User Mobility-Aware UAV-BS Placement Update With Optimal Resource Allocation

MANSI PEER	extsuperscript{1}, VIVEK ASHOK BOHARA	extsuperscript{1} (Senior Member, IEEE), ANAND SRIVASTAVA	extsuperscript{1}, AND GOURAB GHATAK	extsuperscript{2}

	extsuperscript{1}Wirocomm Research Group, Department of Electronics and Communication Engineering, Indraprastha Institute of Information Technology Delhi, New Delhi 110020, India

	extsuperscript{2}Department of Electrical Engineering, Indian Institute of Technology Delhi, New Delhi 110016, India

CORRESPONDING AUTHOR: M PEER (e-mail: mansip@iiitd.ac.in)

ABSTRACT In the presence of mobile ground users, it is imperative to optimize the placement of unmanned aerial vehicle-base stations (UAV-BSs) in a UAV-assisted communication network. Moreover, the placement update interval is also a crucial parameter that impacts the network performance; hence, it needs to be optimized. Our work aims to jointly optimize the mobile users’ association with the UAV-BSs, resource allocation, UAV-BS placement, and the update interval. We propose to divide the above optimization into two phases: phase 1 and phase 2. In phase 1, the user association, resource allocation, and UAV-BS placement are optimized, whereas the update interval is optimized in phase 2. Two different frameworks, namely, max sum rate and max min rate, are utilized for the joint optimization. Specifically, in phase 1 of the max sum rate framework, the objective is to maximize the sum rate of the users, whereas, in phase 1 of the max min rate framework, the worst-off user rate is maximized. In phase 2, the update interval is optimized by minimizing the total UAV-BS flight time and maximizing the user coverage probability. Further, the analytical expression for the coverage probability of the mobile users is also derived. A sequential approach is proposed to solve phase 1 and phase 2 jointly. We prove that the convergence of the sequential approach is guaranteed. It is observed that, in the max sum rate framework, the average update interval is independent of the number of UAV-BSs. However, in the max min rate framework, the average update interval is dependent on the number of UAV-BSs. The proposed work is also compared with a benchmark approach wherein the update interval is not optimized. It has been shown that, unlike the proposed work, the benchmark approach cannot adapt to the desired priority of service time and coverage probability.

INDEX TERMS Multiple UAV base stations, user mobility awareness, UAV base station placement, resource allocation, optimal update interval.

I. INTRODUCTION

UNMANNED aerial vehicles (UAVs) have witnessed tremendous growth in their popularity over the past few years. UAVs have numerous applications such as remote surveillance, disaster relief, crop spraying, aerial inspection and monitoring, etc. [1]. Recently, the telecom sector is exploring ways to reap the benefits from deploying UAVs. Since UAVs have key features of high mobility, fast deployment, and easy access to remote areas, researchers have proposed UAV-assisted communication networks for on-demand wireless connectivity. UAV-assisted communication networks can also facilitate other applications such as emergency communication during disasters, military communication in remote areas, etc.

With the ongoing third generation partnership project (3GPP) standardization for UAV-assisted communication networks, researchers are actively working on optimizing the performance of such networks [2]. In UAV-assisted communication networks, UAVs can either be deployed as aerial relays or as aerial base stations (BSs). These aerial BSs are often referred to as UAV-BSs. Air-to-ground and air-to-air channel modeling, resource allocation, interference

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/
management, UAV-BS placement, or UAV-BS trajectory design are some of the critical challenges in UAV-assisted communication networks [3]. Recently, research in UAV-BS placement optimization and resource allocation in UAV networks has also gained a lot of momentum [4], [5], [6], [7], [8]. This paper broadly focuses on UAV-BS placement and resource allocation in the presence of mobile ground users.

A. RELATED WORK

In the existing literature, placement optimization has been studied for both static and mobile UAV-BS [9]. In the case of static deployment, UAV-BSs are placed at a hovering location and they remain static throughout their mission duration. For instance, [10] has considered a heterogeneous network consisting of both macro BSs and UAV-BSs. The placement of UAV-BSs is optimized to maximize the downlink received signal strength. Further, [11] jointly optimized UAV-BS placement and user association in a heterogeneous network to maximize the spectral efficiency of a hotspot area. The spectral efficiency for both the wireless access as well as the wireless backhaul links is considered. The minimum number of UAV-BSs required to provide coverage to a set of ground users in the absence of fixed infrastructure has been determined in [12]. However, networks with static deployment of UAV-BSs cannot adapt to the varying user locations and demands. In the case of mobile UAV-BSs, the placement of UAV-BSs changes over time. For instance, in order to collect data from the sparsely deployed sensor nodes in a wireless sensor network (WSN) framework, UAV-BSs have to move around the region of interest [13]. Similarly, in [14], a single UAV’s trajectory is optimized to serve some randomly distributed sensor nodes when the data volume of the sensors is unknown.

In [15] a framework is presented to optimize UAV trajectory, power allocation, and user scheduling in order to maximize the minimum rate of users. It considers a multi-UAV network where each UAV serves the users using a time division multiple access (TDMA) protocol. In [16], a single UAV network is considered, which optimizes the UAV trajectory, user association, bandwidth, and power allocation to maximize the overall network energy efficiency. However, unlike [15], it combines TDMA with frequency division multiple access (FDMA) for serving users. Both [15] and [16] have formulated a non-convex UAV-BS optimization problem which they solve using the block coordinate descent (BCD) algorithm. It may be noted that in [15] and [16], the user locations are assumed to be fixed. The optimization is carried out in an offline manner for all time slots at once. Consequently, UAV follows the same trajectory in a periodic manner. Hence, the frameworks proposed in [15] and [16] will not be applicable when users are mobile. In [17], a multi-agent reinforcement learning (RL) framework is proposed to perform distributed intelligent resource management in a UAV-assisted communication network when the UAVs only have individual local information. In order to maintain fairness among the ground users, the authors in [18] proposed a three-dimensional (3-D) UAV scheduling with energy replenishment RL framework. With a limited number of UAVs, the work in [18] tries to efficiently perform the 3-D UAV scheduling so that users are served fairly while maintaining reliable communication. In [19], UAV-BSs are deployed to maximize the coverage area subject to the energy, user coverage fairness, and inter-UAV collision avoidance constraints. In [20], a swarm of UAV-BSs overlaid over macrocells is considered. The 3-D placement of these UAV-BSs is optimized in order to maximize the total data transmitted by all the UAV-BSs in the limited network lifetime.

The recurring placement optimization of UAV-BSs becomes challenging when the ground users are mobile. For instance, in [21], UAV-BS locations are updated in accordance with the user locations over time in order to maximize the network throughput. Further, the authors in [22] propose a RL framework to efficiently update the placement of UAV-BS in a dynamic heterogeneous network while maintaining the desired quality-of-service (QoS). Authors in [23] proposed a RL framework for 3-D movement design of multiple UAVs in order to maximize the sum mean opinion score of users. Specifically, the area of interest is divided into clusters, and it is assumed that each cluster is served by one UAV. The users are supposed to be confined within the cluster and could not roam outside the cluster. Hence, [23] fails to consider a more realistic user mobility model. In [24], an echo state network based prediction algorithm is used to predict the user positions, and then a multi-agent Q-learning based algorithm is used to design UAV-BS trajectory in advance. The related work has been summarized in Table 1.

B. MOTIVATION

It may be noted that the user mobility impacts the UAV network performance. Specifically, to achieve a desired UAV network performance over the period of UAV-BS operation, the time separation between two consecutive UAV-BS placement updates (or update interval) must be determined based on the user mobility. However, most of the prior works fail to characterize the relationship between user mobility and update interval. For example, [21] and [24] assume a fixed update interval whereas [22], [23] lack in quantifying such an update interval. To the best of our knowledge, our previous work was the first paper to investigate the relationship between user mobility and UAV-BS placement update interval [25]. It considered a UAV-assisted communication network to serve the mobile ground users and optimize UAV-BS placement and update interval. However, the analysis was limited to a single UAV-BS network. Moreover, the UAV-BS placement was optimized to maximize the number of users covered at an update instant while accounting for the user fairness as well as UAV-BS flight time.

Unlike [25], in the proposed work, we consider a multi-UAV network where all the users are to be served during the UAV operation period. We aim to optimize the UAV-BS
TABLE 1. Summary of related work.

| Reference | Main Contributions                                                                 | Remarks                                      |
|-----------|-----------------------------------------------------------------------------------|----------------------------------------------|
| [15], [16]| Proposed a framework to optimize UAV trajectory, user scheduling and resource allocation for fixed ground nodes | Framework not applicable to mobile ground users |
| [17]      | Distributed intelligent resource management for UAV-enabled communication networks especially when these UAVs only have individual local information | Multiple UAVs                                |
| [18]      | Efficient and fair 3-D UAV scheduling with energy replenishment                    | No ground user mobility                      |
| [19]      | Coverage Maximization subject to fairness, interference to ground users and UAV collision | No ground user mobility                      |
| [20]      | Studies trade-off among flight altitude, energy expense and travel time            | No ground user mobility                      |
| [22]      | RL framework to update UAV-BS placement in a dynamic heterogeneous network while maintaining desired quality-of-service | Single UAV-BS; considered user mobility but did not quantify update interval |
| [23]      | RL framework for 3-D movement design of multiple UAVs in order to maximize the sum mean opinion score of users | Did not consider practical user mobility Did not quantify update interval |
| [24]      | To use ML techniques to predict the user positions and accordingly design UAV trajectory (offline) | With user mobility but assumed fixed update interval |

placement, resource allocation, user association, and update interval. We propose to divide the above optimization into two phases: phase 1 and phase 2. In phase 1, we jointly optimize UAV-BS placement, bandwidth allocation, and user association, whereas the update interval is optimized in phase 2. We propose the use of two metrics, i.e., total UAV-BS flight time and user coverage probability to optimize the update interval. Further, two different frameworks, namely, max sum rate and max min rate, are utilized. Specifically, in phase 1 of the max sum rate framework, the objective is to maximize the sum rate of the users. This framework is suitable for content caching applications where a single caching user may require a high bandwidth connection while a certain QoS is guaranteed at the rest of the users [26]. While in phase 1 of the max min rate framework, the minimum rate among the users is maximized. This framework is applicable for ensuring fairness of rate across the users in the network. A sequential approach is proposed to solve phase 1 and phase 2. Further, the analytical expression for user coverage probability in terms of user mobility parameter and update interval are derived. In our work, we have overcome the limitation of the existing works by quantifying the update interval.

C. CONTRIBUTIONS

- We jointly optimize the UAV-BS placement, bandwidth allocation, user association, and update interval in a multi-UAV network. This optimization is divided into two phases, i.e., phase 1 and phase 2. In phase 1, the UAV-BS placement, bandwidth allocation, and user association are jointly optimized, whereas the update interval is optimized in phase 2. Two different frameworks, namely, max sum rate and max min rate, are utilized for the joint optimization.

- Specifically, in phase 1 of the max sum rate framework, the objective is to maximize the sum rate of the users, whereas, in phase 1 of the max min rate framework, the minimum rate among the users is maximized. The optimization problems in phase 1, for both frameworks, are mixed-integer non-concave problems. Hence, the block coordinate descent algorithm is utilized. For phase 2, we propose a weighted objective function that minimizes the total UAV-BS flight time and maximizes the user coverage probability. A sequential approach is proposed to solve phase 1 and phase 2 jointly. We prove that convergence is guaranteed for the proposed sequential approach.

- In our work, we have overcome the limitation of the existing works by quantifying the update interval. The analytical expression for the coverage probability that accounts for the user mobility and update interval is also derived. It is shown that the analytical and simulated coverage probability are in agreement.

- We analyze the average update interval with respect to the number of UAV-BSs. Our work is also compared with a benchmark approach wherein the update interval is not optimized. It has been shown that, unlike the proposed work, the benchmark approach cannot adapt to the desired priority of service time and coverage probability.

It may be noted that simultaneous optimization of user association, bandwidth allocation, UAV-BS placement and update interval is not feasible. This is because the user association, bandwidth allocation and UAV-BS placement depends on the flight time of UAV-BS between two consecutive update instants, whereas the optimal update interval depends on the total UAV-BS flight time during the operation period. Consequently, in our work, the above optimization is divided into phase 1 and phase 2 and solved using the
proposed sequential approach. This will be discussed in detail in Section III.

D. TERMINOLOGIES
Below are the key terms used throughout this paper:
- Operation Period: It is the time period during which the multi UA V-BS network is operational.
- Update Instant: An update instant denotes the point in time where the multi UA V-BS network is optimized.
- Update Interval: The time interval between two consecutive update instants is termed as update interval.
- Coverage Probability: The probability that multi UA V-BS network will guarantee the desired rate at the user for the complete update interval.

The above characterization of coverage probability is crucial when the mobile ground users require uninterrupted service, e.g., users in public safety communication networks. The remaining of the paper is organized as follows. In Section II, we present the multiple UA V-BS network model. In Section III, we state the problem and present the optimization problem formulation. Further, we propose algorithms to solve the proposed optimization problem. In Section IV, we discuss the results obtained from our work and compare them with a benchmark approach. Finally, we conclude our work in Section V.

II. NETWORK MODEL
We consider a network model with $K$ UA V-BSs and $N$ mobile ground users, as shown in Fig. 1. The UA V-BS index is denoted as $i \in \{1, 2, \ldots, K\}$ whereas the user index is denoted by $j \in \{1, 2, \ldots, N\}$. The UA V-BS operates for $T$ seconds to serve the ground users. The users are moving around following a random walk mobility model [27]. The distance traveled by a user in each transition of random walk is assumed to be Rayleigh distributed with shape parameter $\sigma$ [28]. For analytical tractability, it is assumed that the velocity of the users is constant and each user has the same velocity, $v_u$. Further, in line with previous work, it is assumed that the altitude of each UA V-BS is fixed and it is denoted by $H$ [19]. Hence, we focus only on the 2-D UA V-BS placement in the horizontal plane. The total available bandwidth is assumed to be fixed (denoted as $BW$), and each user is allocated a non-interfering orthogonal frequency band for transmission.

The mobility of the users necessitates recurring UA network optimization, i.e., repeated optimization of user and UA V-BS association, user bandwidth allocation, and UA V-BS placement. Fig. 2 illustrates the network update timeline for $T$ seconds. $t_{up}(k)$ is the time interval between the $k^{th}$ and $(k+1)^{th}$ update instants. User mobility during the update interval will also impact the QoS at each user. Hence, it is important to optimize the update interval based on user mobility. We assume that the optimization will be carried out at the core network and the necessary control information will be sent to the UA V-BSs [30]. The details of control signaling and information is out of the scope of the current work.

Let the 2-D placement of $i^{th}$ UA V-BS at the $k^{th}$ update instant be denoted as $U_i(k) = [u_{ix}(k), u_{iy}(k)]$ where $u_{ix}(k)$ and $u_{iy}(k)$ are the coordinates of the $i^{th}$ UA V-BS in the horizontal plane. The 2-D location of user $j$ at update instant $k$ is denoted as $W_j(k) = [w_{jx}(k), w_{jy}(k)]$ where $w_{jx}(k)$ and $w_{jy}(k)$ are the coordinates of user $j$. The flight time of UA V-BS $i$ between $k^{th}$ and $(k+1)^{th}$ update instants is given as:

$$F_i(k) = \frac{||U_i(k) - U_i(k-1)||}{v_{uav}},$$  

where $v_{uav}$ is the velocity of each UA V-BS. The path loss between UA V-BS $i$ and user $j$ at the $k^{th}$ update instant assuming a dominant line-of-sight (LoS) component can be written as [16]:

$$L_{ij}(k) = K_0 d_{LOS}^\gamma,$$  

where $K_0 = \left(\frac{4\pi f_c}{c}\right)^2$, $c$ is the speed of light and $f_c$ is the carrier frequency. $\delta_{LOS}$ is the attenuation in LoS path, $d_{ij}(k)$ is the Euclidean distance between UA V-BS $i$ and user $j$ at the $k^{th}$ update instant and can be given as:

$$d_{ij}(k) = \sqrt{H^2 + ||U_i(k) - W_j(k)||^2}.$$  

2. It may be noted that the impact of altitude can be incorporated in the proposed work. This can be achieved by the approach discussed in [29]. However, the approach needs to be modified for mobile user scenario, which is not in the scope of the proposed work.
TABLE 2. List of variables.

| Variable | Description                      |
|----------|----------------------------------|
| $N(\mu, \sigma^2)$ | Denotes a Gaussian distribution with mean $\mu$ and variance $\sigma^2$ |
| $E_x[.]$ | Denotes expectation w.r.t $x$ |
| $||x||$ | Norm of vector $x$ |
| $[-]$ | Cell operator |
| $T$ | Operation Period |
| $BW$ | Total Bandwidth |
| $U_i(k)$ | 2-D coordinates of UAV-BS $i$ |
| $W_j(k)$ | 2-D coordinates of user $j$ |
| $d_{i,j}(k)$ | Euclidean distance between user $j$ and UAV-BS $i$ at $k^{th}$ update instant |
| $L_{i,j}(k)$ | Average path loss between user $j$ and UAV-BS $i$ at $k^{th}$ update instant |
| $\gamma_{i,j}(k)$ | SNR at user $j$ due to UAV-BS $i$ at $k^{th}$ update instant |
| $R_{i,j}(k)$ | Rate achievable at user $j$ due to UAV-BS $i$ at $k^{th}$ update instant |
| $Y_{i,j}(k)$ | Indicator for association between user $j$ and UAV-BS $i$ at $k^{th}$ update instant |
| $B_{i,j}(k)$ | Bandwidth allocated to user $j$ associated with UAV-BS $i$ at $k^{th}$ update instant |
| $t_{up}(k)$ | Update interval at $k^{th}$ update instant |
| $F_{i}(k)$ | Flight time of UAV-BS $i$ between $k^{th}$ and $(k+1)^{th}$ update instant |

The SNR at user $j$ when served by UAV-BS $i$ will be

$$\gamma_{i,j}(k) = \frac{P_t}{N_0 L_{i,j}(k)}, \quad (4)$$

where $P_t$ is the transmit power of UAV-BS and $N_0$ is the noise power at the receiver. The key variables and their descriptions are summarized in Table 2.

III. PROBLEM FORMULATION AND PROPOSED SOLUTION

As mentioned before, we plan to optimize the user association with UAV-BSs, bandwidth allocation, UAV-BS placement and update interval. The above optimization is divided into two phases: phase 1 and phase 2 which are discussed in detail below.

A. PHASE 1

In phase 1, user association with UAV-BSs, user bandwidth allocation and UAV-BS placement are optimized at the $k^{th}$ update instant. Let $Y_{i,j}(k)$ be the association indicator variable. $Y_{i,j}(k)$ is set as ‘1’ when user $j$ is associated to UAV-BS $i$ or ‘0’ otherwise at $k^{th}$ update instant. $B_{i,j}(k)$ is the bandwidth allocated to the user $j$ when associated to UAV-BS $i$ at $k^{th}$ update instant. The achievable rate between user $j$ and UAV-BS $i$ at $k^{th}$ update instant can be written as:

$$R_{i,j}(k) = Y_{i,j}(k)B_{i,j}(k)\log_2(1 + \gamma_{i,j}(k)). \quad (5)$$

Let $\mathcal{Y} = \{Y_{i,j}(k), \forall i, j\}$, $\mathcal{B} = \{B_{i,j}(k), \forall i, j\}$ and $\mathcal{U} = \{U_i(k), \forall i\}$. Now, let us discuss the two optimization frameworks for phase 1:

1) MAX SUM RATE FRAMEWORK

In the max sum rate framework, the user association, bandwidth allocation and UAV-BS placement is optimized in order to maximize the sum rate across all the users.

$$\text{(P1.1) } \max_{\mathcal{Y}, \mathcal{B}, \mathcal{U}} \sum_{i=1}^{K} \sum_{j=1}^{N} R_{i,j}(k) \quad (6a)$$

subject to:

$$\sum_{i=1}^{K} Y_{i,j}(k)B_{i,j}(k) \leq BW, \quad (6b)$$

$$\sum_{i=1}^{K} Y_{i,j}(k)B_{i,j}(k) \geq B_{\text{thres}}, \quad \forall j = 1, \ldots, N, \quad (6c)$$

$$\sum_{i=1}^{K} Y_{i,j}(k) = 1, \quad \forall j = 1, \ldots, N, \quad (6d)$$

$$F_i(k) < t_{up}(k), \quad \forall i = 1, \ldots, K, \quad (6e)$$

$$Y_{i,j}(k) \in [0, 1], \quad \forall i, j. \quad (6f)$$

Constraint (6b) limits the total bandwidth availability as $BW$. Constraint (6c) ensures that the minimum bandwidth requirement of $B_{\text{thres}}$ is met for all the users. $B_{\text{thres}}$ is required to meet the desired QoS at each user. Constraint (6d) means that a user can only be associated with one UAV-BS at a time. Constraint (6e) ensures that, at $k^{th}$ update instant, $F_i(k)$ must be upper-bounded by the update interval. Further, constraint (6f) represents that $Y_{i,j}(k)$ is a binary variable. Since the objective is a non-convex function of UAV-BS placement, the problem (P1.1) is a mixed-integer non-concave optimization problem. Hence, (P1.1) is a non-trivial problem to solve. Consequently, we propose to solve this problem using the block coordinate descent (BCD) algorithm. According to BCD, we split the problem into three sub-problems. These sub-problems are solved alternately in each iteration [16].

1) Sub-Problem 1: Keeping UAV-BS placement and bandwidth allocation fixed, the user association $Y_{i,j}(k)$ is optimized. Hence, we solve the below optimization problem:

$$\max_{\mathcal{Y}} \sum_{i=1}^{K} \sum_{j=1}^{N} R_{i,j}(k) \quad (7)$$

subject to:

$$(6b) - (6d), (6f).$$

The above problem is an integer linear programming (ILP) problem that can be solved using the IBM CPLEX solver [31]. CPLEX by default uses the dual simplex method for solving ILP problems.

2) Sub-problem 2: Keeping UAV-BS placement and user association fixed, the bandwidth allocation $B_{i,j}(k)$ is optimized. Hence, we solve the below optimization problem:

$$\max_{\mathcal{B}} \sum_{i=1}^{K} \sum_{j=1}^{N} R_{i,j}(k) \quad (8)$$

subject to:

$$(6b), (6c).$$
Algorithm 1: Solution to Phase 1 at $k^{th}$ Update Instant

Input: $U_i(k - 1) \forall i$, $W_j(k) \forall j$, $t_{up}(k)$, $\epsilon$
Output: $Y_{i,j}(k)$, $B_{i,j}(k)$, $U_i(k) \forall i, j$
Initialize: $B_{i,j}(k), U_i(k) \forall i, j$ and $m = 1$

while Fractional increment in objective value > $\epsilon$ do
  Solve Sub-problem 1 keeping $B_{i,j}(k), U_i(k)$ fixed $\forall i, j$
  Update user association as $Y_{i,j}(k) = Y_{i,j}(k, m) \forall i, j$
  Solve Sub-problem 2 keeping $Y_{i,j}(k), U_i(k)$ fixed $\forall i, j$
  Update bandwidth allocation as $B_{i,j}(k) = B_{i,j}(k, m) \forall i, j$
  Solve Sub-problem 3 keeping $Y_{i,j}(k), B_{i,j}(k)$ fixed $\forall i, j$
  Update UAV-BS placement as $U_i(k) = U_i(k, m) \forall i$
  $m = m + 1$
end while

The above problem is a standard linear programming (LP) problem that can be solved using the IBM CPLEX solver.

3) Sub-problem 3: Keeping bandwidth allocation and user association fixed, UAV-BS placement is optimized. However, the objective function for sub-problem 3 is still a non-convex function of UAV-BS placement. To convexify the objective function, successive convex optimization needs to be carried out in each iteration of Algorithm 1. In successive convex optimization, a function is approximated by a more tractable function, in our case by using first-order Taylor approximation, at a given local point. The convexified problem is given in (9), shown at the bottom of the page, where $A = \frac{P}{\log_2\ln(\frac{1}{\lambda})}$, $B = H_2$, $z = ||U_i(k) - W_j(k)||^2$ and $z_0 = ||U_i(k, m - 1) - W_j(k)||^2$ at the $m^{th}$ iteration of Algorithm 1. It is a quadratic programming problem that can be solved using IBM CPLEX solver.

Algorithm 1 presents the BCD algorithm for solving subproblems 1, 2, and 3. Here, $m$ denotes the number of iterations. In each iteration, we first optimized the user association keeping bandwidth allocation and UAV-BS placement fixed. Accordingly, the user association is updated. Then, bandwidth allocation is optimized, keeping user association and UAV-BS placement fixed. This is followed by updating the bandwidth allocation. After this, UAV-BS is optimized, keeping user association and bandwidth allocation fixed. Finally, the UAV-BS placement is updated. The algorithm will converge when the fractional increment in the objective value, in this case, sum rate, is less than $\epsilon$. The convergence of the BCD algorithm with successive convex optimization is guaranteed, as discussed in [15].

2) MAX MIN RATE FRAMEWORK

In the max min rate framework, at update instant $k$, user association, bandwidth allocation and UAV-BS placement are optimized to maximize the minimum rate across the users.

$$\max_{\zeta, Y, B, U} \min_{i} \left( \sum_{j=1}^{K} R_{i,j}(k) \right)$$

s.t. (6b), (6d) – (6f).

The max min structure of the above problem can be reformulated as follows:

$$\max_{\zeta, Y, B, U} \zeta$$

s.t. $\sum_{i=1}^{K} R_{i,j}(k) \geq \zeta, \forall j$ (11b)

where $\zeta$ is the lower bound on the rate of each of the users and $\zeta$ is to be maximized. In this framework, except for the minimum bandwidth constraint, all the constraints of max sum rate framework will be applicable. Since the max min rate framework is equivalent to ensuring a minimum rate at each of the user, the minimum bandwidth constraint becomes unnecessary. Due to the non-convex constraint (11b), (P1.2) is a mixed-integer non-concave optimization problem. Similar to (P1.1), (P1.2) is non-trivial to solve. Hence, we solve this problem using the BCD algorithm. According to the BCD algorithm, we split the problem into three sub-problems.

1) Sub-problem 1: Keeping UAV-BS placements and bandwidth allocation fixed, the user association $Y_{i,j}(k)$ is optimized. Hence, we solve the below optimization problem:

$$\max_{\zeta, Y} \zeta$$

s.t. (6b), (6d), (6f), (11b).

The above problem is an ILP problem that can be solved using the IBM CPLEX solver.

2) Sub-problem 2: Keeping UAV-BS placement and association fixed, the bandwidth allocation $B_{i,j}(k)$ is optimized. Hence, we solve the below optimization problem:

$$\max_{\zeta, B} \zeta$$

s.t. (6b), (11b).

The above problem is a standard LP problem that can be solved using the IBM CPLEX solver.

$$\max_{U_i(k)} \sum_{i=1}^{K} \sum_{j=1}^{N} \left[ Y_{i,j}(k)B_{i,j}(k) \log_2 \left( 1 + \frac{A}{B + z_0} \right) - \frac{(\log_2 e)A(\zeta - z_0)}{(B + z_0)(B + z_0 + A)} \right]$$

s.t. (6e)
3) Sub-problem 3: Keeping bandwidth allocation and association fixed, UAV-BS placement is optimized. However, constraint (11b) is still a non-convex function of UAV-BS placement. As mentioned above, successive convex optimization needs to be carried out in each iteration of the BCD algorithm. The convexified problem is given in (14a)-(14b), shown at the bottom of the page. It is a quadratically constrained programming problem that can be solved using the IBM CPLEX solver.

Similar to max sum rate framework, Algorithm 1 will be used for solving the three sub-problems and its convergence is guaranteed. The objective value in this case will be the min rate.

### B. PHASE 2

In phase 2, the update interval between \( k^{th} \) and \( (k + 1)^{th} \) update instants is optimized. According to the fly-hover-and-communicate protocol of UAV-BS operation, an increase in the flight time of UAV-BS decreases its service time [30]. Hence, minimization of total UAV-BS flight time must be considered. In our work, total UAV-BS flight time corresponds to the sum of the flight time during \( T \), averaged over all the UAV-BSs. Further, the user mobility will impact the achievable rate at the user. Hence, we propose that the choice of update interval should depend on two factors: 1) total UAV-BS flight time and 2) user coverage probability. In the following, we will discuss in detail the coverage probability metric.

**Coverage Probability:** Coverage probability is defined as the probability that the rate achievable at a user is greater than the rate threshold \( R_{th} \) for all the user transitions within the update interval \( t_{up}(k) \). It may be noted that during \( t_{up}(k) \) user may have multiple transitions. The number of transitions depends on \( \sigma \) and \( v_u \). The coverage probability expression for user \( j \) associated to UAV-BS \( i \) for update interval \( t_{up}(k) \) is given in (15), shown at the bottom of the page. In (15), \( r_n \) denotes the displacement of user \( j \) from UAV-BS \( i \) after its \( n^{th} \) transition and is given in (16), shown at the bottom of the page. \( n \in \{1, 2, \ldots, q_{up}(k)\} \) where \( q_{up}(k) \) is the average number of user transitions in \( t_{up}(k) \).

**Lemma 1:** When the distance traveled in each user transition is governed by a Rayleigh distribution, with shape parameter \( \sigma \), \( q_{up}(k) \) is given as:

\[
q_{up}(k) = \frac{t_{up}(k)v_u}{\sigma \sqrt{\pi/2}}.
\]

**Proof:** During \( t_{up}(k) \), the distance traveled by user moving with velocity \( v_u \) is \( v_u t_{up}(k) \). Further, the average distance traveled by a user in each transition of random walk is \( \sigma \sqrt{\pi/2} \). Hence, the average number of user transitions during \( t_{up}(k) \) will be as follows:

\[
q_{up}(k) = \frac{t_{up}(k)v_u}{\sigma \sqrt{\pi/2}}.
\]

\( X_{in} \) and \( Y_{in} \) are the coordinates of a user at \( k^{th} \) update instant. Further, \( X_{in}, Y_{in} \sim \mathcal{N}(0, \sigma^2) \) are the change in the x and y coordinates of a user due to the \( n^{th} \) transition. \( \beta_j \) is the upper bound on the displacement of user \( j \) and is given in (18), shown at the bottom of the page.

Let \( W_1 = X_1 + X_{in} - u_{i,x}(k) \) and \( W_2 = Y_1 + Y_{in} - u_{i,y}(k) \). Hence, \( W_1 \in \mathcal{N}(\mu_1, \sigma^2) \) and \( W_2 \in \mathcal{N}(\mu_2, \sigma^2) \) where \( \mu_1 = X_{in} - u_{i,x}(k) \) and \( \mu_2 = Y_{in} - u_{i,y}(k) \). The first term on the R.H.S of (15) can be expressed as follows:

\[
P[r_n < \beta_j] = P \left[ \sqrt{W_1^2 + W_2^2} < \beta_j \right] = \int_{-\beta_j}^{\beta_j} \int_{-\beta_j}^{\beta_j} f_{W_1}(w_1)f_{W_2}(w_2) \, dw_1 \, dw_2,
\]

where

\[
\Phi \left( \frac{C_1}{\sqrt{2\sigma}} \right) \, dw \, dv \bigg|_{-\beta_j}^{\beta_j} \int_{-\beta_j}^{\beta_j} \int_{-\beta_j}^{\beta_j} C_2 e^{\frac{(w_1-\mu_1)^2}{2\sigma^2}} e^{\frac{(w_2-\mu_2)^2}{2\sigma^2}} \Phi \left( \frac{C_1}{\sqrt{2\sigma}} \right) \, dw \, dv.
\]

\[
P_{r_{in}} = \int_{-\beta_j}^{\beta_j} \int_{-\beta_j}^{\beta_j} C_2 e^{\frac{(w_1-\mu_1)^2}{2\sigma^2}} e^{\frac{(w_2-\mu_2)^2}{2\sigma^2}} \Phi \left( \frac{C_1}{\sqrt{2\sigma}} \right) \, dw \, dv.
\]

\[
P_{r_{in}} = \int_{-\beta_j}^{\beta_j} \int_{-\beta_j}^{\beta_j} C_2 e^{\frac{(w_1-\mu_1)^2}{2\sigma^2}} e^{\frac{(w_2-\mu_2)^2}{2\sigma^2}} \Phi \left( \frac{C_1}{\sqrt{2\sigma}} \right) \, dw \, dv.
\]
where $C_1 = \sqrt{\beta_j^2 - w^2}$. The generalized expression for rest of the terms on the R.H.S of (15) is given in (20), shown at the bottom of the previous page, where $C_2 = \sqrt{\beta_j^2 - u^2}$, $C_3 = \sqrt{\beta_j^2 - (u + v)^2} - w$ and $\Phi(.)$ is the error function [25], [32]. Now, we will discuss phase 2 optimization problem corresponding to max sum rate and max min rate frameworks.

1) MAX SUM RATE FRAMEWORK

Since there are two factors impacting the choice of $t_{up}(k)$, we propose the minimization of a weighted single objective function as given below [25]:

$$
\begin{align}
\text{(P2.1)} & \quad \min \alpha \left( \frac{Q} {T} \right) \sum_{i=1}^{K} F(l) \\
& + (1-\alpha) \left( \frac{1} {\sum_{i=1}^{K} \sum_{j=1}^{N} Y_{i,j} P_{i,j,t_{up}(k)}} \right) \Delta_2
\end{align}
$$

s.t. $t_{min} \leq t_{up}(k) \leq t_{max}$.

where $t_{up}(k) \in [t_{min}, t_{max}]$. $t_{min}$ and $t_{max}$ denote the lower and upper limit for $t_{up}(k)$, respectively. The numerator of $\Delta_1$ is total UAV-BS flight time if update interval $t_{up}(k)$ is utilized for the remainder of operation period $T$. Hence, $\Delta_1$ corresponds to the fraction of $T$ during which UAV-BS is in flight and cannot serve. Let $F_{i,t_{up}(k)}$ denote the flight time during $t_{up}(k)$ for UAV-BS $i$. $F_{i,t_{up}(k)} = \sum_{l=1}^{N} F_{i,t_{up}(k)}$ is the flight time during $t_{up}(k)$ averaged over all $K$ UAV-BSs. As mentioned before, user mobility impacts the UAV-BS placement which in turn decides the flight time. Hence, $F_{i,t_{up}(k)}$ is also averaged over random user locations $A = \{W_j(k), \forall j\}$. Further, $Q = \left[ \frac{T - \sum_{l=1}^{N} t_{up}(l)} {t_{up}(k)} \right]$ denotes the number of updates that may occur if update interval $t_{up}(k)$ is utilized for the remainder of operation period $T$. Here, $l \leq (k-1)$ denotes the previous update instants. $F(l)$ is the flight time between $l^{th}$ and $(l+1)^{th}$ update instants, averaged over the UAV-BSs. It may be noted that $F(l)$ will be same for each $t_{up}(k)$ value. $\Delta_2$ is the reciprocal of the coverage probability of the user with maximum rate. The reason for considering the maximum rate will be discussed in detail in Section IV. A weight of $\alpha$ and $1-\alpha$ has been assigned to $\Delta_1$ and $\Delta_2$, respectively. $\alpha$ can be tuned according to the network operator's requirement. For instance, if maximizing the coverage probability is the only requirement, the operator may set $\alpha$ as 0. However, if minimizing total UAV-BS flight time is the only requirement, $\alpha$ may be set as 1.

2) MAX MIN RATE FRAMEWORK

(P2.2) $\min \alpha \Delta_1$

$$
+ (1 - \alpha) \left( \frac{N} {\sum_{i=1}^{K} \sum_{j=1}^{N} Y_{i,j} P_{i,j,t_{up}(k)}} \right) \Delta_2
$$

s.t. (21b).

The phase 2 formulation for max min rate framework is similar to the max sum rate framework except that the second term, i.e., $\Delta_3$ is the reciprocal of the coverage probability averaged over all the users.

Algorithm 2 presents the solution to phase 2. Specifically, we exhaustively search for the optimal update interval. We discretize the update interval values with a step size, $s_{step} = 5$. Due to the for loop in line 4 of Algorithm 2, the complexity of Algorithm 2 is $O(\text{max}-\text{min} + 1) \approx O(\text{max}_{t_{up}})$. Within each for loop, $\Delta_1$, $\Delta_2$ and $\Delta_3$ are utilized. The details of obtaining $\Delta_1$ are presented in Section IV. Moreover, $\Delta_2$ and $\Delta_3$ can be computed using (22a). For each of the update interval values, for (P2.1), $\Delta_1$ and $\Delta_2$ are computed and stored in $T_1$ and $T_2$ respectively. In case of (P2.2), $\Delta_1$ and $\Delta_3$ are computed and stored in $T_1$ and $T_2$ respectively. Further, the range of $T_1$ and $T_2$ is normalized. Functions Min() and Max() are used to find the minimum and maximum value in a list, respectively. Function In() finds the index of the minimum value in a list.

C. PROPOSED SEQUENTIAL APPROACH FOR JOINTLY SOLVING PHASE 1 AND PHASE 2

In this section, a sequential approach to jointly solve phase 1 and phase 2 is proposed [33]. First, at a given update instant, we solve the phase 1 problem using Algorithm 1 to obtain user association, bandwidth allocation, and UAV-BS placement. At the $r^{th}$ iteration of the sequential approach, UAV-BS placement is initialized as follows:

$$
U_i(k) = U_i(k, r-1), \text{ for } r > 1, \text{ else } U_i(k-1)
$$

where $U_i(k, r-1)$ is the UAV-BS placement of UAV-BS $i$ after $r-1$ iterations. Then, the output of phase 1 is given as input to phase 2. Using Algorithm 2, we obtain the update interval. The output of phase 2 is then fed back to phase 1.
This goes on iteratively till the update interval value converges. In general, for the convergence of the sequential approach, the condition \(|t_{up}(k, r) - t_{up}(k, r-1)| < \tau\) must be met. We have kept \(\tau = 0\) to ensure that the flight time from phase 1 as well as total UAV-BS flight time and coverage probability in phase 2 are based on same update interval. Further, the update interval converges within 2 iterations.

1) CONVERGENCE OF SEQUENTIAL APPROACH

In the sequential approach, at \(r = 1\), we initialize update interval as \(t_{\text{min}}\) in phase 1. Further, Algorithm 2 will return \(t_{up}(k, 1) \geq t_{\text{min}}\). Hence, in phase 1 and at \(r = 2\), the flight time averaged over the UAV-BSs will be greater or equal to the flight time in iteration \(r - 1\), i.e.,

\[
\frac{\sum_{i=1}^{K} F_i(k, r)}{K} \geq \frac{\sum_{i=1}^{K} F_i(k, r-1)}{K}. \quad (24)
\]

This is because with increase in update interval, UAV-BSs may fly longer distances to maximize minimum rate in phase 1. Consequently,

\[
\Delta_2(k, r) \leq \Delta_2(k, r - 1), \quad \text{for (P2.1)},
\]

\[
\Delta_3(k, r) \leq \Delta_3(k, r - 1), \quad \text{for (P2.2)}, \quad (25)
\]

where \(\Delta_2(k, r)\) and \(\Delta_3(k, r)\) is the reciprocal of coverage probability at update instant \(k\) after \(r^{th}\) iteration for max sum rate and max min rate frameworks, respectively. It may be noted that the first term in the objective function of phase 2 is independent of the instantaneous output of phase 1. Hence, the non-decreasing nature of coverage probability will ensure that update interval is also non-decreasing with each iteration, i.e.,

\[
t_{up}(k, r + 1) \geq t_{up}(k, r). \quad (26)
\]

When the flight time and, in turn, coverage probability saturates with the change in update interval, convergence criteria will be met. Further, update interval is also upper bounded by \(t_{\text{max}}\). Hence, the convergence of the sequential approach is guaranteed.

IV. RESULTS AND DISCUSSION

In the following, we present the results for the sequential approach to jointly solve phase 1 and phase 2. We consider that, initially, all the users and UAV-BSs are randomly distributed. Then, at \(k = 1\), phase 1 and phase 2 are solved to optimize the initial placement of all the UAV-BSs, user association, bandwidth allocated to each user, and update interval, \(t_{up}(k)\). After this, the network will be optimized at \(t_{up}(k)\) seconds. This process goes on till \(T\) seconds. In our study, we consider \(H = 100\) m, \(f_c = 2\) GHz, \(N_o = -100\) dBm, \(v_u = 1.5\) m/s and \(v_{uav} = 25\) m/s. Please note that \(\alpha = 0\) and \(\alpha = 1\) refers to update interval of \(t_{\text{min}}\) seconds and \(t_{\text{max}}\) seconds respectively. The other simulation parameters are mentioned in Table 3. Further, the results are averaged over 100 UAV-BS operation periods. First, we will present the results for standalone phase 1 followed by joint phase 1 and phase 2. We further compare our results with a benchmark approach. In the benchmark approach, the update interval is not optimized [24]. Specifically, the network is optimized, or phase 1 occurs after a fixed update interval of \(t_{\text{max}}/2\) seconds.

| Parameter | Value |
|-----------|-------|
| \(\sigma\) | 8 m |
| \(\epsilon\) | 0.1 |
| \(N\) | 50 |
| \(K\) | \([1, 7]\) |
| \(T\) | 900 s |
| \(P_t\) | 0.15 W |
| \(BW\) | 20 MHz |
| \(B_{thres}\) | 100 kHz |
| \(\delta_{LOS}\) | 3 dB [16] |
| Area | 800 x 800 sq. m |
| \(t_{\text{min}}\) | 5 s |
| \(t_{\text{max}}\) | 100 s |
A. PHASE 1

1) MAX SUM RATE FRAMEWORK

Fig. 4 presents the sum rate of the users with respect to the number of UAV-BSs in the network for an update interval $t_{up} = 100$ s. It can be observed that as $K$ increases sum rate also increases. We also observe in Fig. 4 that the sum rate in max min rate framework is lower than that of the max sum rate framework. Further, Fig. 5 depicts the convergence of sum rate with the increase in iterations of Algorithm 1. It can be seen that the convergence is obtained in three iterations. The optimal bandwidth allocation at one of the update instants is demonstrated in Fig. 6. The bandwidth threshold of $B_{thres} = 100$ kHz (in log scale, $\log_{10}(10^5) = 5$) is met at all the users. However, there is one user who is allocated the maximum bandwidth. Please note that this user may vary during the operation period.

As mentioned before, for update interval $t_{up}$, the flight time of UAV-BS averaged over user locations will be $E_{\Delta}[F_{t_{up}}]$ and can be given as:

$$E_{\Delta}[F_{t_{up}}] = \sum_{i=1}^{K} \frac{\sum_{k=1}^{[T/t_{up}]} F_i(k)}{K([T/t_{up}])}.$$  (27)

assuming the updates are done after every $t_{up}$ seconds. The term $\sum_{k=1}^{[T/t_{up}]} F_i(k)$ can be determined in an offline manner by solving (P1.1) for $[T/t_{up}]$ update instants. A typical plot of total UAV-BS flight time is shown in Fig. 7. It can be observed that as $t_{up} \in [t_{min}, t_{max}]$ increases the total UAV-BS flight time decreases. This is because lower update interval corresponds to frequent UAV-BS placement updates or vice versa. Consequently, the UAV-BSs fly more frequently resulting in higher total UAV-BS flight time. Further, with increase in $K$ total UAV-BS flight time decreases. This is because SNR of the user with maximum bandwidth governs the maximum sum rate. Hence, with increase in $K$, UAV-BSs will have to fly less to cater to that maximum bandwidth user.

Coverage probability is defined as the probability that the rate achieved at the maximum bandwidth user is above the rate threshold for the complete update interval, $t_{up}$. Fig. 8 shows the plot for the coverage probability at each $t_{up} \in [t_{min}, t_{max}]$. Due to the fact that the network will always try to improve the SNR of the maximum bandwidth user, the achievable rate at each update instant will be the same for each $K$. Hence, it is interesting to observe that the coverage probability of the user with maximum bandwidth is unchanged due to increase in $K$. However, the coverage probability degrades with an increase in $t_{up}$.
2) MAX MIN RATE FRAMEWORK

As shown in Fig. 9, it is quite intuitive that with an increase in $K$, the minimum user rate increases. Further, Fig. 10 exhibits that the minimum rate converges in two iterations of Algorithm 1. Fig. 11 shows that, unlike the max sum rate framework, the optimal bandwidth allocation for the max min rate framework is well distributed across the users. This is because, unlike the max sum rate framework, in max min rate framework, there is a lower bound on the user rate.

Similar to the max sum rate framework, total UAV-BS flight time can be evaluated for the max min rate framework. Fig. 12 presents the total UAV-BS flight time with respect to update interval. Unlike the max sum rate framework, the total UAV-BS flight time initially increases with increase in $K$ and then decreases (as observed for $K = 7$). This is because, in order to maximize the minimum rate, the UAV-BSs will tend to fly more; hence, increasing the total UAV-BS flight time. However, for a given area, when $K$ increases sufficiently (in the present case $K = 7$), the need to fly around decreases.

Unlike the max sum rate framework, the coverage probability for max min rate framework is averaged over the coverage probability of all the users in the network. For a fair comparison of coverage probability with respect to $K$, we consider only those realizations where the min rate at $k = 1$ is greater than or equal to $R_{th}$. Fig. 13 presents the coverage probability with respect to update interval. As evident, the coverage probability decreases with increase in update interval. It is because, on an average, with increase in update interval, the displacement of a user from its associated UAV-BS increases. Consequently, the user rate decreases more at a higher update interval, and this decreases the coverage probability. Further, the coverage probability improves with increase in $K$. This is because the displacement of a user from its associated UAV-BS decreases with increase in $K$.

We also compared our analytical coverage probability results with the simulated coverage probability. In Fig. 14, it can be...
observed that the analytical plot upper bounds the simulated plot. This is because for analytical tractability we considered only the average number of user transitions per update interval, as shown in (15).

B. JOINT SOLUTION OF PHASE 1 AND PHASE 2
To jointly solve phase 1 and phase 2, we employ the sequential approach proposed in Section III. We have compared the results of the sequential approach to the benchmark approach. Further, in scenarios where the coverage probability is zero for all users at each update interval, $t_{\min}$ is selected as the optimal update interval.

1) MAX SUM RATE FRAMEWORK
In the max sum rate framework, as shown in Fig. 15, the average update interval increases with increase in $\alpha$. This is because, with increase in $\alpha$, more priority is given to minimizing the total UAV-BS flight time. Further, the average update interval is the same for all $K$. This is due to the fact that, as seen in Fig. 7, the rate of decrease of total UAV-BS flight time with increase in update interval is the same for all $K$. Further, Fig. 8 shows that the coverage probability is the same for all $K$. Figs. 16 and 17 show that the benchmark approach prioritizes service time$^5$ over coverage probability. Unlike the proposed optimization of update interval, the benchmark approach cannot adapt to the desired priority of service time or coverage probability.

2) MAX MIN RATE FRAMEWORK
In Fig. 18, we observe an increase in average update interval with an increase in $K$. From Fig. 13, it is obvious that the gradient of coverage probability, with an increase in update interval, lowers at higher $K$. Hence, lesser number of updates will be required at higher $K$, i.e., longer update interval at higher $K$. Further, similar to max sum rate framework, the average update interval increases with increase in $\alpha$. This is because, with increase in $\alpha$, more priority is given to minimizing the total UAV-BS flight time. In Figs. 19 and 20, the sequential approach is compared with the benchmark approach. It can be observed that the benchmark approach prioritizes coverage probability over service time. Once again, the benchmark approach cannot adapt to the desired priority of service time or coverage probability. Please note that, in Fig. 19, the variation in service time will become more significant with increase in area.

$^5$Service time is obtained by subtracting total UAV-BS flight time from $T$. 
V. CONCLUSION
We considered a multiple UAV-BS network where all the mobile ground users are served during the operation period. The joint optimization of user association, UAV-BS placement, bandwidth allocation, and update interval has been proposed. The optimization is divided into two phases: phase 1 and phase 2. Phase 1 optimized the user association, UAV-BS placement, and bandwidth allocation, whereas update interval is optimized in phase 2. These phases are solved using a sequential approach. It has been shown that the convergence of the sequential approach is guaranteed. Further, max sum rate and max min rate frameworks have been utilized for the joint optimization. Phase 1 of the max sum rate framework focused on maximizing the sum rate of the users, whereas phase 1 of max min rate framework maximized the worst-off user rate. We showed that the total UAV-BS flight time decreases with an increase in UAV-BSs in the max sum rate framework. However, in the max min rate framework, the total UAV-BS flight time first increases and then decreases. In the max sum rate framework, the coverage probability does not change with the number of UAV-BSs. However, in the max min rate framework, coverage probability improves with an increase in UAV-BSs. The analytical expression for the coverage probability while accounting for the user mobility has also been derived. It has been shown that the analytical and simulated coverage probability are in agreement. In the max sum rate framework, the update interval does not change with increase in UAV-BSs whereas in the max min rate framework, the update interval increases with increase in UAV-BSs. Our work has been compared with a benchmark approach wherein the update interval is not optimized. It has been observed that, in the max sum rate framework, the benchmark approach prioritizes service time, whereas, in the max min rate framework, the benchmark approach prioritizes coverage probability. However, in both frameworks, the proposed work can adapt to the desired priority of service time and coverage probability.

APPENDIX

SNR at user $j$ due to UAV-BS $i$ can be written as:

$$
\log_2 \left( 1 + \frac{P_i}{d_{ij}^2(k)} \right) = \log_2 \left( 1 + \frac{P_i}{\frac{\delta_{LOS}}{K_{\infty}N_0} H^2 + ||U_i(k) - W_j(k)||^2} \right).
$$

Using first-order Taylor approximation of $f(z) = \log_2(1 + \frac{A}{B+z})$ at point $z = z_0$ will be \cite{15}:

$$
\log_2 \left( 1 + \frac{A}{B+z} \right) \geq \log_2 \left( 1 + \frac{A}{B+z_0} \right) - \frac{(\log_2 e)A(z-z_0)}{(B+z_0)(B+z_0+A)}.
$$

Hence, at the $m^{th}$ iteration of Algorithm 1, the first-order Taylor approximation of (28) can be obtained by substituting $A = \frac{P_i}{\delta_{LOS}K_{\infty}N_0}$, $B = H^2$, $z = ||U_i(k) - W_j(k)||^2$ and $z_0 = ||U_i(k,m-1) - W_j(k)||^2$ in (29).

ACKNOWLEDGMENT

This paper is an outcome of the research and development work undertaken under the Visvesvaraya Ph.D. Scheme of Ministry of Electronics Information Technology, Government of India, being implemented by Digital India Corporation.
REFERENCES

[1] Y. Zeng, Q. Wu, and R. Zhang, “Accessing from the sky: A tutorial on UAV communications for 5G and beyond,” Proc. IEEE, vol. 107, no. 12, pp. 2327–2375, Dec. 2019.

[2] A. S. Abdalla and V. Marojevic, “Communications standards for unmanned aircraft systems: The 3GPP perspective and research drivers,” 2021, arXiv:2009.03533.

[3] 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.

[4] Y. Zeng, J. Xu, and R. Zhang, “Energy minimization for wireless communication with rotary-wing UAV:” IEEE Trans. Wireless Commun., vol. 18, no. 4, pp. 2329–2345, Apr. 2019.

[5] L. Ruan et al., “Energy-efficient multi-UAV coverage deployment in UAV networks: A game-theoretic framework,” China Commun., vol. 15, no. 10, pp. 194–209, Oct. 2018.

[6] B. Wang et al., “Graph-based file dispatching protocol with D2D-enhanced UAV-NOMA communications in large-scale networks,” IEEE Internet Things J., vol. 7, no. 9, pp. 8615–8630, Sep. 2020.

[7] Y. Lin, T. Wang, and S. Wang, “UAV-assisted emergency communications: An extended multi-armed bandit perspective,” IEEE Commun. Lett., vol. 23, no. 5, pp. 938–941, May 2019.

[8] Q. Wang, W. Zhang, Y. Liu, and Y. Liu, “Multi-UAV dynamic wireless networking with deep reinforcement learning,” IEEE Commun. Lett., vol. 23, no. 12, pp. 2243–2246, Dec. 2019.

[9] F. Lagun, I. Bor-Yaliniz, and H. Yanikomeroglu, “Strategic densification with UAV-BSs in cellular networks,” IEEE Wireless Commun. Lett., vol. 7, no. 6, pp. 384–387, Jun. 2018.

[10] B. Galkin, J. Kibilda, and L. A. DaSilva, “Deployment of UAV-mounted access points according to spatial user locations in two-tier cellular networks,” in Proc. Wireless Days (WD), 2016, pp. 1–6.

[11] X. Sun and N. Ansari, “Jointly optimizing drone-mounted base station placement and user association in heterogeneous networks,” in Proc. IEEE Int. Conf. Commun. (ICC), 2018, pp. 1–6.

[12] J. Lyu, Y. Zeng, R. Zhang, and T. J. Lim, “Placement optimization of UAV-mounted mobile base stations,” IEEE Commun. Lett., vol. 21, no. 3, pp. 604–607, Mar. 2017.

[13] C. Zhan, Y. Zeng, and R. Zhang, “Trajectory design for distributed estimation in UAV-enabled wireless sensor network,” IEEE Trans. Veh. Technol., vol. 67, no. 10, pp. 10155–10159, Oct. 2018.

[14] J. Cui, Z. Ding, Y. Deng, A. Nallanathan, and L. Hanzo, “Adaptive UAV-trajectory optimization under quality of service constraints: A model-free solution,” IEEE Access, vol. 8, pp. 112253–112265, 2020.

[15] 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.

[16] F. Zeng et al., “Resource allocation and trajectory optimization for QoE provisioning in energy-efficient UAV-enabled wireless networks,” IEEE Trans. Veh. Technol., vol. 69, no. 7, pp. 7634–7647, Jul. 2020.

[17] J. Cui, Y. Liu, and A. Nallanathan, “Multi-agent reinforcement learning-based resource allocation for UAV networks,” IEEE Trans. Wireless Commun., vol. 19, no. 2, pp. 729–743, Feb. 2021.

[18] H. Qi, Z. Hu, H. Huang, X. Wen, and Z. Lu, “Energy efficient 3-D UAV control for persistent communication service and fairness: A deep reinforcement learning approach,” IEEE Access, vol. 8, pp. 53172–53184, 2020.

[19] H. V. Abeywickrama, Y. He, E. Dukiewicz, B. A. Jayawickrama, and M. Mueck, “A reinforcement learning approach for fair user coverage using UAV mounted base stations under energy constraints,” IEEE Open J. Veh. Technol., vol. 1, pp. 67–81, 2020.

[20] S.-F. Chou, A.-C. Pang, and Y.-J. Yu, “Energy-aware 3D unmanned aerial vehicle deployment for network throughput optimization,” IEEE Trans. Wireless Commun., vol. 19, no. 1, pp. 563–578, Jan. 2020.

[21] L. Liu, S. Zhang, and R. Zhang, “CoMP in the sky: UAV placement and movement optimization for multi-user communications,” IEEE Trans. Commun., vol. 67, no. 8, pp. 5645–5658, Aug. 2019.

[22] R. Ghanavi, E. Kalantari, M. Sabbaghian, H. Yanikomeroglu, and A. Yongacoglu, “Efficient 3D aerial base station placement considering users mobility by reinforcement learning,” in Proc. IEEE Wireless Commun. Netw. Conf. (WCNC), 2018, pp. 1–6.

[23] X. Liu, Y. Liu, and Y. Chen, “Reinforcement learning in multiple-UAV networks: Deployment and movement design,” IEEE Trans. Veh. Technol., vol. 68, no. 8, pp. 8036–8049, Aug. 2019.

[24] X. Liu, Y. Liu, Y. Chen, and L. Hanzo, “Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach,” IEEE Trans. Veh. Technol., vol. 68, no. 8, pp. 7957–7969, Aug. 2019.

[25] M. Peer, V. A. Bohara, A. Srivastava, and G. Ghatak, “User mobility-aware time stamp for UAV-BS placement,” in Proc. IEEE WCNC Workshop, 2021, pp. 1–6.

[26] M. Peer, V. A. Bohara, and A. Srivastava, “Cache selection in dynamic D2D multicast networks using inhomogeneous Markov model,” IEEE Trans. Netw. Sci. Eng., vol. 7, no. 4, pp. 3235–3245, Oct./Dec. 2020.

[27] H. Tabassum, M. Salehi, and E. Hossain, “Fundamentals of mobility-aware performance characterization of cellular networks: A tutorial,” IEEE Commun. Surveys Tuts., vol. 21, no. 3, pp. 2288–2308, 3rd Quart., 2019.

[28] M. Banagar and H. S. Dhillon, “Performance characterization of canonical mobility models in drone cellular networks,” IEEE Trans. Wireless Commun., vol. 19, no. 7, pp. 4994–5009, Jul. 2020.

[29] Y. Liu, K. Liu, J. Han, L. Zhu, Z. Xiao, and X.-G. Xia, “Resource allocation and 3-D placement for UAV-enabled energy-efficient IoT communications,” IEEE Internet Things J., vol. 8, no. 3, pp. 1322–1333, Feb. 2021.

[30] M. Peer, V. A. Bohara, and A. Srivastava, “Multi-UAV placement strategy for disaster-resilient communication network,” in Proc. IEEE VTC Fall Workshop, 2020, pp. 1–7.

[31] “IBM CPLEX optimizer.” Accessed: Aug. 20, 2022. [Online]. Available: https://www.ibm.com/in-en/analytics/cplex-optimizer

[32] I. S. Gradshteyn and I. M. Ryzhik, Table of Integrals, Series, and Products, 7th ed. Amsterdam, The Netherlands: Elsevier/Academic, 2007.

[33] T. D. Humphries, R. D. Haynes, and L. A. James, “Simultaneous and sequential approaches to joint optimization of well placement and control,” Comput. Geosci., vol. 18, nos. 3–4, pp. 433–448, 2013.