snapshot t to the location (x_m, y_m) at snapshot $t+1$ with the minimum total distance

$$\min_{S} \sum_{m\in M} \sum_{n\in N} S_{mn} * \text{dist}_{mn} \tag{12}$$

s.t.

$$\sum_{m\in M} S_{mn} \leq 1 \qquad \forall n \in N \tag{13}$$

$$\sum_{n\in N} S_{mn} \leq 1 \qquad \forall m \in M \tag{14}$$

$$\sum_{m=1}^{M} \sum_{n=1}^{N} S_{mn} = \max(\mathcal{M}, \mathcal{N}). \tag{15}$$

The (12), shows the objective function of the problem. The sets M and N denote the points at snapshot t and $t+1$ respectively. dist_{mn} is the distance between the point m and n. We want to minimize the total dist_{mn} if the FBS moves from point m to n. S_{mn} is a 2-D array of binary variables indicating if drone moves from point m at snapshot t to the point n at snapshot $t+1$. According to the constraint (13), the sum of the values of each row of the 2-D array (S_{mn}) must be less than or equal to one. Therefore, each FBS at time t can only move to the one point at snapshot $t+1$. Constraint (14) indicates that sum of the values of each column of the 2-D array (S_{mn}) must be less than or equal to one. Therefore, each point at snapshot $t+1$ can only maintain one FBS. Constraint (15) states that the number of determined routes between points at snapshot t and points at snapshot $t+1$ has to be equivalent to the points at snapshot $t+1$. This restriction prevents the number of routes from approaching zero during the minimization.

After solving the trajectory problem, each FBS's path is specified between two snapshots. We may require more or fewer FBSs in the following snapshot. Moreover, if we require fewer

Algorithm 1: Fuzzy-Based Trajectory Algorithm.

Inputs: Number of candidate points, Number of users, Fuzzy exponent parameter, FBS's minimum height, FBS's bandwidth, Users' required data rate, and users' location in each snapshot
Outputs: number of required FBSs in each snapshot, FBSs' location in each snapshot, Assign users to FBSs, and Optimal FBSs' 3-D trajectory between snapshots
Divide the operation time into several snapshots
while snapshot remains
Determine candidate points using FCPS Section IV-B
Calculate $P_{\min}$ Section IV-C
while $(P_{\max} - P_{\min} \geq 1)$
    $P \leftarrow \lfloor \frac{P_{\max}+P_{\min}}{2} \rfloor$
    Solve the proposed positioning model with P FBSs IV-A
    if (positioning model is feasible)
        $P_{\max} \leftarrow P$
    else
        $P_{\min} \leftarrow P$
    end if
end while
Solve the proposed trajectory model Section IV-D
if (more FBSs are needed than the last snapshot)
    move FBSs to the destinations to cover users
else if (fewer FBS is needed than the last snapshot)
    land extra FBSs on the nest to recharge
end while

FBSs, they may hover at their positions or land on the nest to be recharged and prepared for future snapshots.

Algorithm 1 describes the whole approach of the proposed model. To review, we divide the operation time into several snapshots. Then, while there is a remaining snapshot, the following process continues; first, we find the appropriate candidate points using FCPS. Then, we find the minimum number of required FBS using (11). After that, while $P_{\max} - P_{\min} \geq 1$, we solve the proposed positioning model. If the positioning model had a feasible solution, we replace $P_{\max}$ with P, otherwise; we replace $P_{\min}$ with P. This loop is called bisection. After finding the best positions of FBSs in each snapshot, we solve the proposed trajectory problem. Then, if more FBSs are needed than in the previous snapshot, the FBSs fly to the determined destinations to cover users. Otherwise, if fewer FBS is needed, each FBS lands on the nest to recharge.

V. Numerical Results

A. Experiment Setup

In this section, the implementation results of the optimization models for the FBSs deployment and trajectory are evaluated in an example scenario utilizing the given methods. For simulation, as shown in Table II, we uses a 3000×3000 m area including 1000 users dispersed around the center of 15 random spots through the Poisson point process. In the deployment optimization model, we intend to obtain the minimum number

TABLE II
TEST PARAMETERS TO EVALUATE THE PROBLEM MODEL

Parameters	Description
Region	$3\,000 \times 3\,000$ m
Number of users (U)	1000
FBS's backhaul (B)	100 Mbps
Users' required data rate (φ_i)	500-1500 kbps
Minimum altitude ($H_{\min}$)	100 m
Fuzzy exponent parameters	1.1, 1.8, 2.4
Number of candidate points (K)	100, 120, 140

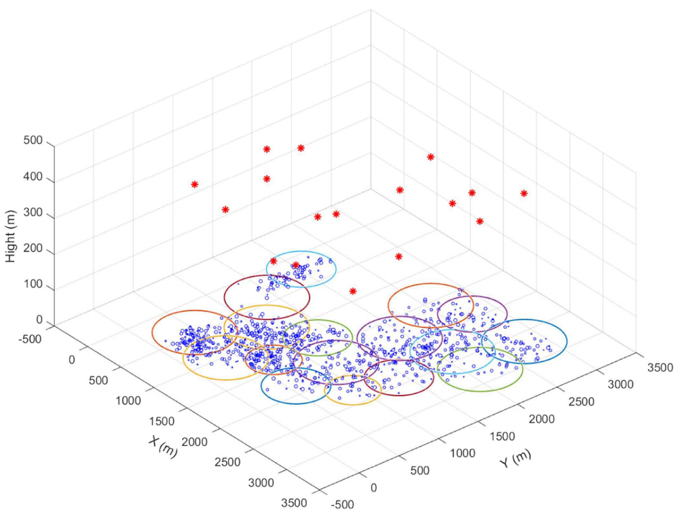

Fig. 4. Optimal FBS 3-D positioning with exponent parameter 1.1 and 120 candidate points.

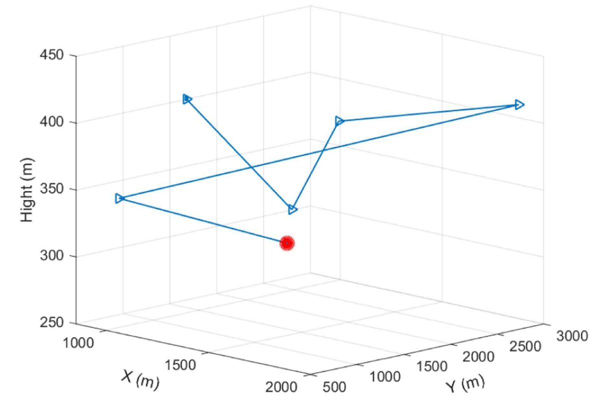

Fig. 5. Optimal FBS 3-D Trajectory in 6 time slots.

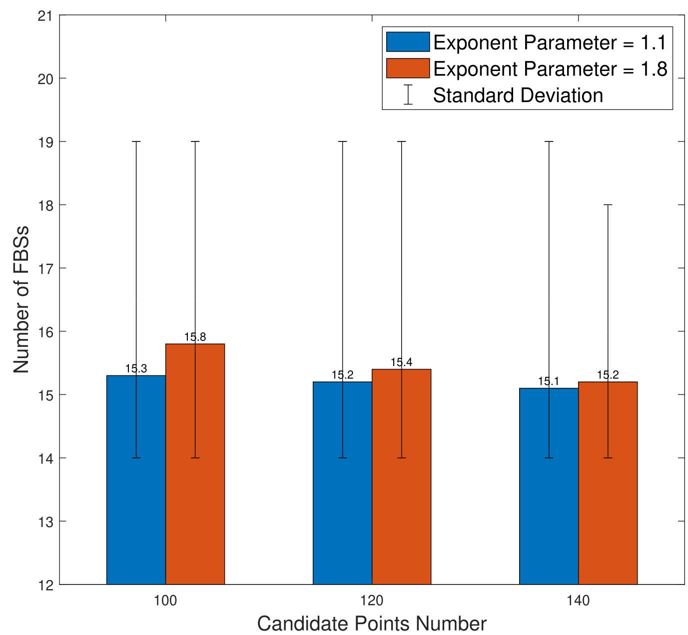

Fig. 6. Average number of FBSs required in each exponent parameter and number of candidate points.

of FBSs needed to cover more than 99.5% of users, considering the backhaul limits. A maximum of 0.5% of users, which means 5 out of 1000 users, will be considered outlier data and will not be served if located far from other users. However, the system will try to serve 100% of the users.

We assume that each FBS's data rate is 100 Mbps similar to a 5G picocell, with necessary user data rate following the uniform distribution and random between 500 and 1500 kbps. The FBS coverage radius is proportional to its elevation. We considered eight elevation levels for each candidate point determined to achieve the 3-D model. The first elevation is adjusted at 100 m and each subsequent level is planned to expand the coverage area by 1.5 times. The Cplex software is employed for solving the optimization model. Furthermore, we perform runs of the given method for three different fuzzy exponent parameters (1.1, 1.8, and 2.4) and three different numbers of candidate points (100, 120, and 140) to obtain a good average result and determine the effects of the considered parameters. Fig. 4 illustrates the output of the proposed model with fuzzy-based candidate point selection focused on users' required data rate. It shows the positions of users as blue points. The red points are the 3-D location of FBSs gathered from the proposed model. The circles are the coverage range of each FBS. In this run, the exponent parameter is set to 1.1, and 120 candidate points are assumed. As it shows, all users are covered by FBSs. Also, each FBS has a specific altitude due to the proposed positioning model.

To provide service to users at different time slots, we need to move the FBSs through the target area. The destination point of each FBS will be determined with the help of transportation theory. The proposed trajectory model ensures that the total distance traveled by the FBSs is minimized. Fig. 5 shows the trajectory obtained for FBSs through six consecutive time slots. The red point shows the start point in the first time slot and the direction is shown by an arrow. As it is shown, the FBS's altitude will change during the operation time to cover users more efficiently.

To evaluate the proposed model, we ran the simulations 90 times. In these evaluations, three exponent parameters (1.1, 1.8, and 2.4) and three different numbers of candidate points (100, 120, and 140) are run for ten different locations of users. Fig. 6

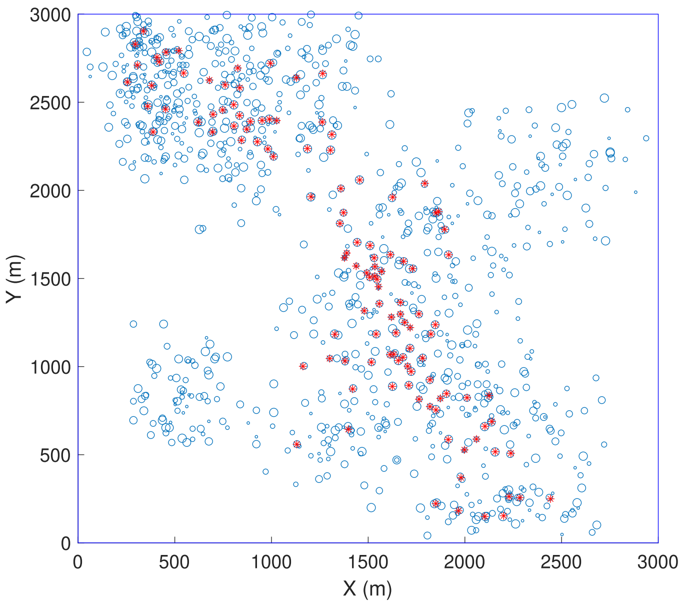

Fig. 7. Candidate points presented in fuzzy algorithm with 2.4 exponent parameter.

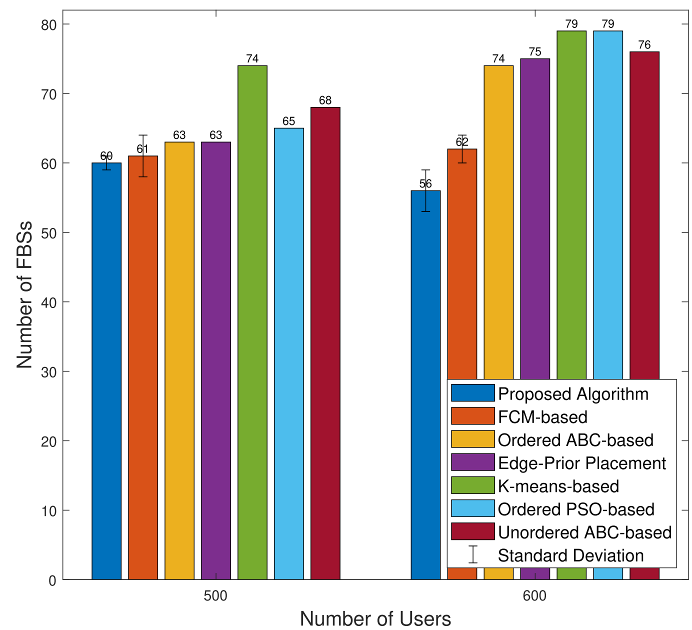

Fig. 8. Number of FBSs required in different algorithms.

illustrates the average number of FBSs deployments achieved by solving the optimization problem.

B. Simulations and Experiments Results

In comparison, as it is shown in Fig. 6, increasing the fuzzy exponent parameter will increment the number of required FBSs in a certain number of candidate points. The number of necessary FBSs must increase because increasing the fuzzy exponent parameter will bring the candidate points closer to the center of the users' cluster. Therefore, serving distant users will necessitate a separate FBS. This problem increases to such an extent that it will not be possible to optimize with the help of the candidate points produced by the fuzzy exponent parameter 2.4; the problem with this parameter will not be feasible because the candidate points are very close to each other and users further away are never covered by FBSs. Fig. 7 shows the candidate points provided by the fuzzy exponent parameter 2.4, and it shows the candidate points are located in the center of the users' cluster, which will cause a large part of the users not to be served. Hence, in the following result comparisons, we emit the fuzzy exponent parameter 2.4.

Moreover, Fig. 6 displays a comparison of various candidate points numbers. This figure shows that increasing the number of candidate points can reduce the required FBSs because, with more candidate points, the proposed mathematical model can select better positions for FBSs.

To evaluate the proposed algorithm, we compare it with the algorithms in [18]. As considered in [18], we ran the proposed algorithm in 6 km $\times$ 6 km area where 500 or 600 users are randomly distributed. Also, we considered elevation in 9 levels from 100 to 500 m, as we explained earlier. Since in [18], all users are not covered, and path loss is considered, we covered all users, but instead of path loss factor, we minimize the sum of the distance between users and FBSs, which can be assumed as an alternate for path loss in a free space area. We compare our proposed model with traditional FCM clustering, ordered artificial bee colony (ABC)-based, edge-prior placement, K-means-based, ordered partial swarm optimization (PSO)-based, and unordered ABC-based approaches, which were proposed and compared in [18]. The simulation result in Fig. 8 shows that the proposed algorithm can solve the problem with the least number of FBSs compared with traditional FCM and other methods.

In the trajectory part, the values of the proposed model's objective function are compared in Fig. 9. This comparison considers the total distance traveled by FBSs among six consecutive time slots, equivalent to five moves. This comparison reveals that utilizing the 140 candidate points produces more sum of distances than other cases. This comes from the fact that the number of required FBSs with this parameter is fewer, so on average FBSs must navigate more distance to meet the point in the next time slot.

The efficiency of the backhaul is directly influenced by the number of FBSs. In Fig. 10, the average data rate served by each FBS is depicted across 90 simulation instances, considering different exponent parameters and numbers of candidate points. The results demonstrate that increasing the number of FBSs with an exponent parameter of 1.8 leads to a decrease in the average data rate provided by each FBS. Conversely, reducing the number of FBSs with an exponent parameter of 1.1 results in higher data rate utilization per FBS. Moreover, increasing the number of candidate points yields better FBS placements, ultimately enhancing backhaul efficiency. Thus, the careful selection of the appropriate number of FBSs holds significant potential to enhance backhaul efficiency within the system.

The experiments have shown that the coefficient of the exponent parameter and the number of candidate points directly affect

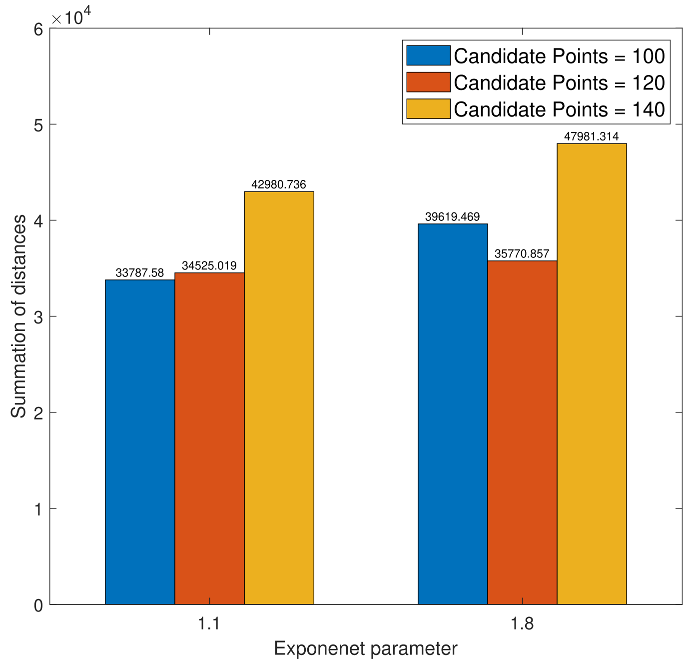

Fig. 9. Summation of distances passed by FBSs considering different exponent parameters and the number of candidate points.

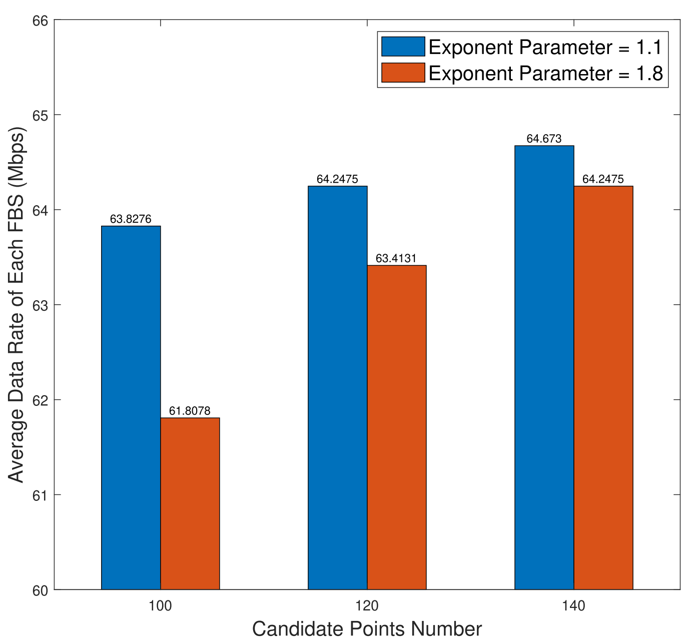

Fig. 10. Average data rate that each FBS must serve.

the running time of our proposed trajectory model. As shown in Fig. 11, in the scenario of fuzzy exponent parameter 1.1, with the increase of candidate points number, the overall optimization time increases. Contrariwise, in the 1.8 parameter scenario, the overall optimization time decreases with the increase in the number of candidate points. Therefore, if we must quickly obtain the optimal trajectory and our exponent parameters are small, we must choose fewer candidate points. However, if our exponent parameters are large enough, we must use more candidate points.

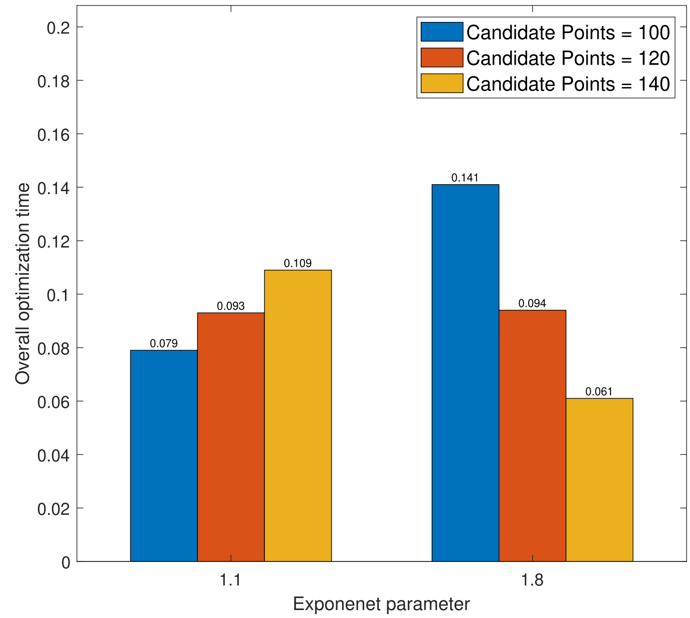

Fig. 11. Overall optimization time considering different exponent parameters and the number of candidate points.

Overall, choosing the right exponent parameter and the optimal number of candidate points is crucial for solving this optimization problem. Comparing different scenarios of candidate point selection reveals some key insights. Using an exponent value of 1.1 and 140 candidate points results in fewer required FBSs to cover all users. However, if minimizing the trajectory objective function is more important, using 100 candidate points generally leads to lower objective function values. Among the cases with 100 exponent parameters, the objective function value is minimized when using 100 candidate points. Therefore, the selection of exponent parameters and candidate points depends on the specific optimization goals. To minimize the number of required FBSs, it is recommended to use an exponent of 1.1 and a higher number of candidate points (e.g., 140). Conversely, if minimizing the trajectory objective function is the priority, a lower number of candidate points (e.g., 100) should be considered.

VI. Conclusion

In this study, a FBS infrastructure was proposed to guarantee the required QoS and coverage for terrestrial cellular users that suffer from communication outages due to damages to cellular infrastructure during a disaster. The mathematical optimization model and algorithms were presented to perform positioning and trajectory for FBSs. Moreover, we have used a FCPS algorithm to help us to solve the optimization model in a reasonable time. Simulation results confirm that the proposed model and FCPS algorithm could be an efficient method to perform positioning and trajectory in 5G and beyond cellular networks. For future works, we can predict users' positions, or we can estimate users' distribution to find FBSs positions more efficiently. Also, deploying the digital twin of the problem is another future work.

We aim to develop more extensive and accurate datasets for analysis and experimentation by using digital twin models. The other concept that can be considered in future works is stochastic constraints. The constraints, such as users' positions, and their required data rate are stochastic. Therefore, we can solve the problem using stochastic approaches.

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