# Joint Optimization of Resource Allocation and Trajectory Control for Mobile Group Users in Fixed-Wing UAV-Enabled Wireless Network

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Abstract-Owing to the controlling flexibility and costeffectiveness, fixed-wing unmanned aerial vehicles (UAVs) are expected to serve as flying base stations (BSs) in the air-ground integrated network. By exploiting the mobility of UAVs, controllable coverage can be provided for mobile group users (MGUs) under challenging scenarios or even somewhere without communication infrastructure. However, in such dual mobility scenario where the UAV and MGUs are all moving, both the non-hovering feature of the fixed-wing UAV and the movement of MGUs will exacerbate the dynamic changes of user scheduling, which eventually leads to the degradation of MGUs' quality-of-service (QoS). In this paper, we propose a fixed-wing UAV-enabled wireless network architecture to provide moving coverage for MGUs. In order to achieve fairness among MGUs, we maximize the minimum average throughput between all users by jointly optimizing the user scheduling, resource allocation, and UAV trajectory control under the constraints on users' OoS requirements, communication resources, and UAV trajectory switching. Considering the optimization problem is mixed-integer non-convex, we decompose it into three optimization subproblems. An efficient algorithm is proposed to solve these three subproblems alternately till the convergence is realized. Simulation results demonstrate that the proposed algorithm can significantly improve the minimum average throughput of MGUs.

Index Terms—fixed-wing UAV, throughput maximization, mobile grouping, trajectory control, resource allocation.

#### I. INTRODUCTION

With the rapid development of wireless communications, the unmanned aerial vehicle (UAV)-enabled network is expected to become an essential component of the future sixthgeneration (6G) wireless networks to achieve ubiquitous connectivity [1]–[3]. Compared with terrestrial wireless communication systems, one major advantage of UAV base stations (BSs) is their high probability of providing line-of-sight (LOS) communication links to ground users, which directly alleviates the challenge of extremely weak signal strength at the receivers caused by shadowing and fading in urban or mountainous

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areas [3]. In general, UAVs used in wireless networks can be divided into rotary-wing and fixed-wing categories based on architectural and aerodynamic differences. Rotary-wing UAVs are equipped with propellers to help them hover steadily in a fixed position [4]. However, the use of propellers requires high power consumption, which leads to frequent energy replenishment for rotary-wing UAVs. The flight endurance time of rotary-wing UAVs is only dozens of minutes due to their limited battery capacity [5]. In contrast, fixed-wing UAVs have larger payloads and higher flight altitudes, allowing them to stay in the air for more than a day (even more than 47 hours for gasoline-driven UAVs) [6]. Hence, fixed-wing UAVs are more appropriate for providing moving coverage for users where long service time is necessary (e.g., rural/hilly coverage [5], [7], emergency rescue [6], [8], and long-term surveillance applications [9], [10]).

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## A. Literature Review

Before fully reaping all the aforementioned benefits of fixed-wing UAVs, several technical challenges must be addressed, including trajectory control [11]-[15], the air-toground propagation channel model [16], [17], and resource allocation [18]-[21] in UAV-enabled wireless networks. According to aerodynamic principles [6], fixed-wing UAVs have to fly continuously to maintain lift, so they cannot hover in a fixed position. To change the flight direction, fixed-wing UAVs must tilt the fuselage to generate centripetal force, which makes them move along a curved path. Therein, the curvature is inversely proportional to the turning radius [12], that is to say, with the curvature constraint, the minimum turning radius is limited. Thus, some studies have considered fixed flight paths for fixed-wing UAVs, which were planned according to the properties of fixed-wing UAVs, relaying the data from the source to the destination [22]. This unfavorably limits the degree of freedom (DoF) for trajectory optimization and the performance of UAV-enabled wireless systems. To further obtain the benefits of the mobility of fixed-wing UAVs, the Dubins path generation method has been extensively studied [13]-[15]. This is because the Dubins path can propose a feasible and safe path of minimal length for a UAV, especially for meeting the requirement of maneuvering control of highspeed fixed-wing UAVs [13]. Moreover, the shortest Dubins path can help the UAV save time and energy, so it is often used in emergency rescue and surveillance scenarios [15].

UAV trajectory design critically depends on air-to-ground channel modeling. The deterministic LOS channel model has

been widely investigated in UAV-enabled wireless networks [18]–[20] due to its ease of optimization. However, such simplified model may be actually inaccurate in urban/hilly areas, because it neglects stochastic shadowing and small-scale fading [17]. The Rician fading model consists of a deterministic LOS component and a random multipath component generated by reflection, scattering, and diffraction from ground obstacles [17]. This model is applicable to urban/suburban/hilly areas with UAVs at a sufficiently high altitude, where there is less shadowing but still a non-negligible amount of small-scale fading. Moreover, because of channel fading and trajectory constraints, relying only on trajectory control is insufficient to guarantee the performance of ground users. To enhance communication quality, one key aspect is the resource allocation design. In [18], the UAV was dispatched as a mobile BS to serve ground users with service delay constraints, and the minimum average throughput of all users was maximized by jointly optimizing the orthogonal frequency-division multiple access (OFDMA) resource allocation and UAV trajectory. To achieve fairness in secure communication, the communication/jamming subcarrier allocation strategy and UAV trajectory are jointly optimized to maximize the average minimum secrecy rate of each user [19]. Such optimization methods can ensure fairness in multiuser networks by redistributing resources from strong users to weak users.

# B. Motivation

Most of the existing research on fixed-wing UAVs only focuses on serving static users on the ground, where only the user position of the current time slot is known and assumed to remain unchanged during the communication process. However, in some practical applications (e.g., disaster relief operations and fleet transportation [23]-[25]), users are often involved in group activities and exhibit common mobility behavior. Currently, there are numerous models, such as tree model, deep neural network, etc., which can offer effective solutions for precise mobility prediction. Studying the pre-deployment of UAVs based on the full user location information implies that the position and mobility information of users is known or predictable [26]. With this proviso, the flight trajectory of UAVs can be effectively designed to improve the service quality. Unfortunately, there is a paucity of research on the problem of joint trajectory control and resource optimization design based on the fixed-wing UAV tracking user mobility to provide moving coverage, which motivates this paper.

In the dual mobility system, the mobility of UAVs will cause intermittent communication links and frequent handovers for ground users, resulting in degraded network qualityof-service (QoS). Simultaneously, frequent user movement will not only result in a continuous alteration in the channel state information but also cause users to move beyond the original coverage area of the UAV BS. To overcome such challenges of the dual mobility system, trajectory control can shorten the transmission distance between ground users to maximize the communication signal-to-noise ratio (SNR). Resource allocation is a favorable means to ensure fairness among multiple users and boost the communication capacity of the system. However, to the best of our knowledge, how to improve the communication performance in an air-ground integrated system with dual mobility of the fixed-wing UAV and ground users is still unsolved. Therefore, we explore the fixed-wing UAV-enabled OFDMA system, where the UAV BS is employed to provide moving coverage for mobile group users (MGUs). To adapt to the variations and achieve fairness between MGUs, we jointly optimize the user scheduling, resource allocation, and UAV trajectory to maximize the minimum average throughput among users in the UAV-enabled wireless network.

## C. Main Contributions

Against the above background, the main contributions of this paper are highlighted as follows.

- We propose a novel framework for the fixed-wing UAVenabled wireless network, where the UAV is equipped with BS to provide moving coverage for MGUs when terrestrial BSs are unavailable. Based on the proposed model, we maximize the minimum average throughput among users to achieve fairness in multiuser networks, considering the communication resources, users' QoS requirements, and UAV trajectory constraints.
- We conceive an efficient iterative algorithm to solve the formulated mixed-integer non-convex problem. Specifically, we decompose it into three more tractable subproblems: i) we obtained user scheduling by using variable relaxation; ii) we applied Lagrange duality to jointly optimize bandwidth allocation and power control; iii) we solved the UAV trajectory control subproblem by successive convex approximation (SCA). Finally, these subproblems are alternatively iterated until convergence is achieved.
- We verify that our proposed iterative algorithm can significantly improve the minimum average throughput of MGUs. Through trajectory optimization, the fixed-wing UAV switches trajectory conforming to the movement characteristics of ground MGUs to provide better channel conditions and obtain higher user throughput gain. Moreover, user scheduling and resource allocation are optimized according to the wireless channel conditions and the available resources of the UAV BS, greatly enhancing the system performance.

# D. Organization

The remainder of this paper is organized as follows. In Section II, we introduce the system model and formulate the optimization problem. In Section III, we propose an efficient iterative optimization algorithm. In Section IV, we prove that the proposed algorithm has good convergence and effectiveness through simulation results. Finally, we summarize the work and propose some future work prospects in Section V.

#### II. SYSTEM MODEL AND PROBLEM FORMULATION

# A. System Model

As shown in Fig. 1(a), a fixed-wing UAV is employed as an aerial BS to cover MGUs in the downlink scenario. We assume



Fig. 1. The 3D and 2D illustrations of the fixed-wing UAV-enabled wireless network.

that MGUs move in the area according to the Reference Point Group Mobility (RPGM) model [24]. To represent the group mobility of MGUs, the model defines a logical reference center whose movement is followed by all users in the group [25]. In this paper, we set the initial distribution center of MGUs, namely User Center (UC), as the reference center. Furthermore, it is assumed that the UAV can obtain the location of MGUs through its wireless sensing capability or from the positioning information of global positioning system (GPS) delivered by MGUs. In this way, the UAV can estimate the movement trajectory of MGUs over a period of time through mobility prediction based on the historical data [27] and then set its own flying trajectory. Since the fixed-wing UAV cannot hover and requires larger centripetal force to maintain a more curved trajectory, too small turning radius may cause the roll angle to exceed safety limits [28]. Here, we adopt the Dubins switch trajectory model (DSTM) [14] for the UAV to provide moving coverage for MGUs. In general, the Dubins path consists of three segments, i.e., initial and final arcs/circles and lines shown in Fig. 1(b). We take the right-straight-right (RSR) model [14] as an example for analysis, which is a typical Dubins path generated by clockwise rotation. When the UAV flies in the arc/circle path segment, the UAV takes UC as its flying center on the two-dimensional (2D) top view projection plane. The flying radius of the UAV in the arc/circle path segments depends on the distribution of MGUs and the threshold of safe turning radius. For simplicity, we assume that the time for the fixed-wing UAV to switch trajectory along a straight line is negligible due to its sufficiently high flight speed [13].

Without loss of generality, we establish a three-dimensional (3D) Cartesian coordinate system with UC as the origin (0,0,0). Since DSTM is continuous and repetitive, it only needs to observe and analyze within the initial trajectory adjustment period T. For ease of exposition, the period T is divided into N time slots, indexed by  $\mathcal{N} = \{1, 2, ..., N\}$ , and the length of each time slot is  $\delta = \frac{T}{N}$ . The initial

and final flight radii in period T are denoted as  $r_I$  and  $r_F$ , respectively. To ensure flying security, there is a minimum flight radius  $r_{\min}$  which is related to the flight speed and the roll angle [28]. To balance the number of users inside and outside the UAV trajectory circle,  $\frac{\bar{r}_I}{2}$  is a reasonable value for the circle radius [29]. Hence, we take the UAV flight radii  $r_I = \max\{\bar{r}_1/2, r_{\min}\}$  and  $r_F = \max\{\bar{r}_N/2, r_{\min}\},$ respectively, where  $\bar{r}_1$  and  $\bar{r}_N$  are the distribution radii of MGUs in time slot n = 1 and n = N, respectively. Then the horizontal position of the UAV in time slot n can be expressed as  $\mathbf{q}[n] = \left(-r_I \cos[\frac{v}{r_I}n], r_I \sin[\frac{v}{r_I}n]\right), \forall n$ , where v is the velocity of the UAV. On the 2D projection plane shown in Fig. 1(b), the initial circle center coordinate, denoted as  $CR_I$ , is (0,0). The final circle center coordinate  $CR_F = (x_{RF}, y_{RF})$ can be obtained according to user mobility prediction within period T. Since the linear velocity of the UAV is constant on the circular trajectory, the UAV needs to switch the trajectory along the tangent F of the two circles in RSR model [14]. Please refer to Appendix A for the detailed calculation of the coordinate F. Then, the UAV needs to satisfy initial/final position constraints, which can be expressed as

$$\mathbf{q}[1] = \mathbf{q}_I, \ \mathbf{q}[N] = \mathbf{q}_F, \tag{1}$$

where  $\mathbf{q}_I$  and  $\mathbf{q}_F$  represent the UAV's destined initial and final locations, respectively. In addition, the maximum and minimum flight distance of each time slot are given by  $S_{\text{max}} = V_{\text{max}}\delta$  and  $S_{\text{min}} = V_{\text{min}}\delta$ , respectively, with  $V_{\text{max}}$  and  $V_{\text{min}}$  respectively denoting the maximal and minimal flying speeds of the UAV. We denote  $\mathbf{q}[n]\mathbf{q}[n+1]$  as the arc length of the UAV moving from time slot n to time slot n+1. The specific calculation of  $\mathbf{q}[n]\mathbf{q}[n+1]$  can be referred to Appendix A. Thus, the UAV trajectory is restricted by the following contraints

$$S_{\min} \le \widehat{\mathbf{q}[n]} \mathbf{q}[n+1] \le S_{\max}, \ \forall n,$$
 (2)

$$\|\mathbf{q}[n]\| = r_I, \ \forall n. \tag{3}$$

We consider that the fixed-wing UAV-enabled OFDMA system consists of K MGUs denoted by the set  $\mathcal{K} = \{1, 2, ..., K\}$ . The initial locations of K MGUs are randomly distributed, and the horizontal position are denoted as  $\mathbf{u}_k[n] = (x_k[n], y_k[n]), k \in \mathcal{K}$ . The UAV is assumed to fly at a fixed altitude H. Then, the distance from the UAV to user k in time slot n can be written as

$$d_{k}[n] = \sqrt{H^{2} + \left\|\mathbf{q}[n] - \mathbf{u}_{k}[n]\right\|^{2}}, \ \forall n, k,$$
(4)

where  $\|\cdot\|$  represents Euclidean norm.

Although the UAV is likely to establish LOS channels with ground MGUs at a sufficiently high altitude, there are still scattering effects in these links, causing the UAV to experience small-scale fading. Therefore, it is more accurate to use the elevation-angle-dependent Rician fading model [17] to formulate the communication link between the UAV and the ground MGUs. The channel between the UAV and user k during the time slot n can be modeled as

$$h_k[n] = \rho_0 f_{AG_k}[n] d_k^{-a}[n], \ \forall n, k,$$
(5)

where  $\rho_0$  denotes the channel power gain at the reference distance  $d_0 = 1$  m, *a* represents the path-loss exponent with the value generally between 2 and 6. Here,  $f_{AG_k}[n]$  denotes the effective fading power of the channel between the UAV and user *k* at time slot *n*, which can be approximated as [16], [17]

$$f_{AG_{k}}[n] = C_{1} + \frac{C_{2}}{1 + \exp(-(B_{1} + B_{2}\vartheta_{AG_{k}}[n]))}$$
  
=  $C_{1} + \frac{C_{2}}{1 + \exp\left(-\left(B_{1} + B_{2}\frac{H}{\sqrt{\|\mathbf{q}[n] - \mathbf{u}_{k}[n]\|^{2} + H^{2}}}\right)\right)}, \forall n, k,$   
(6)

where  $C_1$ ,  $C_2$ ,  $B_1$ , and  $B_2$  are constants determined by the maximum tolerable outage probability, and the maximum and minimum Rician factors of the channels [17].  $\vartheta_{AG_k}[n] = \frac{H}{\sqrt{\|\mathbf{q}[n] - \mathbf{u}_k[n]\|^2 + H^2}}$  is the Sine function of the elevation angle between user k and the UAV. It can be observed from (5) that  $f_{AG_k}[n]$  can be adjusted by optimizing the UAV trajectory.

In this paper, the OFDMA protocol is applied for the UAV BS to serve multiple users. The total bandwidth of the UAVenabled system is  $B_{\text{max}}$  and the peak transmission power of the UAV is  $P_{\text{max}}$ .  $b_k[n]$  and  $p_k[n]$  represent the bandwidth allocation and the downlink transmission power of the UAV to user k in time slot n, respectively. The constraints of bandwidth and transmission power can be expressed as

$$\sum_{k=1}^{K} \alpha_k[n] b_k[n] \le B_{\max}, \ \forall n, \tag{7}$$

$$\sum_{k=1}^{K} \alpha_k[n] p_k[n] \le P_{\max}, \ \forall n,$$
(8)

where  $\alpha_k[n]$  is a binary variable used to distinguish different scheduling statuses.  $\alpha_k[n] = 1$  indicates user k is scheduled by

UAV BS in time slot n, otherwise,  $\alpha_k[n] = 0$ . The achievable rate of user k in time slot n, denoted by  $R_k[n]$  in bits/second (bps), can be expressed as

$$R_{k}[n] = b_{k}[n] \log_{2} \left( 1 + \frac{p_{k}[n]h_{k}[n]}{N_{0}b_{k}[n]} \right), \ \forall n, k, \qquad (9)$$

where  $N_0$  represents the power spectral density of the additive white Gaussian noise (AWGN) at the receivers. Due to the dual mobility of the UAV and ground MGUs, the air-to-ground channel condition is not stable. To guarantee the QoS of MGUs, the data rate cannot be lower than a predetermined threshold  $\gamma^{\text{th}}$ . Therefore, we have

$$R_k[n] \ge \alpha_k[n]\gamma^{\text{th}}, \ \forall n, k.$$
(10)

As a result, the average achievable throughput of user k over N time slots is the function of  $\alpha_k[n]$ ,  $b_k[n]$ ,  $p_k[n]$ , and  $\mathbf{q}[n]$ , which is given by

$$\bar{R}_k(\alpha_k[n], b_k[n], p_k[n], \mathbf{q}[n]) = \frac{1}{N} \sum_{n=1}^N \alpha_k[n] R_k[n], \forall k.$$
(11)

# B. Problem Formulation

In this paper, we investigate the joint optimization problem of user scheduling, bandwidth allocation, power control as well as UAV trajectory control to maximize the minimum average throughput among users. For notational simplicity, let user scheduling  $\boldsymbol{\alpha} = \{\alpha_k[n], \forall k, n\}$ , bandwidth allocation  $\mathbf{B} = \{b_k[n], \forall k, n\}$ , power control  $\mathbf{P} = \{p_k[n], \forall k, n\}$ , and UAV trajectory control  $\mathbf{Q} = \{\mathbf{q}[n], \forall n\}$ . Define  $\eta(\boldsymbol{\alpha}, \mathbf{B}, \mathbf{P}, \mathbf{Q}) \triangleq \min_{k \in \mathcal{K}} \bar{R}_k$  as a function of  $\boldsymbol{\alpha}$ ,  $\mathbf{B}$ ,  $\mathbf{P}$ , and  $\mathbf{Q}$ . The optimization problem can be formulated as

$$\max_{\eta, \alpha, \mathbf{B}, \mathbf{P}, \mathbf{Q}} \qquad \eta \qquad (12a)$$

s.t. 
$$(1) - (3), (7) - (8), (10),$$
 (12b)

$$\alpha_k[n] \in \{0,1\}, \ \forall k, n, \tag{12c}$$

$$\frac{1}{N}\sum_{n=1}^{N}\alpha_k[n]R_k[n] \ge \eta, \ \forall k, \tag{12d}$$

$$b_k[n] \ge 0, \ \forall k, n,$$
 (12e)

$$p_k[n] \ge 0, \ \forall k, n. \tag{12f}$$

It can be proved that at the optimal solution to problem (12), we must have  $\eta^* = \frac{1}{N} \sum_{n=1}^{N} \alpha_k[n] R_k[n]$ ,  $\forall k$ , since otherwise one can always increase  $\eta$  to obtain a strictly larger objective value. The flying position constraints of the UAV are shown in (1)-(3). Constraint (12c) is the binary constraint to indicate whether the user k is scheduled in time slot n. Constraint (12d) is imposed to guarantee an average minimum rate  $\eta$  for each user within period T. To ensure the QoS, the minimum communication rate constraint is given in (10). Bandwidth allocation constraints are shown in (7) and (12e). Power control constraints are shown in (8) and (12f).

# III. JOINT USER SCHEDULING, RESOURCE ALLOCATION, AND TRAJECTORY CONTROL ALGORITHM DESIGN

It can be seen that problem (12) is a mixed-integer nonconvex optimization problem, which is difficult to obtain the optimal solution in general. There are three challenges to solve problem (12). Firstly, multivariate variables are coupled and the objective function  $\eta$  is non-concave. Secondly, the user scheduling  $\alpha_k[n]$  in constraints (7)-(8), (10), and (12c)-(12d) is a binary variable, which cannot be solved directly. Finally, even though with the fixed user scheduling  $\alpha$ , objective function  $\eta$  and constraints (10) and (12d) are not jointly concave w.r.t. the optimization variables **B**, **P**, and **Q**. Here, we decompose the original problem into three optimization subproblems and propose an efficient iterative algorithm to solve problem (12).

#### A. User Scheduling Optimization

Since we assume that the UAV BS employs OFDMA to serve MGUs, user scheduling optimization will be performed in each time slot. In order to make the optimization problem (12) tractable, we first relax the binary variable  $\alpha$  into a continuous variable as follows

$$0 \le \hat{\alpha}_k[n] \le 1, \ \forall k, n. \tag{13}$$

We denote  $\hat{\alpha} = {\hat{\alpha}_k[n], \forall k, n}$  as a set of user scheduling variables. With fixed bandwidth allocation, power control, and UAV trajectory control (i.e., **B**, **P**, **Q**), problem (12) can be rewritten as

$$\max_{\eta, \hat{\boldsymbol{\alpha}}} \qquad \eta \qquad (14a)$$

s.t. 
$$(7) - (8)$$
,  $(10)$ ,  $(12d)$ ,  $(13)$ .  $(14b)$ 

It is straightforward to observe that problem (14) is a standard LP problem, which can be solved efficiently by using the optimization toolbox CVX [30].

#### B. Joint Bandwidth Allocation and Power Control

In this subsection, we jointly optimize the bandwidth allocation **B** and power control **P** by assuming that user scheduling  $\hat{\alpha}$  and UAV trajectory **Q** are fixed. Thus, the resource allocation optimization in problem (12) can be reformulated as

$$\max_{\eta, \mathbf{B}, \mathbf{P}} \qquad \eta \qquad (15a)$$

s.t. 
$$(7) - (8), (10), (12d) - (12f), (15b)$$

where  $g_k[n] \triangleq \frac{\rho_0 f_{AG_k}[n]}{N_0(\|\mathbf{q}[n]-\mathbf{u}_k[n]\|^2+H^2)^{a/2}}$ ,  $\forall k, n$ . Obviously, constraints (7)-(8) and (12e)-(12f) are all affine constraints. According to [19], problem (15) is a convex optimization problem since the function  $b_k[n] \log_2 \left(1 + \frac{p_k[n]g_k[n]}{b_k[n]}\right)$  is jointly concave w.r.t.  $b_k[n]$  and  $p_k[n]$ . Besides, problem (15) satisfies the Slater's constraint, so the strong duality holds [19]. In other words, the duality gap between problem (15) and its dual problem is zero and the optimization can be achieved

by solving the Lagrange duality. The Lagrangian function of problem (15) can be written as

$$\mathcal{L}(\eta, \mathbf{B}, \mathbf{P}, \boldsymbol{\mu}, \boldsymbol{\beta}, \boldsymbol{\xi}, \boldsymbol{\varpi}) = \eta - \sum_{n=1}^{N} \xi_n \left( \sum_{k=1}^{K} \hat{\alpha}_k[n] b_k[n] - B_{\max} \right) - \sum_{n=1}^{N} \varpi_n \left( \sum_{k=1}^{K} \hat{\alpha}_k[n] p_k[n] - P_{\max} \right) - \sum_{k=1}^{K} \mu_k \left( \eta - \frac{1}{N} \sum_{n=1}^{N} \hat{\alpha}_k[n] b_k[n] \log_2 \left( 1 + \frac{p_k[n]g_k[n]}{b_k[n]} \right) \right) - \sum_{k=1}^{K} \sum_{n=1}^{N} \beta_{k,n} \left( \hat{\alpha}_k[n] \gamma^{\text{th}} - b_k[n] \log_2 \left( 1 + \frac{p_k[n]g_k[n]}{b_k[n]} \right) \right),$$
(16)

where  $\boldsymbol{\mu} = \{\mu_k, \forall k\}, \boldsymbol{\beta} = \{\beta_{k,n}, \forall k, n\}, \boldsymbol{\xi} = \{\xi_n, \forall n\}, \text{ and } \boldsymbol{\varpi} = \{\boldsymbol{\varpi}_n, \forall n\}$  denote the non-negative Lagrange multiplier vectors for constraints (12d), (10), (7), and (8), respectively. Constraints (12e) and (12f) will be absorbed into the Karush-Kuhn-Tucker (KKT) conditions [31] when deriving the optimal solution of resource allocation. Hence, the dual problem of problem (15) can be expressed as

$$\min_{\boldsymbol{\mu},\boldsymbol{\beta},\boldsymbol{\xi},\boldsymbol{\varpi}\geq 0} \max_{\boldsymbol{\eta},\mathbf{B},\mathbf{P}} \mathcal{L}(\boldsymbol{\eta},\mathbf{B},\mathbf{P},\boldsymbol{\mu},\boldsymbol{\beta},\boldsymbol{\xi},\boldsymbol{\varpi}).$$
(17)

Next, we solve the dual problem iteratively by decomposing it into two layers [18], [19].

1) Solution of Layer 1 (Power Control and Bandwidth Allocation): By dual decomposition, we first solve the Lagrange dual function with fixed dual variables  $\mu$ ,  $\beta$ ,  $\xi$ , and  $\varpi$ , i.e.,

$$\max_{\eta, \mathbf{B}, \mathbf{P}} \mathcal{L}(\eta, \mathbf{B}, \mathbf{P}, \boldsymbol{\mu}, \boldsymbol{\beta}, \boldsymbol{\xi}, \boldsymbol{\varpi}).$$
(18)

Since the objective function  $\eta$  represents the minimum average throughput of users, for simplicity, we set  $\eta^* = 0$ as the initial optimal solution to obtain the dual function (18). With the given dual variables  $\mu$ ,  $\beta$ ,  $\xi$ , and  $\varpi$ , problem (18) is jointly concave w.r.t.  $p_k[n]$  and  $b_k[n]$ . According to the KKT conditions, the optimal power allocation for user k in time slot n, denoted as  $p_k^*[n]$ , is given by

$$p_{k}^{*}[n] = b_{k}[n] \left[ \frac{\mu_{k} + N\beta_{k,n}}{\varpi_{n}N\ln 2} - \frac{1}{g_{k}[n]} \right]^{+}, \quad (19)$$

where  $[p]^+$  represents  $\max\{p, 0\}$ . The power control in (19) follows the multi-level water-filling policy [18]. Let  $\tilde{p}_k[n] \triangleq \frac{p_k^*[n]}{b_k[n]} = \left[\frac{\mu_k + N\beta_{k,n}}{\varpi_n N \ln 2} - \frac{1}{g_k[n]}\right]^+$ , which is uniquely determined with fixed  $\mu$ ,  $\beta$ , and  $\varpi$ . By substituting  $\tilde{p}_k[n]$  back into problem (18), we have

$$\max_{\mathbf{B}} \quad \sum_{k=1}^{K} \sum_{n=1}^{N} f(\tilde{p}_k) b_k[n] - \Gamma$$
(20a)

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where

$$f(\tilde{p}_{k}) = \frac{\mu_{k} + N\beta_{k,n}}{N} \hat{\alpha}_{k}[n] \log_{2} \left(1 + g_{k}[n]\tilde{p}_{k}[n]\right) - \varpi_{n} \hat{\alpha}_{k}[n]\tilde{p}_{k}[n] - \xi_{n} \hat{\alpha}_{k}[n],$$
(21)

$$\Gamma = \sum_{k=1}^{K} \sum_{n=1}^{N} \beta_{k,n} \hat{\alpha}_{k}[n] \gamma^{\text{th}} - \sum_{n=1}^{N} \xi_{n} B_{\text{max}} - \sum_{n=1}^{N} \varpi_{n} P_{\text{max}}.$$
 (22)

Obviously, problem (20) is an LP problem about optimizing the variable  $b_k[n]$ . Therefore, the optimal bandwidth allocation for user k in time slot n, denoted as  $b_k^*[n]$ , is given by

$$b_k^*[n] = \begin{cases} B_{\max}, & f(\tilde{p}_k) > 0, \ \forall k, n, \\ 0, & \text{otherwise.} \end{cases}$$
(23)

Note that we set  $b_k^*[n] = 0$  when  $f(\tilde{p}_k) = 0$  holds, since the objective function value in problem (20) is not affected by the value of  $b_k^*[n]$ .

2) Solution of Layer 2 (Solving the Dual Problem (17)): After obtaining  $\eta^*$ ,  $\mathbf{B}^*$ , and  $\mathbf{P}^*$ , we can update the Lagrange multipliers by applying the gradient method [19], because the dual function (17) is differentiable. Then, the gradient update equations of dual variables are given at the bottom of this page, where  $m \ge 0$  represents the iteration index and  $\zeta_u(m)$ ,  $u \in 1, 2, 3, 4$ , are positive step sizes. In addition, the details such as selecting the step size and proving the convergence of the gradient method can be found in [31], [32].

The optimal solution that maximizes the Lagrangian function is equal to the optimal primal solution if and only if the solution is feasible and unique [33]. However, from the solution analysis of Layer 1, the optimal values of  $\eta^*$  and  $\mathbf{B}^*$ are not unique because of the initial set  $\eta^* = 0$  and  $f(\tilde{p}_k) = 0$ . Therefore, additional steps are needed to further confirm the values of  $\eta^*$  and  $\mathbf{B}^*$ . We denote  $\tilde{p}_k^*[n] = \frac{p_k^*[n]}{b_k^*[n]}$  as the optimal power spectrum density. Since  $\tilde{p}_k^*[n]$  can be uniquely obtained from (19), we substitute it into the original problem (15) to obtain an LP problem w.r.t. **B** and  $\eta$ , which can be solved by CVX [30]. Finally, the corresponding power control  $\mathbf{P}^*$  can be calculated by  $p_k^*[n] = \tilde{p}_k^*[n]b_k^*[n]$  with the optimal bandwidth allocation  $\mathbf{B}^*$ .

#### C. UAV Trajectory Optimization

Given any feasible user scheduling and resource allocation (i.e.,  $\hat{\alpha}$ , **B**, **P**), the achievable rate  $R_k[n]$  of user k in time slot n can be re-expressed as

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$$R_{k}[n] = b_{k}[n] \log_{2} \left( 1 + \frac{f_{AG_{k}}[n]\hat{g}_{k}[n]}{\left( \|\mathbf{q}[n] - \mathbf{u}_{k}[n]\|^{2} + H^{2}\right)^{a/2}} \right)$$

$$= b_{k}[n] \log_{2} \left( 1 + \frac{\hat{g}_{k}[n]}{\left( \|\mathbf{q}[n] - \mathbf{u}_{k}[n]\|^{2} + H^{2}\right)^{a/2}} \right)$$

$$\times \left( C_{1} + \frac{C_{2}}{1 + \exp(-(B_{1} + B_{2}\vartheta_{AG_{k}}[n]))} \right), \forall n, k,$$
(28)

where  $\hat{g}_k[n] = \frac{p_k[n]\rho_0}{N_0 b_k[n]}$ . Then, problem (12) can be represented as the following optimization problem

$$\max_{n \mathbf{Q}} \qquad \eta \qquad (29a)$$

s.t. 
$$(1) - (3), (10), (12d).$$
 (29b)

However, problem (29) is non-convex due to constraints (2)-(3), (10), and (12d) are not concave w.r.t.  $\mathbf{q}[n]$ . Considering that the concavity and convexity of  $R_k[n]$  in  $\mathbf{q}[n]$  cannot be determined, we introduce a slack variable  $\mathbf{\Xi} \triangleq \{\Xi_k[n] = B_1 + B_2 \vartheta_{AG_k}[n], \forall k, n\}$ . Thus, problem (29) can be reformulated into the following more tractable problem

$$\max_{\eta,\mathbf{Q},\Xi} \qquad \eta \qquad (30a)$$

s.t. 
$$\Xi_k[n] \leqslant B_1 + B_2 \vartheta_{AG_k}[n], \forall k, n,$$
 (30b)

$$(1) - (3), (10), (12d).$$
 (30c)

It can be shown that at the optimal solution to problem (30), constraint (30b) must hold with equality. This can be proved by contradiction. Specifically, if there is an optimal solution satisfying constraint (30b) with strict inequality. Another solution can always increase  $\Xi_k[n]$  to obtain a strictly larger objective value. Therefore, problem (30) is equivalent to problem (29). It is observed that the constraints (10) and (12d) in problem (30) are non-convex w.r.t.  $\mathbf{q}[n]$ , which makes solving (30) still difficult. To solve this difficulty, we apply the SCA technique to solve (30) in an iterative manner. It can be proved that

$$\mu_k(m+1) = \left[\mu_k(m) - \zeta_1(m) \times \left(\frac{1}{N} \sum_{n=1}^N \hat{\alpha}_k[n] b_k[n] \log_2\left(1 + \frac{p_k[n]g_k[n]}{b_k[n]}\right) - \eta\right)\right]^+, \ \forall k,$$
(24)

$$\beta_{k,n}(m+1) = \left[\beta_{k,n}(m) - \zeta_2(m) \times \left(b_k[n] \log_2\left(1 + \frac{p_k[n]g_k[n]}{b_k[n]}\right) - \hat{\alpha}_k[n]\gamma^{\text{th}}\right)\right]^+, \ \forall k, n,$$
(25)

$$\xi_n(m+1) = \left[\xi_n(m) - \zeta_3(m) \times \left(B_{\max} - \sum_{k=1}^K \hat{\alpha}_k[n]b_k[n]\right)\right]^+, \ \forall n,$$
(26)

$$\xi_n(m+1) = \left[\xi_n(m) - \zeta_3(m) \times \left(B_{\max} - \sum_{k=1}^K \hat{\alpha}_k[n]b_k[n]\right)\right]^+, \ \forall n,$$
(27)

 $R_k[n]$  in (28) is a convex function w.r.t.  $(1 + e^{-\Xi_k[n]})$  and  $(\|\mathbf{q}[n] - \mathbf{s}_k[n]\|^2 + H^2)$  [17]. Since a convex function is lower bounded by its first-order Taylor expansion, a lower bound of  $R_k[n]$  at a given local point  $\mathbf{q}^l[n]$  in the *l*-th iteration can be obtained as

$$R_{k}[n] \geq R_{k}^{\text{lb},l}[n] \triangleq R_{k}^{l}[n] - \Phi_{k}^{l}[n] \left( e^{-\Xi_{k}[n]} - e^{-\Xi_{k}^{l}[n]} \right) - \Psi_{k}^{l}[n] \left( \left\| \mathbf{q}[n] - \mathbf{u}_{k}[n] \right\|^{2} - \left\| \mathbf{q}^{l}[n] - \mathbf{u}_{k}[n] \right\|^{2} \right), \forall k, n,$$
(31)

where the equality holds at the point  $\mathbf{q}[n] = \mathbf{q}^{l}[n]$ . The coefficients  $R_{k}^{l}[n]$ ,  $\Phi_{k}^{l}[n]$ , and  $\Psi_{k}^{l}[n]$  are given by

$$R_k^l[n] = b_k[n] \log_2 \left( 1 + \left( C_1 + \frac{C_2}{x_0} \right) \frac{\hat{g}_k[n]}{y_0^{a/2}} \right), \qquad (32)$$

$$\Phi_k^l[n] = b_k[n] \frac{C_2 \hat{g}_k[n] \log_2(e)}{x_0 \left( x_0 y_0^{a/2} + (C_1 x_0 + C_2) \hat{g}_k[n] \right)}, \qquad (33)$$

$$\Psi_k^l[n] = b_k[n] \frac{(C_1 x_0 + C_2)\hat{g}_k[n]\log_2(e)(a/2)}{y_0\left(x_0 y_0^{a/2} + (C_1 x_0 + C_2)\hat{g}_k[n]\right)},$$
(34)

where  $x_0 = 1 + e^{-\Xi_k^l[n]}, y_0 = \left\| \mathbf{q}^l[n] - \mathbf{u}_k[n] \right\|^2 + H^2.$ 

Another difficulty for solving problem (30) is that  $\vartheta_{AG_k}[n] = \frac{H}{\sqrt{\|\mathbf{q}[n] - \mathbf{u}_k[n]\|^2 + H^2}}$  is not concave w.r.t.  $\mathbf{q}[n]$ . However, we observe that  $\vartheta_{AG_k}[n]$  is convex w.r.t.  $(\|\mathbf{q}[n] - \mathbf{u}_k[n]\|^2 + H^2)$ . This useful property allows us to lower-bound  $\vartheta_{AG_k}[n]$  by applying its first-order Taylor expansion at a given local point. Specifically, with given local point  $\mathbf{q}^l[n]$  in the *l*-th iteration, we have

$$\vartheta_{AG_{k}}[n] \geq \vartheta_{AG_{k}}^{\mathsf{lb},l}[n] \triangleq \frac{H}{\sqrt{\|\mathbf{q}^{l}[n] - \mathbf{u}_{k}[n]\|^{2} + H^{2}}} - \left( \left( \|\mathbf{q}[n] - \mathbf{u}_{k}[n]\|^{2} - \|\mathbf{q}^{l}[n] - \mathbf{u}_{k}[n]\|^{2} \right) \quad (35) \\ \times \frac{H}{2(\|\mathbf{q}^{l}[n] - \mathbf{u}_{k}[n]\|^{2} + H^{2})^{3/2}} \right), \forall k, n,$$

where the  $\vartheta_{AG_k}^{\text{lb},l}[n]$  is the lower bounds of  $\vartheta_{AG_k}[n]$  in the *l*-th iteration.

Since 
$$\widehat{\mathbf{q}[n]\mathbf{q}[n+1]} = r_I \arccos\left(\frac{2r_I^2 - \|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2}{2r_I^2}\right)$$
,  $\forall n$ , according to the properties of the accosine function, we can transfer the constraint (2) into the following two inequalities

$$\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2 \le 2r_I^2 \left(1 - \cos\frac{S_{\max}}{r_I}\right), \forall k, n, \qquad (36)$$

$$2r_I^2\left(1-\cos\frac{S_{\min}}{r_I}\right) \le \left\|\mathbf{q}[n+1] - \mathbf{q}[n]\right\|^2, \forall k, n.$$
(37)

To make constraint (37) convex, we introduce the slack variables  $\mathbf{Z} \triangleq \{\mathbf{Z}[n] = \|\mathbf{q}[n+1] - \mathbf{q}[n]\|, \forall n\}$ . The term  $\|\mathbf{q}[n+1] - \mathbf{q}[n]\|$  can be replaced by  $\mathbf{Z}[n]$ , and the additional constraint  $\|\mathbf{Z}[n]\|^2 \leq \|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2$  is required. Since a convex function is lower bounded by its first-order Taylor expansion, we scale  $\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2$  by its globally lower bound with a given local point  $\mathbf{q}^l[n]$  in the *l*-th iteration, which

can be obtained as

$$\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^{2} \ge \mathbf{\Lambda}^{\mathrm{lb},l}[n] \triangleq - \|\mathbf{q}^{l}[n+1] - \mathbf{q}^{l}[n]\|^{2} + 2\left(\mathbf{q}^{l}[n+1] - \mathbf{q}^{l}[n]\right)^{T} (\mathbf{q}[n+1] - \mathbf{q}[n]).$$
(38)

As for constraint (3), it may be converted into  $\|\mathbf{q}[n]\| \leq r_I$ , and  $\|\mathbf{q}[n]\| \geq r_I$ . Similarly, we can introduce the slack variables  $\mathbf{Z}_1 \triangleq \{\mathbf{Z}_1[n] = \|\mathbf{q}[n]\|, \forall n\}$ . Thus, we have

$$\|\mathbf{q}[n]\|^{2} \ge \mathbf{\Upsilon}^{\mathrm{lb},l}[n] \triangleq \|\mathbf{q}^{l}[n]\|^{2} + 2\left(\mathbf{q}^{l}[n]\right)^{T} (\mathbf{q}[n] - \mathbf{q}^{l}[n]).$$

$$(39)$$

By substituting the terms  $R_k^{\text{lb},l}[n]$ ,  $\vartheta_{AG_k}^{\text{lb},l}[n]$ ,  $\Lambda^{\text{lb},l}[n]$  and  $\Upsilon^{\text{lb},l}[n]$  into (12d), (10), and (2)-(3), respectively, problem (30) can be transformed to the following approximate problem

$$\max_{\eta^{\mathrm{lb},l},\mathbf{Q},\mathbf{\Xi},\mathbf{Z},\mathbf{Z}_{1}} \eta^{\mathrm{lb},l}$$
(40a)

s.t. 
$$\|\mathbf{Z}[n]\|^2 \le \Lambda^{\mathrm{lb},l}[n], \forall n,$$
 (40b)  
 $\|\mathbf{Z}_{-}[n]\|^2 \le \Upsilon^{\mathrm{lb},l}[n], \forall n,$  (40c)

$$\|\mathbf{Z}_1[n]\|^2 \le \Upsilon^{10,\epsilon}[n], \ \forall n, \tag{40c}$$

$$\|\mathbf{q}[n]\| \le r_I, \ \forall n, \tag{40d}$$

$$(10), (12d), (30b), (36).$$
 (40e)

With concave objective function and constraints, problem (40) can be solved by applying the CVX [30]. It is worth noting that by approximating the concave constraint to a convex lower bound, the feasible set of problem (40) is always a subset of problem (30). That is to say, solving problem (40) gives the lower bound of the objective value in problem (30).

# D. Overall Algorithm Optimization Order, Convergence, and Complexity

The original problem (12) is divided into three subproblems, where the user scheduling problem is solved by relaxing binary variables in problem (14), the power and bandwidth resource allocation problem is jointly solved by the Lagrangian dual method in problem (15), and the UAV trajectory problem is approximated by the SCA in problem (40). Due to the strong duality of problem (15), the duality gap between problem (15) and its dual problem is zero, which means that the optimal solution can be efficiently obtained by applying the Lagrangian dual. However, the SCA method in problem (40) will lead to a local optimal solution when using the iterative optimization algorithm to solve the original problem. Since different optimization orders affect the search direction, we consider all possible orders that are mathematically feasible as shown in Appendix C. According to the iteration speed and convergence values, the overall iterative algorithm to solve the original problem (12) is summarized in Algorithm 1.

Next, we address the convergence of Algorithm 1. It is worth pointing out that for the user scheduling subproblem (14) and the UAV trajectory control subproblem (29), we only optimally solve their approximate problems. Define  $\eta\left(\alpha^{l}, \mathbf{B}^{l}, \mathbf{P}^{l}, \mathbf{Q}^{l}\right)$ as the objective value of the original problem (12) at the *l*-th iteration. In step 3 of Algorithm 1, since  $\alpha^{l+1}$  is suboptimal user scheduling of problem (14) with the fixed  $\mathbf{B}^{l}, \mathbf{P}^{l}, \mathbf{Q}^{l}$ , Algorithm 1: Joint Optimization of User Scheduling, Resource Allocation, and Trajectory Control

- 1: Initialization: Initialize iterative index l = 0, maximal iterations  $L_{\text{max}}$ , user scheduling  $\alpha^0$ , bandwidth allocation  $\mathbf{B}^0$ , power allocation  $\mathbf{P}^0$ , UAV's trajectory  $\mathbf{Q}^0$ , and tolerance error  $\epsilon$ .
- 2: repeat
- 3: Given  $\mathbf{B}^l$ ,  $\mathbf{P}^l$ , and  $\mathbf{Q}^l$ , update user scheduling  $\alpha^{l+1}$  by solving problem (14);
- 4: Initialize iterative index  $m_i = 0$ ,  $m_o = 0$ , maximal iterations  $M_{\text{inner}}$ ,  $M_{\text{outer}}$ ,  $\mu$ ,  $\beta$ ,  $\xi$ , and  $\varpi$ ;
- 5: repeat
- 6: Given  $\alpha^{l+1}$ ,  $\mathbf{Q}^l$ ,  $\mu^{m_i}$ ,  $\beta^{m_i}$ ,  $\xi^{m_i}$ , and  $\boldsymbol{\varpi}^{m_i}$ , obtain  $\eta^*$ ,  $\mathbf{B}^*$ , and  $\mathbf{P}^*$  by solving problem (18);
- 7: repeat
- 8: Given  $\eta^*$ ,  $\mathbf{B}^*$ , and  $\mathbf{P}^*$ , update  $\mu^{m_i+1}$ ,  $\beta^{m_i+1}$ ,  $\boldsymbol{\xi}^{m_i+1}$ , and  $\boldsymbol{\varpi}^{m_i+1}$  by applying the gradient method to solve problem (17);
- 9: **until** convergence has been reached or  $m_i \ge M_{inner}$ ;
- 10: Update  $m_0 = m_0 + 1$ ;
- 11: **until** convergence has been reached or  $m_0 \ge M_{outer}$ ;
- 12: Given  $\mu^*$ ,  $\beta^*$ , and  $\varpi^*$ , compute  $\tilde{p}_k^*[n]$  by using (19), then determine the optimal  $\eta^*$ ,  $\mathbf{B}^*$ , and  $\mathbf{P}^*$  by solving problem (15) with given  $\tilde{p}_k^*[n]$ ;
- 13: Set  $\mathbf{B}^{l+1} \leftarrow \mathbf{B}^*$ ,  $\mathbf{P}^{l+1} \leftarrow \mathbf{P}^*$ ;
- 14: Given  $\alpha^{l+1}$ ,  $\mathbf{B}^{l+1}$ , and  $\mathbf{P}^{l+1}$ , obtain the trajectory  $\mathbf{Q}^{l+1}$  by solving problem (40);
- 15: Update l = l + 1;
- 16: **until**  $\left|\eta(\boldsymbol{\alpha}^{l}, \mathbf{B}^{l}, \mathbf{P}^{l}, \mathbf{Q}^{l}) \eta(\boldsymbol{\alpha}^{l-1}, \mathbf{B}^{l-1}, \mathbf{P}^{l-1}, \mathbf{Q}^{l-1})\right| \leq \epsilon \text{ or } l \geq L_{\max}.$

we have

$$\eta\left(\boldsymbol{\alpha}^{l}, \mathbf{B}^{l}, \mathbf{P}^{l}, \mathbf{Q}^{l}\right) \leq \eta\left(\boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l}, \mathbf{P}^{l}, \mathbf{Q}^{l}\right).$$
 (41)

From step 4 to step 13 of Algorithm 1,  $\mathbf{B}^{l+1}$  and  $\mathbf{P}^{l+1}$  are the optimal bandwidth allocation and power control of problem (15) with fixed  $\alpha^{l+1}$  and  $\mathbf{Q}^{l}$ , which follows that

$$\eta\left(\boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l}, \mathbf{P}^{l}, \mathbf{Q}^{l}\right) \leq \eta\left(\boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l+1}, \mathbf{P}^{l+1}, \mathbf{Q}^{l}\right).$$
 (42)

In step 14 of Algorithm 1, since  $R_k^{\text{lb},i}[n]$ ,  $\vartheta_{AG_k}^{\text{lb},i}[n]$ ,  $\Lambda^{\text{lb},l}[n]$ and  $\Upsilon^{\text{lb},l}[n]$  are the lower bound of the first-order Taylor expansion of  $R_k[n]$ ,  $\vartheta_{AG_k}[n]$ ,  $\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2$  and  $\|\mathbf{q}[n]\|^2$ at the local point shown in (31), (35), (38), and (39), respectively, the objective value of convex problem (40) is a lower bound of problem (30). Thus, for given  $\alpha^{l+1}$ ,  $\mathbf{B}^{l+1}$ ,  $\mathbf{P}^{l+1}$ , we have

$$\eta \left( \boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l+1}, \mathbf{P}^{l+1}, \mathbf{Q}^{l} \right) \stackrel{(a)}{=} \eta^{\text{lb}} \left( \boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l+1}, \mathbf{P}^{l+1}, \mathbf{Q}^{l} \right)$$

$$\stackrel{(b)}{\leq} \eta^{\text{lb}} \left( \boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l+1}, \mathbf{P}^{l+1}, \mathbf{Q}^{l+1} \right)$$

$$\stackrel{(c)}{\leq} \eta \left( \boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l+1}, \mathbf{P}^{l+1}, \mathbf{Q}^{l+1} \right),$$
(43)

where  $\eta^{\text{lb}}$  represents the objective value of problem (40).

Here, (a) holds due to the tightness of the first-order Taylor expansions at locally points in problem (40), (b) holds because problem (40) is optimally solved, and (c) holds since the optimal objective value of problem (40) is the lower bound of that of problem (30). The inequality (43) indicates that although an approximate optimization problem (40) is solved to obtain the UAV's trajectory **Q**, the objective value of problem (30) is still non-decreasing after each iteration. Based on (41)-(43), we obtain

$$\eta\left(\boldsymbol{\alpha}^{l}, \mathbf{B}^{l}, \mathbf{P}^{l}, \mathbf{Q}^{l}\right) \leq \eta\left(\boldsymbol{\alpha}^{l+1}, \mathbf{B}^{l+1}, \mathbf{P}^{l+1}, \mathbf{Q}^{l+1}\right).$$
(44)

The inequality (44) suggests that the objective value of problem (12) is non-decreasing after each iteration of Algorithm 1. Since the bandwidth and power in communication systems are limited, the objective value of problem (12) is upper bounded by a finite value. Therefore, the proposed Algorithm 1 is guaranteed to converge.

In this paper, the complexity of Algorithm 1 comes from three aspects. Firstly, in problem (14), as the interior-point method is used to solve the relaxed user scheduling problem based on the given resource allocation and UAV trajectory, the computational complexity is  $O(\log(1/\epsilon)(KN)^{3.5})$ , where  $\epsilon$  is the given solution accuracy of Algorithm 1. Next, to solve problem (15), the overall complexity is  $O(M_{\text{inner}}M_{\text{outer}}\log(1/\epsilon)(KN)^2)$  according to the analytical expression in [33], where  $M_{\text{inner}}$  and  $M_{\text{outer}}$  are the iteration numbers of the inner and outer loops of Lagrange duality. Finally, the complexity of solving problem (40) with CVX is  $O(\log(1/\epsilon)(KN)^{3.5})$ . Assuming L is the iteration number of the overall algorithm, the total complexity of Algorithm 1 can be calculated as  $O(L\log(1/\epsilon)(2(KN)^{3.5} + M_{\text{inner}}M_{\text{outer}}(KN)^2))$ .

# **IV. SIMULATION RESULTS**

In this section, numerical results are provided to verify the effectiveness of joint user scheduling, resource allocation, and UAV trajectory control optimization algorithm in a UAVenabled wireless network. We consider a system with 6 MGUs, which are randomly distributed on a horizontal plane. As explained in Section II, the origin of the 2D Cartesian coordinate is established at UC, and  $\max\{\bar{r}_1/2, r_{\min}\}\$  is the initial flying radius of the UAV, where  $\bar{r}_1$  is the distribution radius of MGUs in time slot n = 1,  $r_{\min} = 200$  m [28]. Thus, the initial position of the UAV is set as  $\mathbf{q}_I = (-\max\{\overline{r}_1/2, r_{\min}\}, 0)$ , while the calculation of UAV's final position  $\mathbf{q}_F = (x_a, y_a)$  can be referred in Appendix A. We assume that the UAV flies at a fixed altitude H = 3000 m [6]. The maximum transmission power of the UAV is  $P_{\text{max}} = 5$  W and the channel power gain at the reference distance  $d_0 = 1$  m is  $\rho_0 = -50$  dB. The data rate threshold is set as  $\gamma^{\text{th}} = 6$  Mbps [21] in a system with the available bandwidth  $B_{\text{max}} = 30$  MHz and the noise power spectrum density is  $N_0 = -169$  dBm/Hz. Furthermore, the minimum and maximum speeds of UAV are  $V_{\rm min} = 20$  m/s and  $V_{\rm max} = 100$  m/s, respectively. The Algorithm 1 convergence threshold is set as  $\epsilon = 10^{-3}$ . The Rician fading model parameters are given by  $B_1 = -4.3221$ ,  $B_2 = 6.0750, C_1 = 0, \text{ and } C_2 = 1$  [17], respectively. If



(a) The flying trajectories of the UAV within different periods T.





(c) Period T = 120 s.

Fig. 2. Optimized trajectories of the UAV under different trajectory adjustment periods T with time slot length  $\delta = 2$  s.

not specified otherwise, the flying trajectory of the UAV is sampled every time slot (i.e.,  $\delta = \frac{T}{N} = 1$  s).

In Fig. 2, we compare the optimal trajectories of the UAV under different trajectory adjustment periods T. All ground MGUs move in the area according to the RPGM model, while the UAV optimizes the trajectory based on our proposed Algorithm 1. In Fig. 2(a), three optimized trajectories under different periods T are depicted. Obviously, as the period T changes, the moving distance and distribution of MGUs change accordingly. Therefore, the switching trajectories of the UAV in different periods T are also different. Such change is the result of the optimization of Algorithm 1, which enables higher throughput of MGUs as much as possible. For clarity, the flying trajectory of the UAV is sampled every 2 s (i.e.,  $\delta = 2$  s), and the sampled points are marked by '\*'. In Fig. 2(b), the UAV makes a detour from the initial position along the track of the red '\*' mark to the switching point within the period T = 60 s. During the period T = 120 s shown in Fig. 2(c), the UAV follows the green '\*' track five times from the initial position to the switching point. Both of the optimization trajectories are obtained according to the users' motion to achieve the best communication channel between the UAV and each MGU. In addition, the moving speed of ground MGUs is much lower than that of the fixed-wing UAV. When the period T changes, the fixed-wing UAV optimizes the trajectory by adjusting the number of flight laps, i.e., by optimizing the UAV's velocity.

In Fig. 3(a), we analyze the relationship between the flight velocity v and the number of laps Cir of the UAV under different periods T. The Cir denotes the number of detour circles from initial point back to initial point, which is a non-negative integer. The position constraint of the switching trajectory point indicates that the number of flight laps Cir must be an integer. Obviously, there is a positive correlation between the velocity v and the number of laps Cir. The UAV's velocity increases by 36.60 m/s, 24.44 m/s, and 18.33 m/s as the number of flight laps adds one turn under periods T = 60s, T = 90 s, and T = 120 s, respectively. In this paper, it is worth noting that the minimum flight velocity  $V_{\min} = 20$ m/s and the maximum flight velocity  $V_{\text{max}} = 100$  m/s of the fixed-wing UAV are constrained, reducing the velocity feasible domain. Furthermore, we can find that the longer the period T, the looser the feasible domain of the velocity v. In Fig. 3(b), we investigate the influence of UAV flying laps and the maximum transmit power P<sub>max</sub> on system performance. It can be observed that the max-min average throughput is the highest when Cir = 5. This is because the better channel gain can be obtained by optimizing the trajectory of the UAV in an air-ground integrated system with dual mobility. Thus, opportunistic communication can be fully utilized to improve the throughput of MGUs. Moreover, the max-min average throughput is positively correlated with the maximum transmit power  $P_{\text{max}}$  for two main reasons. On the one hand, with higher transmit power, the UAV can provide users with a stronger connection and a wider range of communication. On the other hand, increasing the transmission power means enriching the communication resources for users, which can increase the max-min average throughput as well.

In Fig. 4, we explore the impact of ground MGUs' speed and trajectory adjustment period T on max-min average



(a) The optimized UAV velocity versus different laps Cir under different (b) Max-min average throughput versus flying laps of the UAV with periods T. different maximum transmit power  $P_{max}$ .

Fig. 3. Different flight laps Cir versus different periods T and different maximum transmit power  $P_{\text{max}}$ .



Fig. 4. Max-min average throughput versus trajectory adjustment period T with different users' speeds.

throughput. We observe an interesting phenomenon that as the period T increases, the max-min average throughput of the system with the user speed of  $V_e = 5$  m/s fluctuates slightly. For instance, the performance of the system with period T = 110 s is slightly higher than that of T = 100s. This is because, with the slower speed of MGUs, the optimization of the UAVs trajectory becomes more crucial to achieve better channel gain, especially in an air-ground integrated system with dual mobility. However, as the user's moving speed increases, the influence of trajectory adjustment period T is more obvious. In other words, when the period Tincreases, the MGUs move farther and farther away from the initial UAV coverage circle, leading to a sharp decline in maxmin average throughput performance. Thus, the UAV requires timely trajectory switching to improve the moving coverage performance for MGUs.

In Fig. 5, we explore the impact of different environment settings on system performance. For different environment settings, the system performance is different. Specifically, In Fig. 5(a), as the transmit power increases, the max-min

average throughput maintain an increasing trend. In Fig. 5(b), as the number of users increases, the maximum and minimum average rates show a downward trend. It is not difficult to observe that as the factor  $C_1$  increases, the total throughput of the system increases in two different cases, i.e., different power and different user numbers. This is because the increase of  $C_1$  means an increase in the effective fading power, having stronger LOS path signal and less environmental scattering, thus can obtain higher throughput gain. Furthermore, we can see that as the number of users increases, the downward slope of the max-min average throughput curve becomes flatter. This is because when the number of users increases, the elevation gain obtained by the whole system in the Rician channel also increases.

In Fig. 6(a), we compare the max-min average throughput achieved by the following three trajectories: 1) OPT1, the trajectory is obtained by Algorithm 1; 2) OPT2, where the UAV takes the center of the covered area as the flying center and flies in a circle with a radius of 1000 m; and 3) OPT3, where the UAV flies back and forth between the geometric center of the users' distribution locations at the initial time and the final time. Note that the round-trip time cost [28] is included in the straight trajectory scheme, because the fixedwing UAV cannot hover and turn around immediately. In addition, the user scheduling and resource allocation are optimized by Algorithm 1 with the given corresponding trajectory. As shown in Fig. 6(a), OPT1 can achieve higher max-min average throughput than the other two trajectory schemes. One major reason is that the UAV can adjust the flight trajectory to obtain better channel gain. For these three trajectories, the max-min average throughput decreases with the increase of users. This is because the transmit power and bandwidth are assumed to be fixed in the system. As the number of users increases, the resources allocated to each user decrease, thereby reducing the max-min average throughput. Moreover, we can observe that the max-min average throughput gap between the three schemes is narrowing, as the number of users increases. Although the UAV can improve the maxmin average throughput by adjusting the flight trajectory, the



(a) Max-min average throughput versus the transmit power  $P_{\text{max}}$  with (b) Max-min average throughput versus the number of users with different model parameters.



Fig. 5. Achievable max-min throughput with different model parameters  $C_1 + C_2 = 1$ .

(a) Max-min average throughput versus the number of users with (b) Max-min average throughput versus the number of users with different trajectories.

Fig. 6. Max-min average throughput versus the number of users with different optimization schemes.

effect of the trajectory control will become less and less obvious as the number of users increases. In Fig. 6(b), we investigate the following four schemes: 1) Scheme I: All variables are jointly optimized by Algorithm 1; 2) Scheme II: The bandwidth allocation **B** and power control **P** are equally allocated while the user scheduling and UAV trajectory are performed in the same way as in Algorithm 1; and 3) Scheme III: The variables  $\alpha$  are randomly optimized with **B**, and **P** equally allocated, while the UAV trajectory is optimized by Algorithm 1. Similar to Fig. 6(a), due to the limited communication resources, the max-min average throughput of these three schemes decreases with the increase of users. Compared with Scheme III, Scheme II optimizes the user scheduling according to the channel conditions between the UAV and MGUs, thus achieving higher throughput gains in the system with dual mobility. Compared with Scheme II and Scheme III, Scheme I shows obvious advantages, indicating that the resource optimization in Algorithm 1 is effective in improving the max-min average throughput performance of the communication system. In conclusion, Scheme I proposed in this paper has better adaptability to the multi-user system.

#### V. CONCLUSION AND FUTURE WORK

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In this paper, we have investigated a problem of applying the mobile fixed-wing UAV BS to provide moving coverage for MGUs. According to the flight characteristics of the fixedwing UAV and the moving states of MGUs, a fixed-wing UAVenabled wireless network architecture was proposed. Aiming at maximizing the minimum average throughput among users, we first applied variable relaxation, Lagrange dual, and SCA to optimize user scheduling, resource allocation, and UAV trajectory control, respectively. Subsequently, we proposed an efficient iterative algorithm to solve the challenging optimization problem. Extensive simulation results have shown that the proposed algorithm can provide excellent moving coverage performance in such UAV-enabled wireless network. In future work, the optimization of flying radius and number of laps with the fixed flight velocity should be further explored to avoid sharp turnings that require large acceleration and deceleration. Since a single UAV may suffer from reliability problems, it is worth investigating the more general multi-UAV cooperative network based on intelligent mobile user cluster-



Fig. 7. A schematic illustration for the UAV trajectory.

ing in future dynamic network planning. Finally, maximizing the energy-efficient of multi-UAV cooperative networks under the constraints of user mobility and communication requirements is also an interesting problem.

#### APPENDIX A

Derivation of the arc length  $\mathbf{q}[n]\mathbf{q}[n+1]$  and Dubins RSR trajectory switching tangent point F

In Fig. 7, we assume that the center coordinates of circles  $CR_I$  and  $CR_F$  are  $(x_{RI}, y_{RI})$  and  $(x_{RF}, y_{RF})$ , respectively. Thus, the equations of the two circles can be expressed as  $(x - x_{RI})^2 + (y - y_{RI})^2 = r_I^2$  and  $(x - x_{RF})^2 + (y - y_{RF})^2 = r_F^2$ , where  $r_I$  and  $r_F$  denote the radius of  $CR_I$  and  $CR_F$ , respectively. The angle  $\hat{\theta}$  corresponding to the arc length of the UAV moving from time slot n to time slot n + 1, denoted as  $\widehat{\mathbf{q}[n]\mathbf{q}[n+1]}$ , can be obtained by the cosine theorem. Further, the arc length  $\widehat{\mathbf{q}[n]\mathbf{q}[n+1]}$  can be calculated as

$$\widehat{\mathbf{q}[n]\mathbf{q}[n+1]} = r_I \arccos\left(\frac{2r_I^2 - \|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2}{2r_I^2}\right), \,\forall n.$$
(45)

Supposing the equation of the tangent line between these two circles is y = Ax + B. The distance between the center of two circles and the tangent line can be obtained as

$$\begin{cases} \frac{|y_{RI} - Ax_{RI} - B|}{\sqrt{1 + A^2}} = r_I, \\ \frac{|y_{RF} - Ax_{RF} - B|}{\sqrt{1 + A^2}} = r_F. \end{cases}$$
(46)

We assumed that the MGUs are heading towards or staying at the destination, but not in reverse motion. In other words, the UAV follows the Dubins RSR path [14] so that the centers of the two circles fall to the lower right of the tangent, i.e.,

$$y_{RI} - Ax_{RI} - B < 0, \quad y_{RF} - Ax_{RF} - B < 0.$$
 (47)

By substituting (47) into (46), we can obtain  $A = \frac{-2CD\pm\sqrt{4C^2D^2-4(r_I^2-C^2)(r_I^2-D^2)}}{2(r_I^2-C^2)}$ , where  $C = x_{RI} - \frac{x_{RI}r_F - x_{RF}r_I}{r_F - r_I}$ ,  $D = -y_{RI} - \frac{y_{RF}r_I - y_{RI}r_F}{r_F - r_I}$ . However, when  $A = \frac{-CD - \sqrt{C^2D^2 - (r_I^2 - C^2)(r_I^2 - D^2)}}{(-r_I^2 + C^2)}$ , it corresponds to the Dubins right-straight-left (RSL) path [14], which

does not meet the requirements of this paper. Therefore,  $A = \frac{-CD + \sqrt{C^2D^2 - (r_I^2 - C^2)(r_I^2 - D^2)}}{(-r_I^2 + C^2)}$ . Then, we plug A into the equation of the circle to obtain  $B = \frac{(-y_{RF} + Ax_{RF})r_I - (-y_{RI} + Ax_{RI})r_F}{r_F - r_I}$ . By combining the equations of the tangent and the circle, the coordinate of the tangent point  $F = (x_q, y_q)$  can be calculated, where  $x_q = \frac{x_{RI} - (B - y_{RI})A}{A^2 + 1}$ . Since the tangent point F and the center of the circle  $(x_{RI}, y_{RI})$  are related to the equation shown as follows

$$\begin{cases} x_q = x_{RI} - r_I \cos \theta, \\ y_q = y_{RI} + r_I \sin \theta, \end{cases}$$
(48)

thus  $\theta = \arccos\left(\frac{x_{RI} - x_q}{r_I}\right)$  is determined. Substituting  $\theta$  into (48), we can get the coordinate of the tangent point F.

# Appendix B

APPROXIMATION FOR INTER-SUBCARRIER-INTERFERENCE

Due to the dual mobility of the UAV and MGUs, intersubcarrier-interference (ICI) induced by Doppler shift needs to be considered. The received signal over subcarrier s at the user k can be rewritten as

$$Y_k^s = \sqrt{h_k^s p_k^s X_k^s + I_k^s + n_k^s},$$
 (49)

where the available spectrum  $B_{\text{max}}$  of the network is divided into S subcarriers, denoted by  $S = \{1, ..., S\}$ .  $h_k^s$  and  $p_k^s$  are the channel power gain and transmit power of the UAV to user k over subcarrier s, respectively.  $X_k^s$  represents data symbols transmitted by the UAV to user k over subcarrier s with unit power,  $I_k^s$  is the Doppler shift induced ICI to subcarrier sreceived at the user k, and  $n_k^s$  is AWGN over subcarrier swith variance  $\sigma^2$  and zero mean. The maximum achievable rate at the user k from the UAV, denoted by  $C_k$ , is given by [21]

$$C_k = \sum_{s \in \mathcal{S}_k} \log_2 \left( 1 + \frac{h_k^s p_k^s}{\sigma^2 + |I_k^s|^2} \right),\tag{50}$$

where  $S_k$  represents the set of subcarriers allocated to user k. The ICI to subcarrier s can be approximated by [21]

$$I_{k}^{s} = \sum_{s' \in \mathcal{S}_{k}, s' \neq s} X_{k}^{s'} H_{k}^{s'} \frac{\sin(\pi(s'-s+\varepsilon))}{S \times \sin\left(\frac{\pi(s'-s+\varepsilon)}{S}\right)} e^{j\pi(s'+\varepsilon-s)\frac{S-1}{S}} + \sum_{k' \in \mathcal{K}, k' \neq k} \sum_{s' \in \mathcal{S}_{k'}} X_{k'}^{s'} H_{k'}^{s'} \frac{\sin(\pi(s'-s+\varepsilon))}{S \times \sin\left(\frac{\pi(s'-s+\varepsilon)}{S}\right)} e^{j\pi(s'+\varepsilon-s)\frac{S-1}{S}},$$
(51)

where  $\varepsilon = f_d / \Delta f$ ,  $\Delta f$  is the subcarrier spacing. The maximum Doppler shift is given by  $f_d = \frac{vf_c}{c}$ , where v is the relative speed between the UAV and user k,  $f_c$  represents the center frequency, and c is the velocity of light in vacuum.  $H_{k'}^{s'}$  and  $H_{k}^{s'}$  are the channel impulse responses of the s'-th subcarrier of user k' and k, respectively. Similar to prior works [21], [34], the center frequency is set as  $f_c = 3.5$  GHz, the subcarrier spacing is set as  $\Delta f = 30$  kHz [35], the number of subcarriers is S = 1000, the relative speed between the UAV and user k is set as v = 100 m/s. Under the parameter settings, the ratio of the ICI power to the desired signal power is -27.3



Fig. 8. Max-min average throughput versus the transmit power  $P_{\text{max}}$  with different ICI.



Fig. 9. Convergence of different optimization orders for max-min average throughput.

dB, which indicates that the ICI is weak compared with the desired signal and can be regarded as a constant for simplicity. In Fig. 8, we compare the max-min average throughput under different values of ICI. It is easily observed that as the ICI value increases, the max-min average throughput decreases, i.e., the smaller the ICI, the lower the loss in channel capacity. When the ICI is below -115 dBm, the impact from ICI is relatively weak and can be neglected.

# APPENDIX C ANALYSIS OF THE OPTIMIZATION ORDER

The six optimization orders of the three subproblems are denoted as SRT, STR, RST, RTS, TSR, and TRS, where S denotes the user scheduling optimization problem, R denotes the resource allocation optimization problem, and T denotes the trajectory optimization problem. In Fig. 9, the initial values of the iterations of SRT, STR, and TSR are different, but all three optimization orders have the same iteration speed and local optimal value. However, the other three optimization orders, i.e., RST, RTS, and TRS, oscillate during the iterative process, which is the reason why heuristic algorithms [36], [37] usually solve the linear mixed-integer programming empirically at first.

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