Managing Sets of Flying Base Stations Using Energy Efficient 3D Trajectory Planning in Cellular Networks

Mohammad Javad Sobouti, Amir Hossein Mohajerzadeh, Seyed Amin Hosseini Seno, and Halim Yankomeroglu, Fellow, IEEE

Abstract—Unmanned aerial vehicles (UAVs) in cellular networks have garnered considerable interest. One of their applications is as flying base stations (FBSs), which can increase coverage and quality of service (QoS). Because FBSs are battery-powered, regulating their energy usage is a vital aspect of their use; therefore, the appropriate placement and trajectories of FBSs throughout their operation are critical to overcoming this challenge. In this article, we propose a method of solving a multi-FBS 3D trajectory problem that considers FBS energy consumption, operation time, flight distance limits, and intercell interference constraints. Our method is divided into two phases: FBS placement and FBS trajectory. In taking this approach, we break the problem into several snapshots. First, we find the minimum number of FBSs required and their proper 3D positions in each snapshot. Then, between every two snapshots, the trajectory phase is executed. The optimal path between the origin and destination of each FBS is determined during the trajectory phase by utilizing a proposed binary linear problem (BLP) model that considers FBS energy consumption and flight distance constraints. Then, the shortest path for each FBS is determined while taking obstacles and collision avoidance into consideration. The number of FBSs needed may vary between snapshots, so we present an FBS set management (FSM) technique to manage the set of FBSs and their power. The results demonstrate that the proposed approach is applicable to real-world situations and that the outcomes are consistent with expectations.

Index Terms—Cellular networks, flying base station (FBS), FBS set management (FSM), trajectory optimization.

I. INTRODUCTION

C

ELLULAR networks of the next generation offer increased data transfer rates, improved service quality, and greater energy efficiency. Cellular networks, including 5G and beyond, are the backbone of future communication, capable of delivering a dependable and efficient infrastructure, resulting in a sustainable system.

Manuscript received 21 February 2023; accepted 8 March 2023. Date of publication 29 March 2023; date of current version 15 May 2023. The work of Halim Yankomeroglu was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery Grant. The associate editor coordinating the review of this article and approving it for publication was Prof. Bin Gao. (Corresponding author: Amir Hossein Mohajerzadeh.) Mohammad Javad Sobouti, Amir Hossein Mohajerzadeh, and Seyed Amin Hosseini Seno are with the Department of Computer Engineering, Ferdowsi University of Mashhad, Mashhad 9177948974, Iran (e-mail: javad.sobouti@mail.um.ac.ir; mohajerzadeh@um.ac.ir; hosseini@um.ac.ir).

Halim Yankomeroglu is with the Non-Terrestrial Networks (NTN) Laboratory, Department of Systems and Computer Engineering, Carleton University, Ottawa, ON K1S 5B6, Canada (e-mail: halim@sce.carleton.ca).

Digital Object Identifier 10.1109/JSEN.2023.3260168

Cellular networks have garnered substantial attention in recent decades and have significantly impacted human life. Due to the rapid growth in the popularity of cellular networks, communication vendors have been motivated to extend this beneficial technology and industry. For instance, the data transmission rate of cellular networks has increased dramatically from 1.2 kb/s in first-generation (1G) networks to 1 Gb/s or higher in fifth-generation (5G) and beyond networks. As a result, 5G is expected to be a greater step in the evolution of communication technology. Both 5G and 6G technologies will benefit businesses and society in the 2030s by delivering highly reliable and secure communication services [1], [2].

Mobile user satisfaction in cellular networks depends on coverage and quality of service (QoS) metrics. As the quality of calls, movies, and the usage of various applications continues to increase, consumers want to enjoy this quality regardless of location, time, or circumstance, most notably on their smartphones. As a result, future generations of cellular networks’ QoS and coverage must be improved. On the other hand, the increased frequencies required to serve a greater number of clients may result in coverage over a narrower

Authorized licensed use limited to: . Copyrighted material licensed by IEEE for personal use only. Redistribution requires IEEE permission. See https://www.ieee.org/publications/rights/index.html for more information.
region. Therefore, additional base stations (BSs) are required to increase the coverage area, which results in a better quality of experience (QoE) for users. Increased terrestrial BS capacity is very costly, however, and almost unattainable. With the high financial requirements of creating a new BS, assessing its location and viability for installation is exceedingly complex and expensive. Additionally, increasing the bandwidth in future generations of the cellular network reduces the BS’s coverage, assuming constant antenna power. As a result, fixing this matter will need more investigation. In the meantime, flying BSs (FBSs) offer a viable way for expanding network coverage and QoS [3], [4].

FBSs can thus be used when terrestrial BSs are uneconomical, or when they are unfeasible due to mountainous, rough, or rocky terrain. They can also be used when a cellular network is under heavy strain due to major sports or cultural events [5], [6]. Moreover, FBSs are beneficial, since they do not require prearranged equipment and almost eliminate location limits. The other desirable feature of FBSs is their increased line-of-sight (LoS), which is due to their higher placement, thereby reducing multipath fading and shadowing [7]. Additionally, because FBSs are mobile, they can improve QoS and mitigate impairments by shifting their places if the network’s status deteriorates. If necessary, a mobility function can also be used to enhance the number of users covered. Additionally, users may benefit from increased data rates by expanding the coverage and number of FBSs [8].

FBS position and altitude must be defined when employing them in cellular networks. Placement and power allocation (PA) must be considered to improve the performance of the FBSs’ network [9]. Because FBSs are battery-powered, proper placements and pathways will increase the network’s lifespan. Furthermore, the locations of FBSs, while servicing users, are crucial to cover and give the QoS that users require. Yet, because cellular users are mobile, they may move out of a BS’s range. To address this issue, users’ locations are verified on a scheduled basis, and the location of FBSs may be determined using this information [10]. After that, the FBSs are shifted. While FBSs can circumvent the limitations of terrestrial BSs, they face location and trajectory challenges. Numerous studies have been conducted on deploying unmanned aerial vehicles (UAVs) and stations in 2-D and 3-D space in various wireless networks [11], [12]. Also, studies on the movement of FBSs involving wireless networks, the Internet of Things, and sensor networks have been undertaken [13], [14].

This article considers cellular network demand in an urban area. We aim to cover users and serve their required data rate in a period of time using a 5G and beyond cellular network. In doing so, the type of FBS we consider is the DJI S900 UAV helicopter [7], which can fly to an altitude of 3 km.\(^1\) To find the optimal trajectory of FBSs, we first must find the optimal positions of FBSs in different snapshots. We consider orthogonal frequency reuse to avoid interference between FBSs in the network, and we consider the constraint on the number of communication channels in the intracellular network. We change the proposed mathematical model in [15] to find the optimal position of FBSs in each snapshot. We consider non-LoS (NLoS) path loss and aim to cover all users in each snapshot. To find the optimal trajectory of FBSs, we propose a mathematical model based on a transportation problem to minimize the total distance tracked by FBSs. We solve the proposed mathematical model for transiting FBSs between two snapshots in each step. We find the shortest path of each FBS while taking obstacles and potential collisions into account. We also consider that users may be situated at different altitudes, following a Poisson point process (PPP) distribution, with their mobility following a random waypoint. The FBSs battery and flight limitations are also considered, and we introduce an FBS set management (FSM) approach to avoid losing energy in idle hover mode and tackle the energy problem. This article provides a mathematical model and algorithms for FBSs’ positioning and trajectory by considering real-world challenges. The following items are the contributions of this work in comparison with the studies in the literature.

1) We propose a mathematical model to solve the 3D multi-FBS positioning and trajectory problems, where NLoS links and obstacles are considered. The model has a global solution (see Table I).

   a) Using a Lemma, it is proven that the solution of the proposed algorithm is global and definite.

2) We consider different users’ altitudes (e.g., in urban areas at ground level and on the upper floors of high-rise buildings) in the positioning and trajectory problems.

3) To make the problem solvable, the time is considered discrete. An efficient time period for each snapshot is calculated which is not studied in the FBS trajectory field (to the best of our knowledge).

4) We propose an FSM technique to avoid losing energy in idle modes. FBSs can fly to a base to recharge and come back to perform their tasks.

5) We consider power consumption for the hovering and trajectory of FBSs in the proposed model. Alongside the FSM, this helps to prolong the network lifetime.

6) We find the shortest path for each FBS avoiding obstacles and collision with each other.

The rest of this article is as follows. The literature is reviewed in Section II. In Section III, the system model and the channel model are discussed. Section IV includes the problem formulation and proposed positioning and trajectory mathematical models. The proposed algorithm for solving the whole trajectory problem is presented at the end of this section. In Section V, the test system’s parameters and the numerical results are discussed. Finally, the conclusion is in Section VI.

II. RELATED WORKS

Due to the high mobility, maneuverability, adaptive altitude, and low cost of FBSs, they have vital applications in wireless networks. One of the main advantages of using FBSs is that they do not need any preestablished infrastructure and can be deployed anywhere. They can also change their positions on-demand to increase coverage and QoS for users. However, the use of FBSs also has challenges, such as determining the

\(^{1}\) Regulations generally allow UAVs to fly up to about 120 m, but sometimes more altitude is permitted. Therefore, we did not follow these restrictions in this exploratory study.
optimal positioning, the trajectory design, and the number of UAVs [7], [8].

A crucial element of FBS-mounted wireless networks is trajectory design. An FBS’s trajectory involves passing through several points obtained from the deployment problem. The literature on 2-D and 3D positioning problems was discussed in [15] and [16].

Designing an optimal trajectory is challenging because there are an unlimited number of optimization variables (e.g., UAVs’ positions) [17]. Qian et al. [18] proposed a single UAV to function as a mobile server, offloading computation tasks to a group of mobile users on the ground who move according to a random waypoint model. The solution they proposed aimed to maximize average throughput while keeping energy consumption and customer fairness in mind, and their proposed time-saving Monte Carlo tree search (MCTS) algorithm was able to help them achieve that goal. To offload traffic for BSs, Cheng et al. [10] concentrated on the UAV trajectory at the margins of three adjacent cells. In their suggested system, the UAV trajectory is optimized for each flying cycle to maximize the sum rate of UAV-served edge users while still meeting the rate requirements for all users. They transformed the mixed-integer problem into two convex problems to solve the problem in polynomial time. Fontanesi et al. [19] proposed a transfer learning (TL) method, in which they used a teacher policy that had been educated in one domain to help the agent learn the path in the other. The agent improved the path design in the new domain based on the future encounters with the environment, as the exploration activities and training proceeded. They used a Lyapunov-based model-free deep Q-network (DQN) to address the sub-6-GHz path design problem that ensures fulfillment of the connection constraint. The goal of [20]’s formulation of the UAV placement problem as a restricted optimization problem was to maximize fair coverage while minimizing energy consumption while satisfying the backhaul requirements at various time nodes. The authors devised a fairness index to ensure equal communication opportunity and area coverage ratio to prevent excessive QoS on covered places in order to assure fair QoS allocation. Then, a proximal stochastic gradient descent-based alternating approach was presented to optimize the UAV sites, which iteratively executes two optimization phases. This paves the way for quick single point-based first-order methods to address challenging problems with constraints. He et al. [21] looked at the optimization of a 3D multi-UAV trajectory using ground devices (GDs) to choose the target UAV for job computing. First, they created a 3D dynamic multi-UAV-assisted mobile edge computing system that gives GDs real-time task updating and mobility. They then developed goal functions based on fairness among UAVs for the system’s computing, communication, and energy consumption during flight. Then theoretically inferred and quantitatively demonstrated the best GD selectivity and task offloading method, or how GDs choose the best UAV for task offloading and how much to offload, to ensure fairness across UAVs. In [22], a UAV path planning was proposed based on the bat algorithm. This article’s primary goal was to enable UAVs to find a safer and shorter path without crashing through the start and end points in a war operation environment. Pan et al. [23] proposed a deep learning algorithm trained by a genetic algorithm (GA). The GA collected states and paths from different scenarios and then used them to train a deep neural network (NN) so that, when faced with familiar scenarios, it could quickly provide an optimized path.

In [24], a multi-UAV trajectory optimization model was proposed. The model was based on a single time interval and used time segmentation instead of traditional station segmentation, which simplified the calculation of cost functions. Tang et al. [25] aimed to use surveillance UAVs to compensate for the shortcomings of fixed surveillance systems, such as CCTV. In [26], a secure cognitive UAV communication network was studied using the trajectory and high flexibility of a UAV and the possibility of creating direct vision links. Ji et al. [27] investigated the problem of safe transmission in a cache-enabled UAV relay network with device-to-device communications, assuming the presence of a listener. Ji et al. [28] aimed to maximize users’ minimum power by optimizing the UAV trajectory and transmit power. The cache, trajectory,

### Table I

|                         | [35] | [36] | [37] | [38] | [39] | [40] | [41] | [42] | [43] | [44] | Our work |
|-------------------------|------|------|------|------|------|------|------|------|------|------|----------|
| Trajectory design       | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| 3D trajectory           | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Uplink                  | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Downlink                | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Sum-rate maximization   | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Energy optimization     | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Obstacle consideration  | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Time minimization       | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Dynamic environment     | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |
| Mathematical solution   | *    | *    | *    | *    | *    | *    | *    | *    | *    | *    | *        |

2Instead of the terms radio access node on board UAV (UxNB) and FBS, the term most commonly used in the literature is UAV. In this section, we use these terms interchangeably.
and transmit power optimization variables were alternatively optimized in three different blocks.

In [29], the goal was to maximize system power by jointly optimizing a UAV’s 3D trajectory, communication scheduling, and transmit power. In doing so, the authors first considered a specific case where the path between a UAV-BS and a UAV access point (UAV-AP) is predetermined. Subsequently, they proposed an efficient iterative algorithm to optimize the 3D UAV trajectory, and this algorithm alternately optimized the subproblems based on a sequential convex approximation technique. Wang et al. [30] proposed an architecture of relay UAVs to load data from smartphones onto satellites in low-Earth orbit. In doing so, they improved smartphone connection time, power management, and UAV trajectory to increase network capacity. Their approach involved using nonlinear integer programming (NLIP) to simulate the issue. In [31], a UAV trajectory optimization problem was formulated as a nonconvex problem, which took UAV altitudes and wireless coverage performance into consideration. The authors proposed an iterative algorithm with low complexity to tackle this problem, breaking down the main problem into four subproblems and optimizing the variables. First, a convex minimization algorithm was used to find the optimal global 2-D position of the UAV. Next, the optimal altitude of the UAVs was obtained. Then, a multiobjective evolutionary algorithm based on a decomposition algorithm was proposed to control the phase of the antenna elements and achieve the desired performance. Finally, with the variables solved, the main problem was reformulated as a single-variable optimization problem, in which charging time was the optimization variable, and the problem was solved using convex optimization techniques. In [32], the focus was on UAV-enabled emergency networks, where UAVs functioned as FBSs to collect data from terrestrial users in disaster-affected areas. The available energy of users’ devices is insufficient because of the failure of the ground power supply induced by disasters. Terrestrial impediments were also shown to impact UAV flying due to postdisaster environmental conditions. To address the issue, the authors formulated a UAV trajectory optimization problem with user-device energy constraints and the location of terrestrial obstacles to maximize the uplink efficiency of UAV networks during the flight duration. They transformed the problem into a constrained Markov decision-making process (CMDP) using the UAV as an agent because of the dynamic user-device energy constraint. They introduced a UAV path-planning algorithm based on a safe deep Q-network (safeDQN) to address the CMDP problem, in which the UAV learned to choose optimal actions based on rational policies.

Ding et al. [33] addressed the topic of 3D UAV trajectory and spectrum allocation, considering UAV power consumption and fairness to terrestrial users. To do this, they first defined UAV power consumption as a function of 3D mobility. Then, given the restricted energy, the fair throughput was maximized. They suggested a novel deep reinforcement learning (DRL)-based algorithm. The proposed method allows the UAV to control its speed and direction to save energy and arrive at the target destination while still having enough energy and allocating the spectrum band to reach the fairness. Wang et al. [34] examined two types of UAVs in a UAV-assisted secure network. One UAV flew about transmitting secret data to a mobile user, while the second UAV, which was there to help, made bogus noises to distract the attackers. Given the mobility of UAVs and users, the authors aimed to increase the worst case secrecy rate of mobile users. The challenge was handled by optimizing the 3D trajectory of UAVs while taking as constraints time allocation, maximum speed, collision avoidance, placement error, and energy harvesting.

Wu et al. [35] jointly optimized user scheduling and UAV trajectories to maximize average data rates among ground users. They envisioned a wireless communication system where the UAVs served several ground users. The UAVs operated periodically, and each UAV had to return to the starting point at the end of each time interval. The UAV trajectories were also designed such that they respected speed limits and avoided collisions. In [36], a UAV-aided data collection is proposed to gather data from several ground users. The objective of this article is to optimize the UAV’s trajectory, altitude, velocity, and data links with ground users to minimize the total mission time. This article targets emergency applications, where the mission completion time should be the main concern. Gong et al. [37] considered a scenario where a UAV collects data from a set of sensors on a straight line. They considered that the UAV can either cruise or hover while communicating with the sensors. The objective of this article is to minimize the UAV’s total flight time from a starting point to a destination while allowing each sensor to successfully upload a certain amount of data using a given amount of energy. In [38], an on-board DQN is proposed to minimize the overall data packet loss of the sensing devices. The authors have done it by optimally deciding the device to be charged and interrogated for data collection, and the instantaneous patrolling velocity of the UAV. Wang et al. [39] proposed a novel UAV-assisted Internet of Things network, in which a low-altitude UAV platform is employed as both a mobile data collector and an aerial anchor node to assist terrestrial BSs in data collection and device positioning. They aim to minimize the maximum energy consumption of all devices. In [40], the state-of-the-art DRL is merged with the UAV navigation through a massive multiple-input-multiple-output (MIMO) technique to design a DQN for optimizing the UAV trajectory by selecting the optimal policy. Zhan and Zeng [41] considered a scenario where multiple UAVs collect data from a group of sensor nodes on the ground. They study the tradeoff between the aerial cost, which is defined by the propulsion energy consumption and operation costs of all UAVs, and the ground cost, which is defined as the energy consumption of all sensor nodes. The aim is to minimize the weighted sum of the above-mentioned two costs, by optimizing the UAV trajectory jointly with wake-up time allocation, as well as the transmit power of all sensor nodes. In [42], a UAV-aided single-hop vehicular network is considered, wherein sensors on vehicles generate time-sensitive data streams, and UAVs are used to collect and process this data while maintaining a minimum age of information.

Hu et al. [45] investigated how to construct a trajectory for a group of energy-constrained UAVs working in dynamic
wireless network situations. In their model, a group of drone BSs (DBSs) was dispatched to jointly service clusters of ground users with dynamic and unexpected uplink access requests. In this scenario, the DBSs had to maneuver together to maximize coverage for the dynamic requests of ground users. This optimization approach for trajectory design aimed to develop optimal trajectories that increased the fraction of customers served by all FBSs. A value decomposition-based reinforcement learning (VD-RL) method with a meta-training mechanism was proposed to obtain an optimal solution for this nonconvex optimization problem in unpredictable situations. Nguyen et al. [43] developed a UAV-assisted Internet of Things system that maximized the quantity of data gathered from Internet of Things devices while depending on the UAVs’ shortest flight paths. After that, a method based on DRL was developed to determine the best trajectory and throughput within a given coverage region. Following training, the UAV was able to gather all the data from user nodes independently, improving the overall sum rate while utilizing fewer resources. Based on a connected graph, UAV routes were designated to serve Internet of Things devices in [46]. Their proposed method, known as semidynamic mobile anchor guidance (SEDMAG), used a weighted search algorithm to determine the shortest-path energy for conservative planning to meet the nodes dynamically. Hou et al. [44] proposed an NN-based method, to optimize discrete variables. A DRL-based pointer network named advantage pointer critic (APC) and a deep-unfolding NN were used to optimize continuous variables. To do so, they first created a Markov decision process to describe the user association and then to utilize the APC network trained using the advantage actor-critic method. APC networks were made up of a pointer network and a multilayer perceptron. In terms of the deep unfolding NN, they first created a block coordinate descent-based method to optimize the FBSs’ trajectories and transmission power, then unfolded the algorithm into a layerwise NN with inserted trainable parameters.

In this article, several important issues have been considered, which, to the best of our knowledge, have not been addressed independently or jointly in other related works. The most important contribution of the proposed algorithm is to provide an energy management method for FBSs, called FSM, which makes the operation time of FBSs longer and makes the problem closer to reality. In the FSM method, in each snapshot, idle FBSs return to the base and recharged so that they can be used again if needed in the future. Moreover, a method that finds the shortest possible 3D path for each FBS between any two snapshots is presented, avoiding obstacles and collisions between FBSs. In the Appendix, it is proven that the path is the shortest path and the optimal solution to the problem. In addition to the points mentioned, we have provided a solution to find the right duration for each snapshot, which is the right time to recheck the status of network users according to the conditions of the problem. Furthermore, to find the optimal 3D positions of FBSs in each snapshot, we have presented a mathematical model with an optimal solution in the problem space, considering the path loss and the altitude of the users.

In this article, we have tried to be the closest to the real-world conditions compared to the related works. We propose an exact solution in the problem space in both positioning and trajectory phases, while taking constraints related to power consumption, data rate, interference, and FBS collision avoidance into account. Moreover, we have used a mathematical model to have definite and global solution compared to heuristics or learning algorithms, which are time-consuming and do not produce an exact solution.

III. System Model

In this article, we consider a wireless cellular network in an urban environment. Users are present and gathered in different parts of the area at different times, so it is necessary to dynamically change the location of the BSs to provide the best possible services to users. Since deploying a terrestrial BS in short-term scenarios is not economically viable, we aim to offer coverage and service to all cellular users employing FBSs. It is assumed that users in this system have different data rate needs, which we have assumed to be random based on uniform distribution. Also, communication links between users and FBSs are assumed to be both LoS and NLoS. A possible assumed system is shown in Fig. 1.

Our main goal in this article is to solve a 3D trajectory planning problem for FBSs that would provide coverage and service to users with the fewest possible FBSs. To do this, we have divided the problem into several snapshots. In each snapshot, we find the most suitable 3D positions and the minimum possible number of FBSs. Then, we solve the trajectory problem to minimize the energy consumption of FBSs.

We solve the 3D positioning problem of FBSs in each snapshot based on the proposed model in [15] considering NLoS links and assuming 100% users coverage. In doing so, we find the minimum number of FBSs required based on the proposed bisection algorithm. The altitude of FBSs can be assumed between the two values of $H_{\text{min}}$ and $H_{\text{max}}$ based on the characteristics of the FBSs used. In addition, different altitudes have been assumed for users in this problem, which represents the presence of users in high-rise buildings. In order to prevent intercell interference, we have considered the limitation of the number of internal channels in the cell.

To solve the trajectory problem, we find the shortest path between each point of origin and the destination between two consecutive snapshots while taking obstacles and the potential for collisions with FBSs into consideration. To minimize the
FBS’s energy consumption, we propose a linear mathematical model based on the transportation problem between two snapshots, whereby the optimal trajectory of each FBS from origin to destination is obtained. We also assume that users move based on a random waypoint. In Section IV, this will be discussed in more detail. First, however, we should introduce the communication channel between the FBS and the user.

The deployment and service of FBSs are directly related to the air-to-ground (A2G) communication links. Various models for the A2G channel have been introduced in the literature. In this article, we use the A2G model presented in [47]. The channel model generally consists of two parts: LoS and NLoS links. The possibility of an LoS link between the FBS and the ground user is determined by several parameters, including building density, FBS location, and the elevation angle between the FBS and user. In an A2G channel, the probability of an LoS link is calculated as follows:

\[
P_{\text{LoS}} = \frac{1}{1 + a \exp(-b(\theta_u - a))} \quad (1)
\]

where \(a\) and \(b\) are environmental constants, and \(\theta_u\) is the elevation angle between user \(u\) and the FBS, which depends on their altitudes. It is calculated as:

\[
\theta_u = \left(-180/\pi \tan^{-1}(h_{\text{FBS}} - h_u)/d_u\right)
\]

where \(h_{\text{FBS}}\) and \(h_u\) are the altitudes of FBS and user, respectively. \(d_u\) is the distance between the FBS and user. It is calculated as:

\[
d_u = \sqrt{(x_u - x_{\text{FBS}})^2 + (y_u - y_{\text{FBS}})^2 + (h_u - h_{\text{FBS}})^2}^{1/2}
\]

It can be seen from (1) that the probability of an LoS link increases in accordance with the increasing elevation angle between the FBS and the user. The probability of having an NLoS communication link can be calculated as follows:

\[
P_{\text{NLoS}} = 1 - P_{\text{LoS}}. \quad (2)
\]

Hence, the mean path loss (in dB) for LoS and NLoS communication links can be calculated accordingly [48]

\[
L_{\text{LoS}} = 20 \log \left(\frac{4\pi f_c d_u}{C}\right) + \delta_{\text{LoS}} \quad (3)
\]

\[
L_{\text{NLoS}} = 20 \log \left(\frac{4\pi f_c d_u}{C}\right) + \delta_{\text{NLoS}} \quad (4)
\]

where \(\delta_{\text{LoS}}\) and \(\delta_{\text{NLoS}}\) are mean losses in LoS and NLoS communication links, respectively. Also, \(C = 3 \times 10^8\) is the light speed, and \(f_c\) is the carrier frequency. Therefore, the probabilistic long-term mean path loss is obtained as

\[
L (d_u) = L_{\text{LoS}} \times P_{\text{LoS}} + L_{\text{NLoS}} \times P_{\text{NLoS}}. \quad (5)
\]

### IV. Problem Formulation

In aiming to solve the problem of 3D trajectory planning for FBSs in a cellular network, we must find an unlimited number of continuous points for the FBSs’ positions, which is an NP-hard problem [15]. To do this, we divide the problem into several snapshots and find the optimal path of FBSs between every two snapshots, considering FBS energy consumption. We divide the problem into two phases. First, we find the minimum number of FBSs required and their optimal positions in each snapshot to cover and serve users. Then, we find the optimal path of each FBS from the origin to the destination.

#### A. Positioning Phase

In the first phase, the objective function of the positioning problem is to minimize the number of FBSs required and to find the optimal positions of FBSs to cover users. To do this, we reformulate the method proposed for FBS positioning in [15]. We consider NLoS links in this problem and aim to cover all users. We also consider FBS capacity to avoid intercell interference between covered users.

The decision variables considered in this formulation are presented in Table II. \(x_{ij}\) is the variable that represents whether or not user \(j\) is served by an FBS at candidate point \(i\). \(m_i\) shows whether candidate point \(i\) is selected or not. \(h_i\) is the variable of the FBS’s altitude. The path loss between user \(j\) and the FBS at candidate point \(i\) is decided by variable \(k_{ij}\). \(t_{ij}\) is an auxiliary decision variable. Also, the parameters used in this formulation are represented in Table III.

#### TABLE II

| Decision variable | Description |
|------------------|-------------|
| \(x_{ij}\)       | 1, if user \(j\) is served by candidate point \(i\), and 0, otherwise. |
| \(m_i\)          | 1, if candidate point \(i\) is selected for FBS deploying, and 0, otherwise. |
| \(h_i\)          | The altitude of the FBS which is deployed at the candidate point \(i\). |
| \(k_{ij}\)       | The path loss between user \(j\) and candidate point \(i\), if user \(j\) is served by candidate point \(i\), and 0, otherwise. |
| \(t_{ij}\)       | Auxiliary decision variable. |

\[
\begin{align*}
\min & \sum_{i \in I} \sum_{j \in J} k_{ij} \\
\text{s.t} & \sum_{i \in I} x_{ij} \leq 1, \quad \forall j \in J \\
& \sum_{j \in J} x_{ij} \leq \psi_{FBS}, \quad \forall i \in I \\
& x_{ij} \leq m_i, \quad \forall i \in I, \quad j \in J \\
& \sum_{i \in I} \sum_{j \in J} x_{ij} = U \\
& \sum_{j \in J} D_j \times x_{ij} \leq \beta \times m_i, \quad \forall i \in I \\
& \sum_{i \in I} m_i = P \\
& h_i \leq H_{\text{max}} \times m_i, \quad \forall i \in I \\
& h_i \geq H_{\text{min}} \times m_i, \quad \forall i \in I \\
& \cot(\theta) \times x_{ij} \leq \frac{h_i}{d_{ij}}, \quad \forall i \in I, \quad j \in J \\
& k_{ij} \geq \left[ P_{\text{LoS}} \times \left(4\pi f_c/C\right)^2 \right] / \left[ d_{ij}^2 - h_0^2 \right] \times x_{ij} \\
& \quad + \left(4\pi f_c/C\right)^2 \times 2 \times h_0 \times t_{ij} + x_{ij} \times 10^{L_{\text{LoS}}} \\
& \quad + \left(4\pi f_c/C\right)^2 \left[ d_{ij}^2 - h_0^2 \right] \times x_{ij}
\end{align*}
\]
In the proposed model, the objective function (6a) is defined to minimize the sum of path losses. Constraint (6b) stipulates that each user must be served by only one FBS. Constraint (6c) states that each FBS can serve a limited number of users based on its number of channels. Constraint (6d) shows that user $j$ can only be served by the FBS deployed at candidate point $i$. Constraint (6e) stipulates that FBSs must cover all users. Constraint (6f) allows each FBS to serve its maximum data rate based on its backhaul. Constraint (6g) states that the model must select only $P$ points from the given candidate points. Constraints (6h) and (6i) stipulate that if candidate point $i$ is selected as the position of an FBS, the FBS must fly within the permissible range. The FBS altitude will be set to zero if the model does not select the candidate point $i$. Constraint (6j) prevents the assignment of users who are not in the FBS’s coverage range. Constraints (6k) and (6l) are the first-order Taylor expansion of (4), proven in Lemma 1. In constraints (6m)–(6o), the decision variable $t_{ij} = x_{ij} \times h_i$ is used to reduce the nonlinear part to the multiplication of $x_{ij}$ and $h_i$. $t_{ij}$ must be zero if $x_{ij}$ or $h_i$ are equal to zero. Constraints (6m) and (6n) state this requirement. Also, $t_{ij}$ must be equal to $h_i$ when $x_{ij}$ becomes 1. Constraints (6m) and (6o) satisfy this.

**Lemma 1**: Consider $L(d_{ij}) = L_{\text{LoS}} \times P_{\text{LoS}} + L_{\text{NLoS}} \times P_{\text{NLoS}}$ as the path-loss function. If $L(d_{ij}) \geq \text{PL}_{\text{max}}$, then $x_{ij}$ must be equal to 0. The statement can be rewritten as follows:

$$x_{ij} = \begin{cases} 0, & \text{if } L(d_{ij}) \geq \text{PL}_{\text{max}} \\ 0 \text{ or } 1, & \text{otherwise.} \end{cases}$$

**Proof**: We obtain a linear conditional statement in terms of $h_i$ by replacing $L(d_{ij})$ in (7) with its linear approximation achieved from Taylor expansion around some $h_0$

$$L(d_{ij}) = L(h_i - h_0 + h_0) \approx L(h_0) + L'(h_0)(h_i - h_0)$$

$$= \left[ P_{\text{LoS}} \times \left( 4\pi \frac{f_c}{C} \right)^2 d_{ij}^2 + h_0^2 \right] x_{ij} + \left( 4\pi \frac{f_c}{C} \right)^2 \times 2 \times h_0 \times (h_i - h_0) + x_{ij} \times 10^{\delta_{\text{LoS}}}$$

$$+ \left[ P_{\text{NLoS}} \times \left( 4\pi \frac{f_c}{C} \right)^2 d_{ij}^2 + h_0^2 \right] x_{ij} + \left( 4\pi \frac{f_c}{C} \right)^2 \times 2 \times h_0 \times (h_i - h_0) + x_{ij} \times 10^{\delta_{\text{NLoS}}}.$$ 

Now, we have

$$x_{ij} = \begin{cases} 0, & \text{if } P_{\text{LoS}} \times \left( 4\pi \frac{f_c}{C} \right)^2 d_{ij}^2 + h_0^2 \geq 0 \\ 0 \text{ or } 1, & \text{otherwise.} \end{cases}$$

Assume that $A = \left( 4\pi \frac{f_c}{C} \right)^2$. By simplifying the conditional expression, we have

$$x_{ij} = \begin{cases} 0, & \text{if } h_i \geq \frac{\text{PL}_{\text{max}} - \left( A \times (d_{ij}^2 - h_0^2) \times (P_{\text{LoS}} + P_{\text{NLoS}}) \right)}{2Ah_0} \\ 0 \text{ or } 1, & \text{otherwise.} \end{cases}$$

By defining $d_{ij} = \left( \text{PL}_{\text{max}} - \left( A \times (d_{ij}^2 - h_0^2) \times (P_{\text{LoS}} + P_{\text{NLoS}}) \right) \right)/2Ah_0$, the conditional expression will be simplified as follows:

$$x_{ij} = \begin{cases} 0, & \text{if } h_i \geq a_{ij} \\ 0 \text{ or } 1, & \text{otherwise.} \end{cases}$$

To form (9) as a valid constraint in mathematical programming, the following expression can be given:

$$x_{ij} \leq \frac{M - a_{ij}}{M} + 1, \quad \forall i \in I, j \in J$$

where $M$ is a large number.

**B. Trajectory Phase**

In the trajectory phase, our objective is to find the best path for each FBS between two snapshots while taking obstacles and the potential for collisions into account. To do so, we must...
first consider the interval between every two snapshots. Since the velocity of FBSs is considered constant, the time between every two snapshots can also be constant. According to the characteristics of the FBS, a constant speed of 15 m/s has been considered for the FBS. This speed is also acceptable considering the average speed of users in the urban cellular network, including fixed users, pedestrian users (with an average speed of 1 m/s), and vehicular users (with an average speed of 10 m/s). According to (11), \( \Delta t \) can be obtained based on the average speed of users (\( \Gamma \)) and the minimum coverage range of an FBS. This means, on average, \( \Delta t \) seconds for a user to move out of the minimum coverage range of an FBS

\[
\Delta t = \frac{R_{\min}}{\Gamma}. \tag{11}
\]

The average speed of users (\( \Gamma \)) can also be obtained from (12). In this regard, it is assumed that \( \alpha \% \) of users are stationary, \( \beta \% \) are pedestrians, and \( \gamma \% \) are moving in cars

\[
\Gamma = \frac{\alpha \times V_\alpha + \beta \times V_\beta + \gamma \times V_\gamma}{100} \tag{12}
\]

where \( V_\alpha \) is equal to 0.

After finding the hovering positions where FBSs hover and serve users, we tackle the problem of calculating the best FBSs path. The purpose of this is to discover the shortest path between the origin and destination of an FBS for every two snapshots while avoiding obstacles such as buildings. To do this, we first create a graph containing source and destination hovering points and obstacle edge points. As obstacle edges are continuous in 3D, we consider points on their edges with a fixed distance to simplify the problem while keeping generality. This distance should not be so little that the graph grows too vast, causing the problem to take too long to solve. The distance should also not be so great that it substantially impacts the solution, with the result deviating from optimal global solutions. On this point, we should note that small distances of discretizing edges (e.g., less than 5 m) do not significantly affect the solution compared with FBSs’ altitude and problem space. Then, we create each edge between two graph vertices with a cost equal to the Euclidean distance in three dimensions. In the created graph, the edge between two vertices is ignored if an obstacle splits them. Dijkstra’s algorithm \cite{49} should be used to identify the shortest paths between every two hovering spots after the graph and edge cost have been determined. Dijkstra’s algorithm is a graph traversal method that finds the shortest path between two specified vertices in a weighted graph with no negative edges. Therefore, an FBS can fly from one position to another using this graph without colliding with obstacles, as proven in Lemma 2.

**Lemma 2:** In graph \( G(V, E) \), when going only via visited nodes, \( \text{dist}[V] \) is the shortest distance from source to \( V \), or infinite if no such path exists. (Note that we don’t assume that \( \text{dist}[V] \) is the shortest distance for nodes that haven’t been visited.)

**Proof:** The base case is when just one node is visited, namely the initial node source, in which case the hypothesis is straightforward.

Otherwise, we use the \( n-1 \) visited nodes hypothesis. In such an instance, we pick an edge \( V-U \) with the least \( \text{dist}[U] \) of any unvisited nodes, such that \( \text{dist}[U] = \text{dist}[V] + G.E[V, U] \). Because if there was a shorter way and the first unexplored node along that path was \( W \), the original hypothesis would stipulate that \( \text{dist}[W] > \text{dist}[U] \), which is a contradiction. Similarly, if there was a shorter path to \( U \) that did not use any unvisited nodes, and if the last but one node on that path was \( W \), then \( \text{dist}[U] = \text{dist}[W] + G.E[W, U] \) would be a contradiction.

After processing \( U \), if there existed a shorter path that did not pass through \( U \), we would have found it before processing \( U \). Therefore, \( \text{dist}[W] \) will still be the shortest distance from the source to \( W \) using just visited nodes. If a shorter path did go through \( U \), we would have updated it when processing \( U \). Therefore, the shortest path from the source to node \( V \) consists only of visited nodes once all nodes have been visited; hence, \( \text{dist}[V] \) is the shortest distance.

We run the shortest path algorithm for all origin–destination points. So the shortest distance between each origin–destination pair will be found.

In formulating the problem to find the best path, as mentioned in Table IV, \( d_{ij} \) is the decision variable that must be equal to 1 if FBS \( i \) moves to position \( j \); otherwise, it must be equal to 0. The objective function is to minimize the total energy consumed by FBSs due to their flight (16a). \( E_{ij} \) is obtained as follows:

\[
E_{ij} = \text{dist}_{ij} \times E_1 + E_U \tag{13}
\]

where \( E_1 \) is the energy consumption of the FBS for 1 m of flying, which is calculated as

\[
E_1 = \frac{\zeta \times V \times 3600}{D} \tag{14}
\]

where \( \zeta \) is the battery capacity, \( V \) is the battery’s voltage, and \( D \) is the total possible distance of the FBS flight. Also, \( E_U = mg \Delta h \) is the potential energy consumed for FBS \( \Delta h \) altitude change. Therefore, \( E_{ij} \) calculated as

\[
E_{ij} = (\text{dist}_{ij} \times E_1) + (mg \Delta h) \tag{15}
\]

Constraint (16b) states that the model decides the path of each FBS placed in the origin snapshot. Constraint (16c) ensures that each position in the subsequent snapshot is chosen for one FBS. \( M \) and \( N \) are sets of FBS positions in the origin and destination snapshots, respectively. The size of each set is twice the maximum required FBSs to ensure that the mathematical model has a feasible solution in every iteration. Equation (16d) is the constraint of the FSM; when the number of FBSs required in one snapshot is less or more than another, extra FBSs are moved to or from the base to save their energy, recharge, or extend the network coverage. The concept of FSM is similar to that of cell switch-off (CSO). Constraint (16e) ensures that each FBS has enough power to fly to the next
position. $\text{Energy}_{\text{th}}$ is the minimum energy required for each FBS to fly to the base. If an FBS does not have enough power to continue serving users, the $d_{ij}$ variable will choose the path to the base. The FBS will return to the base, and the other FBS will be used to fly from the base to the destination point. We call this process FSM.

$$\min \sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{N}} d_{ij} \times E_{ij}$$

subject to

$$\sum_{j \in \mathcal{N}} d_{ij} = 1, \quad \forall i \in \mathcal{M}$$

$$\sum_{i \in \mathcal{M}} d_{ij} = 1, \quad \forall j \in \mathcal{N}$$

$$\sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{N}} d_{ij} = \max (\mathcal{M}, \mathcal{N})$$

$$d_{ij} \times E_{ij} \leq \text{Energy}_{\text{th}}, \quad \forall i \in \mathcal{M}, \quad j \in \mathcal{N}$$

$$d_{ij} \times \text{dist}_{ij} \leq \text{Distance}_{\text{th}}, \quad \forall i \in \mathcal{M}, \quad j \in \mathcal{N}$$

Constraint (16f) states that no FBS can fly further than its threshold distance based on its constant velocity. The $\text{Distance}_{\text{th}}$ parameter is derived as follows:

$$\text{Distance}_{\text{th}} = V_{\text{FBS}} \times \Delta t$$

where $\Delta t$ is the time interval between two snapshots. The trajectory parameters are described in Table V.

The total energy of the path for each FBS ($E_{\text{path}}$) is obtained as follows:

$$E_{\text{path}} = E_{ij} + E_{\text{hover}}$$

where $E_{\text{hover}}$ is the energy consumed when the FBS hovers.

In theorem presented in the Appendix, we prove that the obtained path considering obstacles is the global shortest path possible for each FBS.

### C. FSM

After finding the path energy ($E_{\text{path}}$) of each FBS for each subsequent snapshot, we must check if the energy of each FBS is enough to fly to the destination through the selected path. Suppose the remaining energy of the FBS after flying to the destination is less than $\text{Energy}_{\text{th}}$, or the number of required FBSs in the subsequent snapshot is less than the current snapshot. In that case, some FBSs must return to the base to recharge and wait. Moreover, if in the subsequent snapshot more FBSs are needed, the FBSs required must fly to the selected destination points through the selected paths.

This whole process is called FSM.

As a general solution to the entire problem, we carry out the following steps. First, we divide the problem into several snapshots. In each snapshot, users may have different positions and data rate demands. In each snapshot, we solve the 3D positioning problem to find the minimum number of required FBSs and their proper positions. Then, we create a graph based on origin and destination hovering points and obstacle edge points. After that, we find the shortest path between each origin-destination pair while considering obstacles. As Theorem 1 proves, the probability of an FBS colliding is almost zero. Next, we solve the trajectory problem between two snapshots in a row using the proposed mathematical model and updating the FBSs’ energy parameter considering trajectory and hovering power consumption. The proposed trajectory model decides the best path for each FBS to minimize the total energy consumption. It also decides whether an FBS should return to base due to a lower number of required FBSs or due to the need to recharge batteries (concept FSM). Both proposed mathematical models are in linear form. The proposed positioning model is a mixed-integer linear problem (MILP), and the proposed trajectory model is a binary linear problem (BLP). Also, Dijkstra’s algorithm has an exact solution. Therefore, the proposed method reaches the exact solution. The process continues until there is no remaining snapshot. The whole process is shown in Algorithm 1.

**Theorem 1:** The probability of an FBS colliding is almost zero.

**Proof:** We know that infinite lines can be drawn in 3D. Therefore, the probability of finite lines colliding is almost zero (1). Also, since the origin and destination points of neither of the two FBS paths in the proposed deployment model are equal, there are no two paths that originate from one point (2). If the destination point of one path intersects with the origin point of another, since the second FBS had moved before and
changed its position, the first FBS will not collide with the second FBS at the end of its path (3). In addition, if two FBS paths collide and only if the intersection point is at the same distance from the origin point of each FBS (assuming the speed of both FBSs is constant and equal), then the FBSs will collide with each other. The probability of this event is almost zero, and by taking turns in the movement of FBSs, this event can also be prevented (4).

By taking 1–4 into consideration, we can conclude that the probability of a collision between the two FBSs in the proposed model is almost zero.

V. NUMERICAL RESULTS

In this section, we first introduce the test system and simulation parameters. We then discuss and compare the results of scenarios for the 3D FBS trajectory problem.

A. Test System

In the simulations, we consider a centralized decision-making system for FBSs’ positioning and trajectory. Referring to [48] and [50], as mentioned in Table VI, we consider a 5000 × 5000 m urban area with scenarios including 80, 200, and 450 users with PPP distribution. The PPP parameter \( \lambda = 20,000 \), and the environment parameters are as follows: \( f_c = 2 \text{ GHz} \), \( P_{\text{Lmax}} = 110 \text{ dB} \), and \((a, b, \delta_{\text{LOS}}, \delta_{\text{NLOS}}) = (9.61, 0.16, 1, 20)\), corresponding to urban environments. Additionally, we consider that the data rate requested by users has a uniform distribution with a maximum value of 6 Mb/s \( (D_{\text{avg}} = 3 \text{ Mb/s}) \). The FBSs’ backhaul data rate \( (\beta) \) is considered equal to 100 Mb/s for each. The FBSs’ flying altitude range is between 110 and 600 m, and users may be situated anywhere from 0 to 150 m, as we consider the maximum obstacle height to be 150 m. The minimum building height is considered to be 30 m. Moreover, we assumed that there are 25 high-rise buildings in the area. The distance between each two edge points of buildings is also considered equal to 10 m. The capacity of the FBSs’ battery \( (\zeta) \) is considered 15 000 mAh. In addition, we assume the maximum distance \( (D) \) that one FBS can fly with this battery to be 15 km. We also consider the FBS’s hovering energy consumption to be equal to 1000 J [7]. The battery assumed in this article for each FBS is a three-cell type, and its output voltage \( (\text{Battery}_v) \) is assumed to be 11.1 V. We also consider 45° to be the elevation angle of FBSs. We use the merge cell method proposed in [15] for the positioning model to find candidate points. We also used the Cplex solver to solve the positioning and trajectory mathematical models. We ran the simulation and solved the models many times; the results of the simulation are presented later.

B. Results

In the following, we discuss the results of the proposed positioning and trajectory approach and compare the results of three different numbers of users.

The number of required FBSs for each scenario with different methods is illustrated in Fig. 2. The proposed FSM method is compared with the NN-based [44], ordered artificial bee colony (ABC)-based placement (OAP) and QoS-GA methods.

In the OAP algorithm, by grouping users into several groups, the service users of each UA V were first identified. One UA V serves each group of users. Then, each UA V’s 3D position was chosen based on the clustering criteria [12]. QoS-GA is a GA-based FBSs’ deployment technique that has been developed to maximize the number of covered user equipment (UEs) while also satisfying their data rate needs within the FBSs’ capacity constraint. The population size, crossover rate, and mutation rate are three variables that affect the fundamental GA process. The number of potential solutions depends on the size of the population. The crossover rate and mutation rate values reflect the variety of potential solutions throughout an iteration. Up until the time step hits an iteration limit, the entire process is repeated. The GA model treats each FBS’s horizontal location and coverage radius as a gene. Some iterations are then run to determine the 2-D deployment outcome [50]. As we can see, the proposed method needs fewer FBSs to cover all users in different scenarios. In the proposed FSM method, on average, for 80 users, about six FBSs are needed to cover all users in each snapshot. For 200 and 450 users, on average, about 12 and 17 FBSs are needed, respectively. It should be noted that, in the original model of [44], one FBS served every three
Fig. 3. FBSs’ trajectories in two subsequent snapshots in the 80-user scenario. (a) FBS trajectories’ phase 1. (b) FBS trajectories’ phase 2.

Fig. 4. FBS trajectories and their obstacle avoidance. (a) FBS trajectories and obstacle avoidance—3D view. (b) FBS trajectories and obstacle avoidance—2D view.

Fig. 5. Mean FBS flight distance per user.

users. We removed this constraint and replaced it with the backhaul constraint of our model. With these conditions, the proposed model of [44] still needs more FBSs in different scenarios than the proposed model in this article.

Each snapshot is 15 s away from the next one, and between each two positioning snapshots, a trajectory problem is solved. Fig. 3 shows the FBSs’ trajectories in two different snapshots. In Fig. 3(a), it is shown that FBSs fly from red points to blue points. Some of them increase their altitude while others do the opposite. This happens because some users move to different positions and a group of them may become very dense. Also, since the power of some of FBSs is not enough to continue their mission, the FBSs which were operated in the last snapshot returned to the base, and the two alternative full-power FBSs flew to the red points to operate. In addition, the two FBSs that returned to the base will be recharged for further missions. Moreover, as we need fewer FBSs than the previous snapshot, the extra FBSs that returned to the base will recharge and wait for future missions. Fig. 3(b) illustrates that, in this snapshot, we need two more FBSs to cover users. Therefore, two new FBSs fly from the base to the destination points. The power of the last two FBSs is not enough for the next operation. All of these trajectories are designed to take obstacles and collision avoidance into consideration.

A scenario of how two FBSs move inside the target area is presented in 3D in Fig. 4(a) and 2-D in Fig. 4(b). Both figures illustrate the trajectory within a snapshot from $t_1$ to $t_2$. FBSs move from their origin to the destination during the snapshot avoiding obstacles by applying the proposed algorithm. It is worth mentioning that the path used by FBSs is the shortest possible path between the origin and the destination which is presented in 2-D and 3D. The red dot in 4 illustrates the place of the base where FBSs can recharge.

Fig. 5 presents a comparison of the mean FBS flight distance per user during the FBS operations. As the number of
users increases, because we have more FBSs, the mean flight distance of an FBS decreases. When we have fewer FBSs, the total distance of FBSs will increase.

In Fig. 6, the average FBS flight energy consumption is compared in different scenarios. Energy includes the hovering and trajectory power consumed. As expected, with the increase in the number of users, the average power consumption of each FBS must decrease because of shorter paths for FBSs and, therefore, less recharging. For example, with 80 users, the number of FBSs is fewer than in other scenarios. As the mean flight distance of each FBS is greater, the mean energy consumption of each FBS is more significant than in other scenarios. To compare with the proposed method in [44], overall, the mean FBSs’ energy consumption of our proposed method is much less than the NN method of [44]. The increase in FBSs’ energy in [44] is because of the number of FBSs.

Fig. 7 shows the comparison of the average solving time of the trajectory problem. As we can see, besides the proposed trajectory mathematical model having an exact solution, the time it takes to solve the problem is less than the time interval between two snapshots. It means that we have enough time to solve the problem in the real world. Moreover, although in [44] a DRL NN-based method was proposed, the mean solving time of our exact method is much less than the [44]’s one. By the way, we might add that a greater number of FBSs will mean more time to solve the problem. However, sometimes to have the optimum solution of the problem and minimize the FBSs’ energy consumption considering the constraints of the problem, the solving time can increase. As Fig. 7 shows, the average time it takes to solve the 80-user scenario is somewhat longer than the 200-user scenario because of some data calculations. It is worth noting that the standard deviation of trajectory solving time with 80 users shows that, in some cases, the solving time of this scenario is less than the minimum solving time of other scenarios.

Fig. 8 shows that, with an increasing number of users, the mean data rate served by each FBS increases. Therefore, we can conclude that Backhaul’s efficiency will increase with a greater number of users, and more backhaul will be used in each small cell during the operation.

Fig. 9 presents the throughput of the proposed algorithm compared with [43] and [44]. These methods are selected because they use RL-based algorithms for trajectory. We have proved the efficiency of the proposed algorithm in Theorem 2 in the Appendix; this evaluation is used as a verification for the claim. Using the mean of achieved throughput in several runs, the throughput of the proposed algorithm is 57 and 34, and 22 for Nguyen-RL and Hou-NN, respectively. The minimum achieved throughput of the proposed algorithm in several runs is more than the maximum achieved throughput of compared methods. It is worth mentioning that [43] used only one FBS, did not consider energy, and did not report...
its processing and training time. Both [43] and [44] did not consider obstacles in their methods.

VI. CONCLUSION

This article proposed an approach with an exact solution for the problem of multiple FBSs’ 3D trajectories, while considering constraints related to energy consumption, operational time, flight distance, intercell interference, and collision avoidance. The approach consisted of two phases, namely an FBS positioning phase and an FBS trajectory phase, where we divided the problem into several snapshots. First, we found the minimum number of FBSs required along with their optimal 3D positions in each snapshot. Then, the trajectory phase ran between every two snapshots. The optimum path between the origin and the destination in the trajectory phase was found using the proposed BLP model, considering FBS’s energy consumption and flight distance limitations. As the proposed method was a BLP, the solution was the optimal one. We used a shortest path heuristic to find the best path of each FBS from the origin to the destination, taking the constraint of collision avoidance into account. In different snapshots, the required number of FBSs could be different. To address this, we introduced the FSM approach to manage the set of FBSs and their power. The results showed that the proposed method is operational in real-world scenarios. The results also showed that the mean FBS flight distance per user and mean FBS energy consumption decreased as the number of users increased. Also, the mean data rate served by each FBS was shown to increase as the number of users increased.

APPENDIX

Here is the proof for the global and definite solution of the proposed algorithm.

Theorem 2: Suppose there is no direct path between points A and B (the connecting line between A and B passes through an obstacle), then the path obtained from the proposed algorithm based on the proposed graph and Dijkstra’s algorithm will be the shortest path from A to B.

Proof: There are two cases for the problem: 1) where the path only passes one vertex of the obstacle and 2) where the path passes two vertexes of the obstacle. We will provide proof for the theorem for each case in the following.

First, the path only passes one vertex of the obstacle, from point A to M and from M to B.

To prove by contradiction, as shown in Fig. 10, we assume that the shortest path between A and B is \( P' \), where \( P' \neq P_1 + P_2 \). If \( P' \) passes from M, it is clear that \( P_1 + P_2 < P' \), because the shortest path from A to M, and from M to B are \( P_1 \) and \( P_2 \), respectively.

If \( P' \) will not pass from M, first we must prove that \( P' \) is not the shortest path. \( P' \) includes two \( L_1 \) and \( L_2 \) segments where they intersect at an arbitrary point like N. Assume N is an arbitrary point on the path of \( P' \). Since \( L_1 \geq L_2 \) and \( L_2 \geq L_1 \), therefore: \( P' = P'_1 + P'_2 \geq L_1 + L_2 \).

Now we must prove \( L_1 + L_2 > P'_1 + P'_2 \). In this case, as shown in Fig. 11, we assume that there is a straight line from A to N (\( L'_1 \)) and then from N to B (\( L'_2 \)).
If one of the paths is tangent, according to “Triangle Sides Inequality Theorem,” $L_1 + R_2 < L_1' + L_2'$ and since $R_1 < R_2 + R_3$ then $L_1 - R_2, R_3$. Therefore, $L_1 + R_1 < L_1' + L_2' + R_3$. Now, it is concluded that the length of every path from A to N that does not pass M1 is longer than the path that passes M1 based on the “Triangle Sides Inequality Theorem.” Similarly, the path from N to B must pass M2 as depicted in Fig. 14.

Knowing the fact that the path including A, N, and B must be re-written as A, M1, N, M2, and B; according to the “Triangle Sides Inequality Theorem”, the A, N, and B path could not be shorter than A, M1, M2, and B path. Therefore, the path that passes the vertices is the shortest.

REFERENCES

[1] X. Foukas, G. Patounas, A. Elmokashfi, and M. K. Marina, “Network slicing in 5G: Survey and challenges,” IEEE Commun. Mag., vol. 55, no. 5, pp. 94–100, May 2017.

[2] K. Sheth, K. Patel, H. Shah, S. Tanwar, R. Gupta, and N. Kumar, “A taxonomy of AI techniques for 6G communication networks,” Comput. Commun., vol. 161, pp. 279–303, Sept. 2020.

[3] I. Bekmezci, O. K. Sahingoz, and S. Temel, “Flying ad-hoc networks (FANETs): A survey,” Ad Hoc Nets., vol. 11, no. 3, pp. 1254–1270, 2013.

[4] S. Hayat, E. Yannaz, and M. Muzaffar, “Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint,” IEEE Commun. Surveys Tuts., vol. 18, no. 4, pp. 2624–2661, 4th Quart., 2016.

[5] E. Kalantari, M. Z. Shakir, H. Yanikomeroglu, and A. Yongacoglu, “Backhaul-aware robust 3D drone placement in 5G+ wireless networks,” in Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops), May 2017, pp. 109–114.

[6] 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 Commun. Lett., vol. 6, no. 4, pp. 434–437, Aug. 2017.

[7] A. Fotouhi et al., “Survey on UAV cellular communications: Practical aspects, standardization advancements, regulation, and security challenges,” IEEE Commun. Surveys Tuts., vol. 21, no. 4, pp. 3417–3442, 4th Quart., 2019.

[8] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, “A tutorial on UAVs for wireless networks: Applications, challenges, and open problems,” IEEE Commun. Surveys Tuts., vol. 21, no. 3, pp. 2334–2360, 3rd Quart., 2019.

[9] X. Liu et al., “Placement and power allocation for NOMA-UAV networks,” IEEE Wireless Commun. Lett., vol. 8, no. 3, pp. 965–968, Jun. 2019.

[10] F. Cheng et al., “UAV trajectory optimization for data offloading at the edge of multiple cells,” IEEE Trans. Veh. Technol., vol. 67, no. 7, pp. 6732–6736, Jul. 2018.

[11] Y. Sun, T. Wang, and S. Wang, “Location optimization and user association for unmanned aerial vehicles assisted mobile networks,” IEEE Trans. Veh. Technol., vol. 68, no. 10, pp. 10056–10065, Oct. 2019.

[12] C. Zhang, L. Zhang, L. Zhu, T. Zhang, Z. Xiao, and X.-G. Xia, “3D deployment of multiple UAV-mounted base stations for UAV communications,” IEEE Trans. Commun., vol. 69, no. 4, pp. 2473–2488, Apr. 2021.

[13] B. Khamidi and E. S. Sousa, “Trajectory design for the aerial base stations to improve cellular network performance,” IEEE Trans. Veh. Technol., vol. 70, no. 1, pp. 945–956, Jan. 2021.

[14] W. Shi et al., “Multi-drone 3-D trajectory planning and scheduling in drone-assisted radio access networks,” IEEE Trans. Veh. Technol., vol. 68, no. 8, pp. 8145–8158, Aug. 2019.

[15] Z. Rahimi et al., “An efficient 3-D positioning approach to minimize required UAVs for IoT network coverage,” IEEE Internet Things J., vol. 9, no. 1, pp. 558–571, Jan. 2022.

[16] M. J. Sobouti et al., “Efficient deployment of small cell base stations mounted on unmanned aerial vehicles for the Internet of Things infrastructure,” IEEE Sensors J., vol. 20, no. 13, pp. 7467–7476, Jul. 2020.

[17] Y. Zeng, R. Zhang, and T. J. Lim, “Wireless communications with unmanned aerial vehicles: Opportunities and challenges,” IEEE Commun. Mag., vol. 54, no. 5, pp. 36–42, May 2016.

[18] Y. Qian, K. Sheng, C. Ma, J. Li, M. Ding, and M. Hassan, “Path planning for the dynamic UAV-aided wireless systems using Monte Carlo tree search,” IEEE Trans. Veh. Technol., vol. 71, no. 6, pp. 6716–6721, Jun. 2022.

[19] G. Fontanesi, A. Zhu, M. Arvaneth, and H. Ahmadi, “A transfer learning approach for UAV path design with connectivity outage constraint,” IEEE Internet Things J., vol. 10, no. 6, pp. 4998–5012, Mar. 2023.

[20] Y. Liu, W. Huangfu, H. Zhou, H. Zhang, J. Liu, and K. Long, “Fair and energy-efficient coverage optimization for UAV placement problem in the cellular network,” IEEE Trans. Commun., vol. 70, no. 6, pp. 4222–4235, Jun. 2022.

[21] Y. He, Y. Gan, H. Cui, and M. Guizani, “Fairness-based 3D multi-UAV trajectory optimization in multi-UAV-assisted MEC system,” IEEE Internet Things J., early access, Jan. 31, 2023, doi: 10.1109/IoT.2023.3241087.

[22] X. Zhou, F. Gao, X. Fang, and Z. Lan, “Improved bat algorithm for UAV path planning in three-dimensional space,” IEEE Access, vol. 9, pp. 20100–20116, 2021.

[23] Y. Pan, Y. Yang, and W. Li, “A deep learning trained by genetic algorithm to improve the efficiency of multi-UAV access,” IEEE Access, vol. 9, pp. 7994–8005, 2021.

[24] Q. Xia, S. Liu, M. Guo, H. Wang, Q. Zhou, and X. Zhang, “Multi-UAV trajectory planning using gradient-based sequence minimal optimization,” Robot. Auto. Syst., vol. 137, Mar. 2021, Art. no. 103728.

[25] Y. Tang, T. Miao, A. Barnawi, B. Alzahrani, R. Alotaibi, and K. Hwang, “A joint global and local path planning optimization for UAV task scheduling towards crowd air monitoring,” Comput. Netw., vol. 193, Jul. 2021, Art. no. 107913.

[26] Y. Zhou, F. Zhou, H. Zhou, D. W. K. Ng, and R. Q. Hu, “Robust trajectory and transmit power optimization for secure UAV-enabled cognitive radio networks,” IEEE Trans. Commun., vol. 68, no. 7, pp. 4022–4034, Mar. 2020.

[27] J. Ji, K. Zhu, D. Niyato, and R. Wang, “Joint trajectory design and resource allocation for secure transmission in cache-enabled UAV- relaying networks with D2D communications,” IEEE Internet Things J., vol. 8, no. 3, pp. 1557–1571, Feb. 2021.

[28] J. Ji, K. Zhu, D. Niyato, and R. Wang, “Joint cache placement, flight trajectory, and transmission power optimization for secure UAV-assisted wireless networks,” IEEE Trans. Wireless Commun., vol. 19, no. 8, pp. 5389–5403, Aug. 2020.

[29] M. Hu, L. Yang, Q. Wu, and A. L. Swindlehurst, “3D UAV trajectory and communication design for simultaneous uplink and downlink transmission,” IEEE Trans. Wireless Commun., vol. 19, no. 6, pp. 5908–5929, Sep. 2020.

[30] Y. Wang et al., “Joint resource allocation and UAV trajectory optimization for space–air–ground internet of remote things networks,” IEEE Syst. J., vol. 15, no. 4, pp. 4745–4755, Dec. 2021.

[31] W. Feng et al., “Joint 3D trajectory design and time allocation for UAV-enabled wireless power transfer networks,” IEEE Trans. Veh. Technol., vol. 69, no. 9, pp. 9265–9278, Sep. 2020.

[32] T. Zhang, J. Lei, Y. Liu, C. Feng, and A. Nallanathan, “Trajectory optimization for UAV emergency communication with limited user equipment energy: A safe-DQN approach,” IEEE Trans. Green Commun. Netw., vol. 5, no. 3, pp. 1236–1247, Sep. 2021.
K. Li, W. Ni, E. Tovar, and A. Jamalipour, “On-board deep Q-network for dual-UAV-enabled secure communications,” IEEE J. Sel. Areas Commun., vol. 39, no. 11, pp. 3334–3347, Oct. 2021.

Q. Wu, Y. Zeng, and R. Zhang, “Joint trajectory and communication design for multi-UAV enabled wireless networks,” IEEE Trans. Wireless Commun., vol. 17, no. 3, pp. 2109–2121, Mar. 2018.

J. Li et al., “Joint optimization on trajectory, altitude, velocity, and link scheduling for minimum mission time in UAV-aided data collection,” IEEE Internet Things J., vol. 7, no. 2, pp. 1464–1475, Feb. 2020.

J. Gong, T.-H. Chang, C. Shen, and X. Chen, “Flight time minimization of UAV for data collection over wireless sensor networks,” IEEE J. Sel. Areas Commun., vol. 36, no. 9, pp. 1942–1954, Sep. 2018.

K. Li, W. Ni, E. Tovar, and A. Jamalipour, “On-board deep Q-network for UAV-assisted online power transfer and data collection,” IEEE Trans. Veh. Technol., vol. 68, no. 12, pp. 12215–12226, Oct. 2019.

Z. Wang, R. Liu, Q. Liu, J. S. Thompson, and M. Kadoch, “Energy-efficient data collection and device positioning in UAV-assisted IoT,” IEEE Internet Things J., vol. 7, no. 2, pp. 1122–1139, Feb. 2020.

H. Huang, Y. Yang, H. Wang, Z. Ding, H. Sari, and F. Adachi, “Deep reinforcement learning for UAV navigation through massive MIMO technique,” IEEE Trans. Veh. Technol., vol. 69, no. 1, pp. 1117–1121, Jan. 2020.

C. Zhan and Y. Zeng, “Aerial–ground cost tradeoff for multi-UAV-enabled data collection in wireless sensor networks,” IEEE Trans. Commun., vol. 68, no. 3, pp. 1937–1950, Mar. 2020.

M. Samir, C. Assi, S. Sharafeddine, D. Ebrahimi, and A. Ghrayeb, “Age of information aware trajectory planning of UAVs in intelligent transportation systems: A deep learning approach,” IEEE Trans. Veh. Technol., vol. 69, no. 11, pp. 12382–12395, Nov. 2020.

K. K. Nguyen, T. Q. Duong, T. Do-Huy, C. Claultsen, and L. Hanzo, “3D UAV trajectory and data collection optimisation via deep reinforcement learning,” IEEE Trans. Commun., vol. 70, no. 4, pp. 2358–2371, Apr. 2022.

Q. Hou, Y. Cai, Q. Hu, M. Lee, and G. Yu, “Joint resource allocation and trajectory design for multi-UAV systems with moving users: Pointer network and unfolding,” IEEE Trans. Wireless Commun., early access, Nov. 7, 2022, doi: 10.1109/TWC.2022.3217176.

Y. Hu, M. Chen, W. Saad, H. V. Poor, and S. Cui, “Distributed multi-agent meta learning for trajectory design in wireless drone networks,” IEEE J. Sel. Areas Commun., vol. 39, no. 10, pp. 3177–3192, Oct. 2021.

S. Kouroshnezhad, A. Peiravi, M. S. Haghighi, and A. Jolfaei, “Energy-efficient drone trajectory planning for the localization of 6G-enabled IoT devices,” IEEE Internet Things J., vol. 8, no. 7, pp. 5022–5029, Apr. 2021.

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 Proc. IEEE Int. Conf. Commun. (ICC), May 2016, pp. 1–5.

E. Kalantari, H. Yanikomeroglu, and A. Yongacoglu, “Wireless networks with cache-enabled and backhaul-limited aerial base stations,” IEEE Trans. Wireless Commun., vol. 19, no. 11, pp. 7363–7376, Nov. 2020.

E. W. Dijkstra, “A note on two problems in connexion with graphs,” Numer. Math., vol. 1, no. 1, pp. 269–271, Oct. 1959.

Z. Zhong, Y. Huo, X. Dong, and Z. Liang, “QoS-compliant 3-D deployment optimization strategy for UAV base stations,” IEEE Syst. J., vol. 15, no. 2, pp. 1795–1803, Jun. 2021.

Mohammad Javad Sobouti received the B.S. degree in software engineering from the Ferdowsi University of Mashhad, Mashhad, Iran, in 2014, and the M.S. degree in computer networks from the Shiraz University of Technology, Shiraz, Iran, in 2017. He is currently pursuing the Ph.D. degree in software engineering with the Ferdowsi University of Mashhad.

His research interests include computer network and optimization.

Amir Hossein Mohajerzadeh received the B.S., M.S., and Ph.D. degrees in computer networks from the Ferdowsi University of Mashhad, Mashhad, Iran, in 2005, 2007, and 2013, respectively.

He has been an Assistant Professor with the Computer Engineering Department, Ferdowsi University of Mashhad, for eight years. As a Computer Network Engineer, he has been participating in several networking projects at the Iran Telecommunication Research Center (ITRC), KREC, and Mashhad Municipality, since 2008. He has authored five books in Farsi in networking field. He has authored more than 50 international conference papers and journal articles. His research interests include BSG and 6G cellular networks, machine learning, wireless sensor networks (WSNs), software-defined networking (SDN), smart grid, target tracking, modeling and analyzing computer networks, quality of services (QoS), and fuzzy logic control.

Seyed Amin Hosseini Seno received the B.Sc and M.Sc. degrees in computer engineering from the Ferdowsi University of Mashhad, Mashhad, Iran, in 1990 and 1998, respectively, and the Ph.D. degree from the University of Sains Malaysia, George Town, Malaysia, in 2010. He is currently an Associate Professor with the Department of Computer Engineering, Ferdowsi University of Mashhad. His research interests include computer networks, QoS, 5G, the Internet of Things, and network security.

Halim Yanikomeroglu (Fellow, IEEE) received the B.Sc. degree in electrical and electronics engineering from Middle East Technical University, Ankara, Turkey, in 1990, and the M.A.Sc. degree in electrical engineering (now ECE) and the Ph.D. degree in electrical and computer engineering from the University of Toronto, Toronto, ON, Canada, in 1992 and 1998, respectively.

Since 1998, he has been with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada, where he is currently a Full Professor. He has given 110+ invited seminars, keynotes, panel talks, and tutorials in the last five years. He has supervised or hosted over 150 postgraduate researchers in his laboratory at Carleton. His extensive collaborative research with industry resulted in 39 granted patents. His research interests include many aspects of wireless communications and networks, with a special emphasis on nonterrestrial networks (NTN) in the recent years.

Dr. Yanikomeroglu is a fellow of the Engineering Institute of Canada (EIC) and the Canadian Academy of Engineering (CAE). He is also a member of the IEEE ComSoc Governance Council, IEEE ComSoc GIM, IEEE ComSoc Conference Conference Council, and IEEE PIMRC Steering Committee. He received several awards for his research, teaching, and service, including the IEEE ComSoc Fred W. Ellersick Prize in 2021, IEEE VTS Stuart Meyer Memorial Award in 2020, and IEEE ComSoc Wireless Communications TC Recognition Award in 2018. He received the best paper awards at the IEEE Competition on Non-Terrestrial Networks for BG and 6G in 2022 (grand prize), IEEE ICC 2021, and IEEE WISEE 2021 and 2022. He is a Distinguished Speaker for the IEEE Communications Society and the IEEE Vehicular Technology Society, and an Expert Panelist of the Council of Canadian Academies (CCA/CAC). He is currently serving as the Chair for the Steering Committee of the IEEE’s flagship wireless event, Wireless Communications and Networking Conference (WCNC). He served as the General Chair and Technical Program Chair for several IEEE conferences. He has also served in the editorial boards of various IEEE periodicals.