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Autonomous 3D Deployment of Aerial Base Stations in Wireless Networks with User Mobility

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***Abstract*—Unmanned aerial vehicles (UAVs) have recently emerged as enablers for multitude use cases in 5G networks, one of which utilizes them as aerial base stations to intermittently serve mobile users in emergency situations or hard-to-reach areas. In this work, we address the problem of deploying multiple UAVs optimally in 3D space while autonomously adapting their positions as users move around within the network. We propose a novel approach with the objective of deploying the least number of UAVs to maintain target quality of service requirements. The problem of positioning UAVs in a 3D space is formulated as a mixed integer programming problem (MIP). To obtain an efficient solution, we propose and evaluate an autonomous positioning algorithm that can easily adapt as the users move within a specific area in the network. We present performance results for the algorithm as a function of various system parameters assuming a random walk mobility model. The simulation results demonstrate the effectiveness of the proposed algorithm compared to the optimal solution and related work in the literature for various network scenarios with user mobility.**

I. Introduction

Unmanned aerial vehicles (UAVs) have recently attracted various industry verticals to enable and create new services and markets. Integrating UAVs into 5G networks brings forward many use cases in search and rescue, disaster management, V2X infotainment services, data gathering in Internet of Things (IoT), and many others. Due to their mobility and ability to cover unreachable sites, UAVs are gaining increased interest in deploying them as aerial base stations to provide wireless connection in high demand and rural areas [1]. Employing UAVs as aerial base stations is strongly effective in situations where large obstacles degrade the quality of wireless links between users and ground base stations and is considered an effective solution to improve the network quality and capacity by offloading traffic from the ground base station in dense locations [2] [3]. Unlike terrestrial base stations, aerial base stations (ABSs) can be dynamically deployed and can also adjust their positions to support mobile users with different quality of service (QoS) requirements [4].

This work extends our previous work in [5] to account for user mobility and allow for autonomous positioning in a continuous 3D space. Specifically, we focus here on the autonomous 3D deployment of UAVs in wireless networks where ABSs are part of the mobile communication infrastructure serving a group of users. Movement decisions are made at each time interval to accommodate network changes and user mobility. First, we formulate the problem of positioning ABSs in the 3D space as a mixed integer program (MIP) and then we propose an autonomous positioning algorithm that is capable of quickly adapting to dynamic networks.

The remainder of this paper is organized as follows. In Section II, we cover the related literature and highlight the main contributions of this work. Section III presents the system model and its key components. Section IV formulate the problem for the problem of 3D deployment of multiple UAVs in wireless systems as a MIP. Section V describes the proposed low complexity autonomous algorithm for deploying multiple UAVs in wireless systems with user mobility. Section VI presents performance results for various scenarios and highlights the effectiveness of the proposed algorithm. Finally, conclusions are drawn in Section VII.

II. Literature Review

Previous work available in the literature tackled either the problem of optimizing the position of a number of ABSs or planning the trajectory of a single ABS where the start point, trajectory path, and end point are optimized. A large number of work exists that study the positioning of static ABSs within wireless networks. In these static wireless environments, the horizontal location and altitude of an ABS are jointly or individually optimized while accommodating for multiple QoS requirements. Some work focused on only optimizing the altitude at which UAVs are deployed. The authors in [6] worked on optimizing the altitude of a single and static UAV to achieve a maximum coverage radius. They studied the height in terms of the maximum pathloss and different environmental parameters. Similarly, in [7] the optimal altitude of two UAVs was derived while maximizing the coverage area and minimizing the needed transmit power.They studied two cases, an interference-free and a full interference scenario.

Other work focused on solely optimizing the 2D position. The work in [8] optimized the horizontal position of multiple ABSs with the aim of minimizing the total number of deployed UAVs. The authors suggested a polynomial time spiral algorithm to position the UAVs where ABSs are first placed on the perimeter to cover the maximum number of users and then distributed along a spiral route towards the center until all users are covered. The work in [9] studied the problems associated with the use of UAVs as wireless base stations in emergency situations. Initially, the authors considered the scenario where all UAVs are launched from the same position and proposed a polynomial time algorithm. Then, this was extended to include the more general case where UAVs are dispatched from different locations. The problem was formulated as a dynamic program and solved with a pseudo-polynomial time algorithm.

Few works tackled the UAV positioning problem in 3D space. In [10], the deployment of a single UAV to provide wireless coverage for ground users was studied as a 3-D circle placement problem. The horizontal and vertical placement of the UAV was decoupled to simplify the problem and then formulated as integer non-linear problem while maximizing the ground user coverage probability. Similarly, the authors in [11] investigated the 3D placement of a single ABS where the objective is to maximize the total number of covered users. First, the problem was modeled as a multiple circles placement problem. Then, an exhaustive search (ES) solution was proposed where the optimal height is searched for within a bounded interval. To further reduce the complexity, they suggested a weighted area algorithm that produced close to the ES simulation results.

On the other hand, some work focused on optimizing the ABS trajectory while considering multiple QoS requirements. For example, in [12] the authors considered an ABS that is dispatched to cover and serve the maximum number of users before exhausting all its energy resources. The problem of jointly optimizing the trajectory, scheduling, and user associations were studied. First, the trajectory optimization problem was modeled as a mixed integer linear problem and then a more efficient iterative algorithm that divides the problem into multiple sub-problems was suggested. The solution was further enhanced to account for inaccurate user location information where two techniques were introduced to tackle this problem.

The aforementioned research contributions considered the deployment of UAVs mostly in a 2D plane, with more recent work studying the deployment of a number of UAVs in a 3D space. In addition, most work considered scenarios where users are static or studied the deployment of UAVs based on a network snapshot within a specific time slot. In this work, we leverage the mobility and flexibility of UAVs to deploy them in dynamic networks with user mobility. The main contribution of this work is to study the 3D autonomous deployment of UAVs in wireless networks where user mobility is taken into account. We propose an efficient and lightweight solution based on electrostatic forces that is capable to adapt to network changes.

III. System Model

Our system model is depicted in Fig. 1. We consider a wireless communication system where a fleet of UAV-mounted base stations, denoted as aerial base stations (ABSs), is deployed to serve a number of ground users in a specific area, where the terrestrial infrastructure was destroyed or had not been installed. These UAVs can dynamically move, when needed, to effectively serve the mobile users. Our objective is to identify the minimum number of ABSs required and their optimized 3D locations to provide efficient connectivity to the set of ground users.

With a 3D Cartesian coordinate system, we denote by $c_i = (x_i, y_i, z_i)$ the three-dimensional coordinate of each ABS i where x_i and y_i represent the horizontal position and z_i represents the altitude. We consider a downlink scenario in which each ABS is equipped with a directional antenna. K_T represents the total number of users in the area and N is the number of needed ABSs out of a maximum of N_D available ABSs.

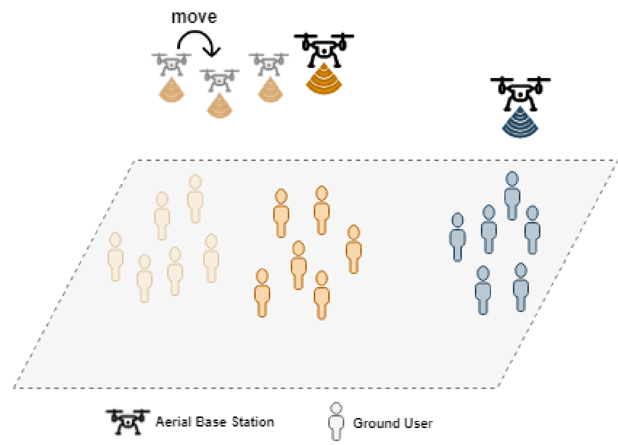

Fig. 1. System model with aerial base stations serving mobile ground users and adapting their positions as users move to maintain the target performance.

We adopt the channel model suggested in [13] which depends on the height and angle formed with respect to the served user, resulting in the following line of sight (LoS) probability:

$$p_{LoS} = \frac{1}{1 + \mu * \exp\left(-\beta\left(\arctan\left(\frac{h}{r}\right) - \mu\right)\right)}, \quad (1)$$

where h and r are the height and the horizontal distance between the ABS and the user, respectively. In addition, μ and β are constants that depend on the environment. The channel model between an ABS and a user can then be modeled as follows:

$$\begin{aligned} PL_{i,j} = \frac{P_T}{P_R} &= p_{LoS}\eta_{LoS}\left(\frac{4\pi f_c d_{i,j}}{c}\right)^{\alpha} \\ &+ p_{NLoS}\eta_{NLoS}\left(\frac{4\pi f_c d_{i,j}}{c}\right)^{\alpha}, \end{aligned} \quad (2)$$

where f_c is the carrier frequency in Hz, c is the speed of light in m/s, α is the pathloss exponent, η_{LoS} and η_{nLoS} are, respectively, the losses corresponding to LoS and non-LoS connections depending on the environment and $d_{i,j}$ is the distance between ABS i and user j.

IV. Problem Formulation

The main objective of this work is to determine the location and number of UAVs to be deployed to serve ground users. In order to minimize the cost we aim to deploy the minimum number of ABSs to serve the users with a specific outage probability. In this section we formulate the problem as a mixed integer programming optimization problem.

Our main goals are 1) to minimize the deployment cost by minimizing the required number of UAVs and 2) to intelligently deploy the ABSs in such a way that maximizes the overall quality of service measured by the received power for all users. First, we introduce a decision variable u_i to indicate whether an ABS i will be deployed or not.

$$u_i = \begin{cases} 1, & \text{if ABS } i \text{ is deployed} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

We also define a $K_T(N_D+1)$ association matrix $\mathbf{A}$ where a_{ki} is a binary value indicating whether or not user k is associated with ABS i.

$$a_{ki} = \begin{cases} 1, & \text{if user k is associated to ABS i} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

We assume a user is in the coverage region of ABS if the power received satisfies the QoS requirement. For a given transmission power of the ABS, let Γ represent the SNR threshold corresponding to the QoS requirement. That is user k is covered by ABS i if

$$SNR_k = \frac{P_{k,i}}{\sigma^2} \geq \Gamma, \tag{5}$$

where $P_{k,i}$ is the received power and σ^2 is the thermal noise. By utilizing the channel model in (2), we can calculate the received power for each user covered by an ABS. The power budget set to each user by a UAV is expressed as $\frac{P_D}{K_D}$ where P_D is the maximum transmit power of the UAV and k_D is its maximum capacity.

Based on the above, the problem is formulated as follows:

$$\min_{d,A} \quad \sum_{i=1}^{N_D}\sum_{k=1}^{K_T} \lambda u_i - (1-\lambda)\frac{P_{k,i}}{P_T} a_{k,i} \tag{6}$$

$$\text{subject to } a_{k,i} \leq u_i \qquad \forall i, \forall k \tag{7}$$

$$\sum_{i=1}^{N_D} a_{k,i} \leq 1 \qquad \forall k \tag{8}$$

$$\sum_{k=1}^{K_T} a_{k,i} \leq K_D \qquad \forall i \in [1, N_D] \tag{9}$$

$$\sum_{k=1}^{K_T}\sum_{i=1}^{N_D} a_{k,i} \geq (1-\beta)K_T \tag{10}$$

$$P_{k,i} \geq \sigma^2 \Gamma a_{k,i} \qquad \forall i, \forall k \tag{11}$$

$$\sum_{j=1}^{N_D}\sum_{k=1}^{N_D} \sqrt{(x_j-x_k)^2+(y_j-y_k)^2+(z_j-z_k)^2} \geq \theta \quad \forall i,j \in [1, N_D] \tag{12}$$

The objective function minimizes the deployment cost by minimizing the number of ABSs deployed and placing them over high demand areas. It also improves the network quality by maximizing the received power for each user. The first part in equation (6) represented by u_i is responsible for minimizing the number of deployed ABSs. The second part accounts for the total received power normalized by the transmit power P_T. Since our objective function consists of two components, we introduce a new parameter λ to balance the need between maximizing the network performance quality and minimizing the number of deployed ABSs. This parameter is configurable by the network operator to either favor minimizing the number of ABSs or maximizing the total received power.

The first constraint represented by equation (7) ensures that a wireless node will be only linked to an available ABS. The constraint defined in equation (8) states that each wireless node should be served by a single ABS. The constraint defined in equation (9) guarantees that the number of users linked to each ABS does not exceed the defined capacities where K_D represents the maximum number of users that can be served by a single ABS. The fourth constraint in (10) ensures that the number of uncovered users is not more than the allowed outage ratio denoted by β. The fifth constraint in (11)) ensures a minimum SNR threshold for a ground user to be served by an ABS i. Finally, the last constraint in (12) enforces a safety distance between any pair of deployed ABSs. We use the Taylor series linearization to handle the nonlinearity in (11) and (12).

After linearization, our problem becomes a mixed integer linear programming problem but remains hard to solve. Specifically, our problem can be easily coupled with the continuous capacitated facility location (CCPL) problem that is known to be NP-hard [14] [15]. The CCPL problem aims to position F facilities with capacity X while minimizing the sum of distances between the demand points and corresponding facilities. We can map the CCPL problem to our problem by setting K_D to X, in addition to setting β and Γ to 0 so we consider all demand points and minimize the sum of distances. Therefore, it would be highly complex to solve the formulated optimization problem except for small scale scenarios.

V. Autonomous Force Algorithm

Due to the high complexity of our problem, we present in this section an efficient and practical solution. The proposed solution autonomously deploys ABSs in wireless environments while taking user mobility into account. Considering an area with a specific number of users, our main goal is to deploy a minimized number of ABSs to serve the ground users. The algorithm utilizes the laws of electrostatic forces to place the ABSs in the best possible position and is adopted from [16].

In the first step, a number of ABSs based on the capacity constraints are released. Then, each of the ABSs and users is assigned a charge forming a non balanced electrical field. ABSs are assigned dynamic positive charges and users are assigned fixed negative charges. Hence, the force formed between the different ABSs is repulsive, while the force formed between the ABSs and the users is attractive. According to Coulomb's Law, the force between two electrically charged points is determined as follows:

$$\vec{F}_{12} = \frac{Q_1 Q_2}{d_{12}^2}\vec{c_{12}}, \tag{13}$$

where Q_1, Q_2 are the charges of the respective charged points, $\vec{c_{12}}$ is the direction vector from point 1 to 2, and d_{12} is the distance separating both points. Since the received signal strength is inversely proportional to a power of the distance as per (2), we model the force among ABSs and users as follows:

$$\vec{F}_{12} = Q_1 Q_2 R_{12} \vec{c_{12}}, \tag{14}$$

where R_{12} is the received signal strength from one user/ABS to another. This step allows the design of a dynamic and autonomous ABS positioning algorithm since the signal strength can be readily measured at the ABS in real time without any knowledge of the users' specific locations or mobility patterns.

As stated above, users are assigned static negative charges that are set to -1. However, the charges of the ABSs are always updated and are inversely proportional to the number of users associated to them. This being said, ABSs with high number of users get less ability to attract additional users. Hence, the charge of an ABS i is calculated as follows:

$$Q_{a_i} = \frac{\alpha}{k_i + 1}, \tag{15}$$

where α is a number between 0 and 1 and k_i is the number of users associated with ABS i.

Based on the above, an electric field is formed between ABSs and users allowing ABSs to be attracted to users due to their opposite charges while they repel from each other due to similar charges. Hence, the formed forces will make ABSs move until electrostatic equilibrium is achieved where the sum of forces is balanced and ABSs reside at fixed positions. The direction of the ABS movement is calculated according to the sum of forces exerted on each ABS, denoted as $\vec{F_{a_i}}$, with a specific step size. By fixing the step size, we calculate the ABS new position at time $\tau + 1$ based on its previous position at time τ as follows:

$$P_{a_i}^{\tau+1} = P_{a_i}^{\tau} + \eta \frac{\vec{F_{a_i}}}{||\vec{F_{a_i}}||}, \tag{16}$$

where η is the step size. This algorithm is summarized in Algorithm 1.

Algorithm 1 Force

Input:
$D : Set\ of\ N\ ABSs$
$U : Set\ of\ ground\ users$
Output:
$P : Set\ of\ coordinate\ vectors\ of\ all\ ABSs$

procedure FORCE
    $N \leftarrow \frac{K_T}{K_D}$
    while (Outage ratio not achieved) **do**
        $Q \leftarrow 0$
        $F \leftarrow 0$
        while (Equilibrium not achieved) **do**
            for each $d_i \in D$ **do**
                $K \leftarrow 0$
                while ($K < N_D$) **do**
                    associate nearest visible user u_i
                    $U \leftarrow U - u_i$
                    $K \leftarrow K + 1$
                $q_i \leftarrow \frac{\alpha}{K+1}$
            for each $d_i \in D$ **do**
                for each $v_j \in D \cup U$ **do**
                    $F_i \leftarrow F_i + Force(d_i, v_j)$
            for each $d_i \in D$ **do**
                $P_i \leftarrow P_i + \eta \frac{F_i}{||F_i||}$
        $N \leftarrow N + 1$
return P

TABLE I
SYSTEM PARAMETERS FOR SIMULATION RESULTS

Parameter	Value
ABS transmit power P_D	5 Watts
ABS maximum capacity K_D	20
path loss exponent α	2
thermal noise power σ	10^{-6} Watts
SNR threshold Γ	2 db
carrier frequency f_c	2.5 GHz
constant μ in (2)	9.61
constant β in (2)	0.16
η_{LoS}	1
η_{NLoS}	20
step size η	0.5
weight λ in (6)	0.6

VI. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

In this section, we present numerical and simulation results to evaluate the performance of our proposed solution. We consider a 100 m x 100 m area where users are randomly distributed. We apply a random walk model [17], with pedestrian ground users moving at a speed randomly picked from $[1.25\ \text{m/s}, 1.5\ \text{m/s}]$ [18]. A wide range of simulations are conducted with averaging over a large-enough number of iterations assuming the system parameters presented in Table I.

First, we start by comparing the optimal solution to the autonomous force algorithm. To do so, we solve the optimization problem at each time interval. Fig. 2 shows the average number of deployed ABSs with respect to the number of users in the network. We can see that the force algorithm provides close-to-optimal results. Fig. 3 shows the execution time of both optimal solution and force algorithm as a function of the number of users. The execution time of the optimal solution increases exponentially with the number of users and is significantly higher than the proposed force algorithm. In Fig. 4, the force algorithm is shown to produce an average rate close to the optimal solution for different number of users.

To further evaluate the effectiveness of the proposed force algorithm, we compare its performance to the work in [19], which is based on a spiral-based approach to deploy ABSs in a wireless network. The algorithm starts by placing the ABSs from the outer boundary and then iteratively moves towards the center to cover all users. To adapt the approach in [19] to network scenarios with user mobility, we rerun the solution from the beginning at each time interval. The key advantage of

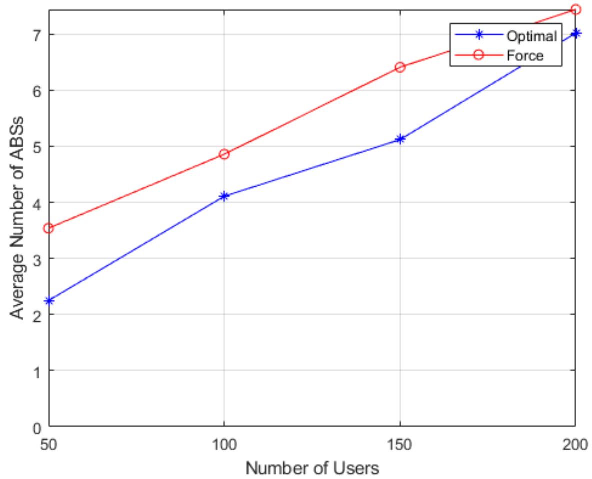

Fig. 2. Average number of ABSs required to cover the users for the optimal solution compared to the force approach, as a function of total number of users.

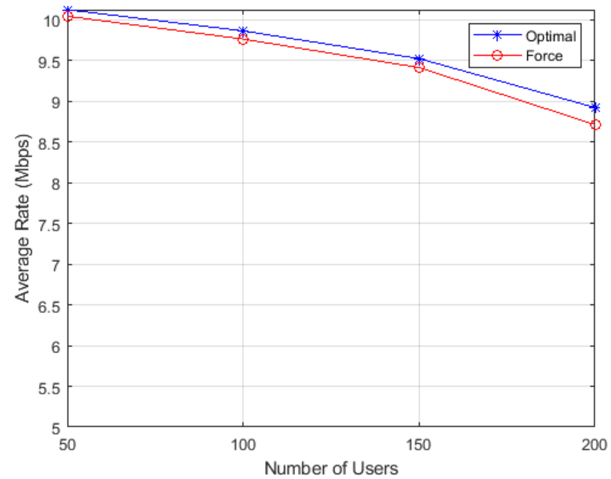

Fig. 4. Average bitrate in Mbps for the force approach compared to the optimal solution, as a function of total number of users.

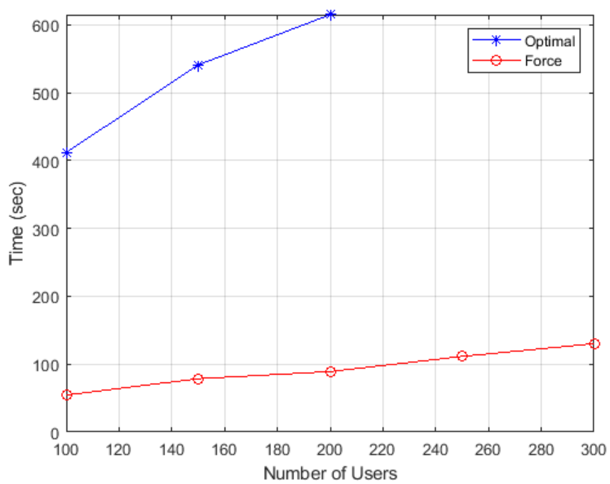

Fig. 3. Execution time of the optimal solution versus the force approach, as a function of the total number of users.

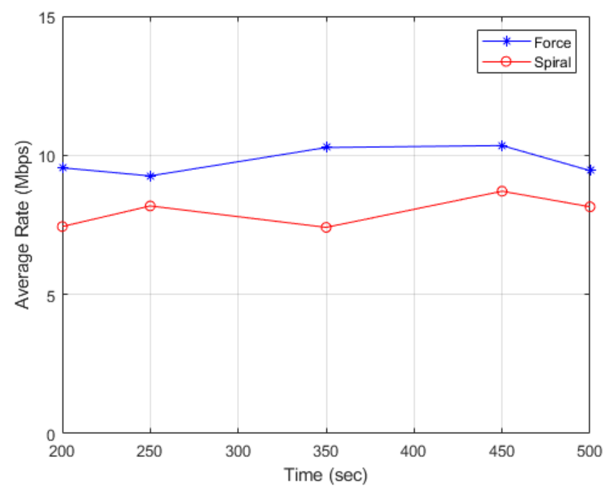

Fig. 5. Average bitrate in Mbps for the force approach compared to the spiral solution, as a function of time.

the force algorithm is its autonomous and dynamic behaviour. Without the need to run the force algorithm from the beginning in each time slot, the ABSs automatically adapt their positions incrementally as users move in the network. Fig. 5 shows the change in average rate over time as users move, and clearly demonstrates the superior performance of the force algorithm.

To better illustrate the behaviour of our proposed solution, we present snapshot results in Fig. 6 and 7. In Fig. 6, we can see the initial positions of the users and their two serving ABSs after the execution of the force algorithm. After 5 min, the users have moved and the new positions are depicted in Fig. 7. We can see the trajectory that both ABSs took to reach the final destinations. This is due to the electrostatic environment and charged fields created in the execution of the force algorithm. This demonstrates the ability of the algorithm to adapt to user mobility in an efficient and autonomous manner.

VII. Conclusion

In this work, we have studied the 3D deployment of aerial base stations in an autonomous manner in wireless network scenarios with user mobility. We first formulate the 3D positioning problem as a mixed integer program to obtain optimized results for evaluation purposes. Then, we propose an efficient and autonomous 3D positioning algorithm based on the notion of electrostatic forces. The proposed algorithm works without any knowledge about the network topology or the users' distribution, and easily adapts to network changes and user mobility. Results are presented as a function of various system parameter, and demonstrate close performance compared to the optimal solution and superior performance compared to recent related work from the literature.

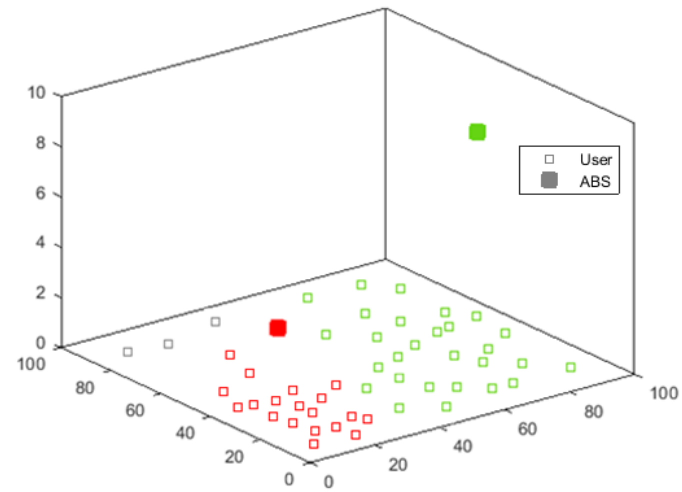

Fig. 6. Network snapshot showing the initial ABS deployments based on the execution of the force algorithm. Users associated with each ABS are marked using the same color.

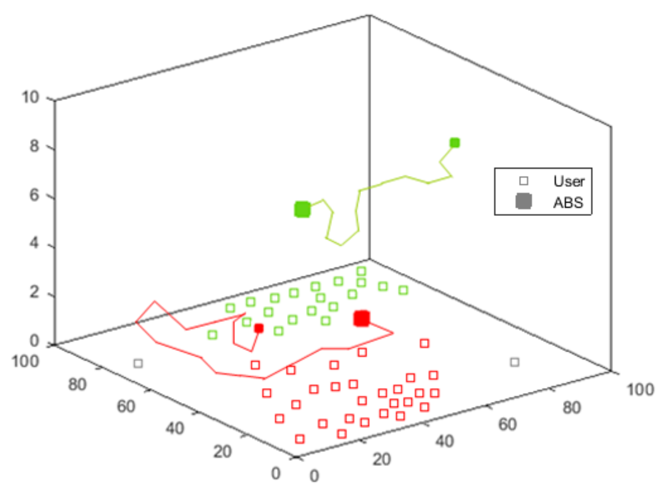

Fig. 7. Network snapshot after 5 min showing the adaptation of the ABSs positions based on the execution of the force algorithm. Initial ABS locations are marked by small filled squares and final locations are marked by larger filled squares.

VIII. Acknowledgements

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