



Trajectory Optimization for UAV Assisted Fog-RAN Network

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Abstract. In this paper, we study an unmanned aerial vehicle (UAV) assisted Fog-RAN network where an UAV perform as mobile remote radio head (RRH) to help base station forwards signals to the multiple users in the downlink transmissions, and a dedicated ground station (GS) acts as baseband unit (BBU) pool. To achieve fairness among users, we minimize the maximum transmission delay for all terrestrial users in downlink communication by jointly optimizing the user scheduling and the UAVs trajectory. Since the formulation problem is an integer non-convex optimization problem, we propose an effective iterative algorithm to find efficient solutions by using Majorize Minimization (MM) algorithm. We also confirm the convergence of our proposed algorithm. Numerical results indicate that the proposed algorithm can significantly reduces transmission delay compared to circular trajectories and fixed base station solutions.

Keywords: UAV communications · Delay minimization · Trajectory design

1 Introduction

With high mobility ability, unmanned aerial vehicle (UAV) wireless communication can fully exploit this potential to more efficiently communicate with terrestrial users. The communication assistance of UAV can significantly reduce the delay between the core network and the ground user comparing with traditional small-cell technology [1]. A large amount of research work has been devoted to studies of UAV-assisted communication. Among them, most researchers focused on optimizing the transmit power and trajectory of the UAV to improve the performance. For example, the authors in [2] describe an UAV wireless network in which a UAV is used to act as airborne mobile base stations to serve some users on the ground, and the objective is to maximize throughput of all ground users by jointly optimizing the UAV trajectories and user scheduling. Wireless communication using UAVs has become an attractive technology for many applications

in the future wireless systems. However, the limited durability of drones greatly hampers the practical implementation of drone communications. To overcome the limited durability of UAVs, the authors in [3] propose a new UAV communication solution that address durability issues by using active caching at the user. Besides, the uplink transmission energy of the ground terminal and propulsion energy of the UAV trade-off via trajectory design is considered in [4]. Regarding the backhaul link between the UAV and the core network, the researchers mainly optimize the UAV antenna transmit power and core network layout to achieve UAV backhaul performance optimization. Unmanned aerial vehicles (UAVs) are considered as wireless access points for services in commercial operating networks. The author models the drone in [5], which operates at a certain height on the ground to provide wireless service in the coverage area covered by its directional antenna, while the drone uses the existing ground base station network performs wireless backhaul. The formula for successfully establishing the probability of a backhaul and the expected data rate on the backhaul link are derived in [6].

The previous studies show the performance optimization of the UAV communication network. However, most of them focus on the communication between the user and the UAV. In the upcoming 5G, Fog-RAN network architecture has become one of promising solutions to reduce the transmission delay by introducing edge computing and edge caching. In this study, we intend to combine the advantages of UAV assisted communication and Fog-RAN by proposing a UAV assisted Fog-RAN network [7]. Specifically, we assume that an UAV are deployed as mobile remote radio head (RRH) to provide wireless connectivity, and a dedicated ground station (GS) acts as baseband unit (BBU) pool. Our aim is to improve the performance of this communication network by optimizing the UAV's trajectory.

In specific, in the considered UAV assisted Fog-RAN network, we assume that an UAV are deployed as RRH to provide wireless connectivity, and a dedicated GS acts as BBU pool as mentioned in [5]. Compared to previous research, this paper firstly considers deploying UAV in Fog-RAN network. To achieve fairness among users, we minimize the maximum transmission delay by optimizing the multiuser communication scheduling, the UAVs trajectory at GS. This optimization problem has not been studied in the previous literature according to the author's knowledge. As the problem is the non-convex optimization problem, we propose an the efficient iterative algorithm to solve it. In particular, we apply the block coordinate descent method to divide the problem into two sub-questions. The UAV trajectory optimization problem with fixed user scheduling is hard to solve due to its non-convexity. Therefore, we apply the Majorize-Minimization algorithm [8] to replace the concave part of the objective function with its first-order Taylor expansion. Through multiple iterations, the solution that is closer to the optimal solution of the objective function can be obtained. By relaxing the binary variables for multiuser communication schedule into continuous variables, the user scheduling problem with fixed UAV trajectory becomes an linear programming (LP) problem. Through formula derivation, we also confirm the

convergence of our proposed algorithm. Numerical results demonstrate that the proposed algorithm is able to significantly reduce transmission delay compared to circular trajectories and fixed base station solutions.

The rest of this article is explained below. Section 2 introduces the drone communication model and problem description. In Sect. 3, by using block coordinate descent method and Majorize-Minimization (MM) algorithm, we propose an iterative algorithm based on UAV delay optimization. In Sect. 4, the convergence performance of the proposed algorithm is verified. Section 5 presents the performance of the newly proposed algorithm can be proved based on numerical results. In the end, we summarize the article in Sect. 6.

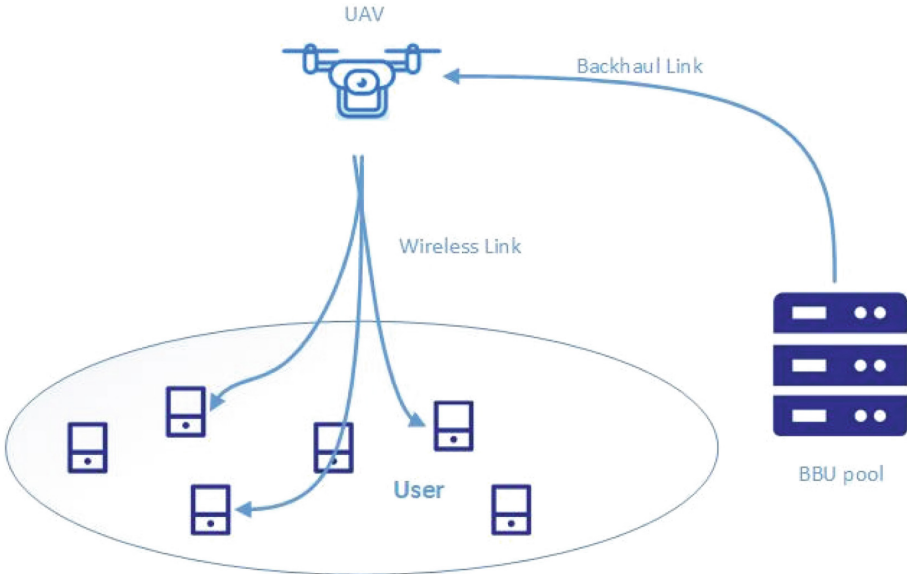


Fig. 1. An UAV assisted Fog-RAN network.

2 System Model and Problem Formulation

2.1 System Model

As shown in Fig. 1, the considered UAV assisted Fog-RAN network consists of the UAV deployed as mobile RRH to serve a set of K ground users (GUs), and GS acts as BBU pool. The level position of GU k is denoted as $w_k \in \mathbb{R}^{2 \times 1}$, $k \in K$. The level position of GS is denoted as $w_S \in \mathbb{R}^{2 \times 1}$ and the dedicated GS height is h . Assume that all UAVs share the common frequency band for each successive period of duration $T > 0$ s. All drones are flying at a fixed ground level for H and the level location of UAV at instant t is denoted by $q(t) = [x(t), y(t)]^T \in \mathbb{R}^{2 \times 1}$ with $0 \leq t \leq T$. For convenience of explanation, the period T is discretized

into N equal time slots with each be $\tau = \frac{T}{N}$. We assume that the UAV needs to return to its initial position at the end of each period T . The trajectories of the UAV are also limited by the maximum speed. In total, the UAV trajectories need to meet the following constraints

$$q[1] = q[N], \forall m, \quad (1)$$

$$\|q[n+1] - q[n]\|^2 \leq V_m^2 \tau^2, \quad n = 1, \dots, N-1. \quad (2)$$

The distance from the UAV to user k in time slot n is

$$d_k[n] = \sqrt{\|q[n] - w_k\|^2 + H^2}. \quad (3)$$

The distance from the UAV to GS in time slot n can be expressed as

$$d[n] = \sqrt{\|q[n] - w_S\|^2 + (H-h)^2}. \quad (4)$$

We assume that the small-scale fading of the links from the UAV to the ground users follows Rayleigh fading. Then, the signal to noise ratio (SNR) of the link between the UAV to user k during slot n can be expressed as

$$r_k[n] = \frac{P_u g_k[n] A_0 d_k[n]^{-\alpha_u}}{N_0}, \quad (5)$$

where P_u denotes the UAV transmit power, N_0 is the noise power, $g_k[n]$ corresponds to the small-scale fading and $g_k[n] \sim \exp(1)$, A_0 is a constant, and α_u is path loss exponent. We suppose that each user is served by at most one UAV per time slot. We use a binary variable $\alpha_k[n] \in \{0, 1\}$, to indicate the fact whether the UAV serves user k in time slot n . This yields the following constraints, $\alpha_{k,m}[n] \leq 1, \forall k, \sum_{k=1}^K \alpha_k[n] \leq 1$ and $\alpha_k[n] \in \{0, 1\}, \forall k$. We mainly aim to improve the transmission reliability, and the transmission reliability is the probability that the signal receiver's SNR is greater than or equal to the preset SNR threshold β . The successful transmission probability of the UAV and the user k during slot n is given by

$$\begin{aligned} P_k[n]^s &= Pr \left\{ g_k[n] \geq \frac{\beta_u N_0}{P_u A_0 d_k[n]^{-\alpha_u}} \right\} \\ &= \exp \left(- \frac{\beta_u N_0}{P_u A_0 d_k[n]^{-\alpha_u}} \right). \end{aligned} \quad (6)$$

The same procedure may be easily adapted to obtain the successful transmission probability of the GS and the UAV communication given by

$$\begin{aligned} P[n]^s &= Pr \left\{ g[n] \geq \frac{\beta_S N_0}{P_S A_0 d[n]^{-\alpha_S}} \right\} \\ &= \exp \left(- \frac{\beta_S N_0}{P_S A_0 d[n]^{-\alpha_S}} \right). \end{aligned} \quad (7)$$

We assume the size of each of the I files is X bit. Suppose each file is divided into $Y = X/R_p$ packets, where R_p represents the packet size (in bits). We also

assume that random linear code [9] is used for each file and a file can be recovered from any $Y_p = (1 + \varepsilon)Y$ coded packets, where $\varepsilon \ll 1$ is the coding overhead. GU k should at least receive the Y encoded packet successfully if it wants to recover the file. We define T_{f_i} as the time required for packet transmission so that on average Y packets are received by GU k during slot n . Otherwise, the UAV can retrieve file f_i from the GS with each transmitted packet having success probability $P[n]^s$ (transmission duration of one packet is t_p). In conclude, file f_i costs time of required packet transmission between the UAV and the GU k during slot n is given by

$$T_{f_i} = \frac{Y}{P_k[n]^s} t_p + \frac{Y}{P_k[n]^s P[n]^s} t_p. \quad (8)$$

We define T_k as the average time required for serving one file request for the GU k , which is given by

$$T_k = \frac{1}{N} \sum_{i=1}^I a_i \sum_{n=1}^N \alpha_k[n] \left(\frac{Y}{P_k[n]^s} t_p + \frac{Y}{P_k[n]^s P[n]^s} t_p \right), \forall k. \quad (9)$$

2.2 Problem Formulation

By assuming that the locations of the GUS and the dedicated GS are known, the optimization problem is formulated as

$$\begin{aligned} \min_{q, \alpha} \quad & \max_{k \in K} T_k \\ \text{s.t.} \quad & \alpha_k[n] = 1, \forall k \end{aligned} \quad (10a)$$

$$\sum_{k=1}^K \alpha_k[n] = 1 \quad (10b)$$

$$\alpha_k \in (0, 1), \forall k \quad (10c)$$

$$\|q[n+1] - q[n]\|^2 \leq V_m^2 \tau^2, n = 1, \dots, N-1 \quad (10d)$$

$$q[1] = q[N]. \quad (10e)$$

3 Proposed Solution

The formulated problem is divided into two sub-questions. The UAV trajectory optimization problem with fixed user scheduling is hard to solve due to its non-convexity. Therefore, we apply the Majorize-Minimization algorithm [8] to replace the concave part of the objective function with its first-order Taylor expansion. Through multiple iterations, the solution that is closer to the optimal solution of the objective function can be obtained. By relaxing the binary variables for multiuser communication schedule into continuous variables, the user scheduling problem with fixed UAV trajectory becomes an LP problem.

3.1 UAV Trajectory Optimization

Define μ is $\max_{k \in K} T_k$, for given user scheduling, the UAV trajectory of problem can be expressed as

$$\min_{\mu, q[n]} \mu \quad \|q[n+1] - q[n]\|^2 \leq V_m^2 \tau^2, n = 1, \dots, N-1 \quad (11a)$$

$$q[1] = q[N] \quad (11b)$$

$$T_k \leq \mu, \forall k. \quad (11c)$$

Note that due to the non-convex constraints (11c) respect to $q[n]$, the problem (11) is not a convex minimization problem. In general, there is no efficient way to obtain the optimal solution. To tackle the non-convexity of (11c), the Majorize-Minimization algorithm can be applied. Under the given conditions, the original function is approximated as a more manageable function. Specifically, define $q^r[n]$ as the UAV trajectory in the r -th iteration. According to prior knowledge, any convex function is globally delimited by its first-order Taylor expansion at any point. Based on this, we get the following lower bound of $T_k[n]$ in r iterations

$$\begin{aligned} T_k[n] &= \frac{Y}{P_k[n]^s P[n]^s} t_p \\ &\geq A_k^r[n](q[n] - q[n]^r) + B_k[n] = \hat{T}_k[n], \end{aligned} \quad (12)$$

where $A_k^r[n]$ and $B_k^r[n]$ are constants which can be written as

$$\begin{aligned} A_k^r[n] &= Y \exp\left(\frac{\beta_u N_0}{P_u A_0 d_k^r[n]^{-\alpha_u}} + \frac{\beta_s N_0}{P_s A_0 d^r[n]^{-\alpha_s}}\right) t_p \\ &\left(\frac{2\beta_u N_0 (q^r[n] - w_k)^T}{P_u A_0} + \frac{2\beta_s N_0 (q^r[n] - w_0)^T}{P_s A_0}\right), \forall k, n, \end{aligned} \quad (13)$$

$$B_k^r[n] = Y \exp\left(\frac{\beta_u N_0}{P_u A_0 d_k^r[n]^{-\alpha_u}} + \frac{\beta_s N_0}{P_s A_0 d^r[n]^{-\alpha_s}}\right) t_p, \forall k, n. \quad (14)$$

To this end, T_k in constraints (11c) are transformed into

$$T_k = \frac{1}{N} \sum_{i=1}^I a_i \sum_{n=1}^N \alpha_k[n] \left[\frac{Y}{P_k[n]^s} t_p + T_k[n]\right] \leq \mu, \forall k. \quad (15)$$

Problem (11) is converted to the following question

$$\min_{\mu, q[n]} \mu \quad \|q[n+1] - q[n]\|^2 \leq V_m^2 \tau^2, n = 1, \dots, N-1 \quad (16a)$$

$$q[1] = q[N] \quad (16b)$$

$$\frac{1}{N} \sum_{i=1}^I a_i \sum_{n=1}^N \alpha_k[n] \left[\frac{Y}{P_k[n]^s} t_p + \hat{T}_k[n]\right] \leq \mu, \forall k. \quad (16c)$$

Since the right side of the constraint (16c) is convex for $q^r[n]$, (16c) becomes convex constraint. Furthermore, (16a) are convex quadratic constraints and (16b) is a linear constraint. Therefore, the problem (16) is a convex problem that can be solved by CVX.

3.2 User Scheduling Optimization

For a given drone trajectory, the user-scheduled optimization variables are binary. We relax the binary variables in (10d) as continuous variables, the user scheduling of problem (10) can be solved by optimizing the following issues

$$\begin{aligned} \min_{\mu, \alpha_k[n]} \quad & \mu \\ \text{s.t.} \quad & T_k \leq \mu, \forall k \end{aligned} \quad (17a)$$

$$\sum_{k=1}^K \alpha_k[n] = 1, \forall n \quad (17b)$$

$$0 \leq \alpha_k[n] \leq 1, \forall k, n. \quad (17c)$$

Since the problem (17) is a standard LP, existing optimization tools can effectively solve this problem. With the obtained continuous-value solution, the binary solution needs to be refactored. Here, we simply assume $\alpha_k[n] = [\alpha_k[n]] = 0$ if $0 < \alpha_k[n] < 0.5$. Otherwise, $\alpha_k[n] = [\alpha_k[n]] = 1$.

4 Convergence Analysis

Based on the solutions obtained from the previous two problems, we propose a global iterative algorithm for the problem (10) by applying the block coordinate descent method. Then, by solving problems (17), and (11) respectively, while keeping the other variable blocks fixed, the UAV trajectory, and user scheduling are alternately optimized. In summary, we obtain Algorithm 1 by combining the solutions of three subproblems. When given user scheduling, the algorithm of UAV trajectory problem are summarized in Algorithm 2. We next demonstrate the convergence of Algorithm 1. In step 4 of Algorithm 1, we obtain the optimal solution for (17) for a given $q^r[n]$. The problem follows that

$$\mu \{\alpha_k^{r+1}[n], q^r[n]\} \geq \mu \{\alpha_k^r[n], q^r[n]\}. \quad (18)$$

For given $q^r[n]$, $\alpha_k^{r+1}[n]$ in step 5 of Algorithm 1, we obtain the approximately optimal solution for (11) and we have

$$\begin{aligned} \mu \{\alpha_k^{r+1}[n], q^r[n]\} &\stackrel{(a)}{=} \mu^t \{\alpha_k^{r+1}[n], q^r[n]\} \\ &\stackrel{(b)}{\geq} \mu^t \{\alpha_k^{r+1}[n], q^{r+1}[n]\} \\ &\stackrel{(c)}{\geq} \mu \{\alpha_k^{r+1}[n], q^{r+1}[n]\}, \end{aligned} \quad (19)$$

Where equation (a) holds because the first-order Taylor in (12) expands at the given point $q^r[n]$. This means that problem (16) has the same target value as the problem (11). Equation (b) holds, because we obtained the optimal solution for (16) in step 6 of Algorithm 1. Equation (c) holds, because the optimal value calculated in the problem (16) is the upper bound of the problem (11). In summary, we obtain

$$\mu\{\alpha_k^r[n], q^r[n]\} \geq \mu\{\alpha_k^{r+1}[n], q^{r+1}[n]\}. \quad (20)$$

Equation (20) indicates that the objective value of the problem (10) after each iteration of Algorithm 1 is non-increasing. On the other hand, the objective function must have a lower bound, for example 0. Therefore, we claim that Algorithm 1 converges to at least the local optimal solution.

Algorithm 1: Block coordinate descent algorithm for problem (10)

- Input** : The objective value μ^{r+1} ;
Output: The optimal solution as $\{q^r, \alpha^r\}$;
- 1 Initialize $b_n^0[i]$ and $q^0[n]$. Let $r = 0$;
 - 2 Set the convergence threshold δ_1 ;
 - 3 **repeat**
 - 4 Optimize problem (17) for given $q^r[n]$, and the solution is expressed as $\alpha_k^{r+1}[n]$;
 - 5 Optimize problem (11) for given $\{q^r[n], \alpha_k^{r+1}[n]\}$ and the solution is expressed as $q^{r+1}[n]$;
 - 6 Update $r = r + 1$;
 - 7 **until** $|\mu^{r+1} - \mu^r| < \delta_1$;
-

5 Simulation Results

In the following, we present some simulations to verify the effectiveness of the algorithm in this work. The basic simulation parameters are listed in Table 1. We

Algorithm 2: Majorization-Minimization Algorithm for problem (11)

- Input** : The objective value $(\mu^r)^{i+1}$;
Output: The optimal trajectory as $q^r[n]$;
- 1 Solve problem (11), initialize the UAV trajectory $(q^r[n])^0$;
 - 2 Set the SNR requirements β ;
 - 3 Set the convergence limit δ_2 ;
 - 4 **repeat**
 - 5 Solve problem (11), and denote the optimal solution as $(q^r[n])^{i+1}$;
 - 6 **until** $|(\mu^r)^{i+1} - (\mu^r)^i| < \delta_2$;
-

Table 1. Simulation parameters

Parameter	Value	Description
Y	100	Coded packets of each of the I files
H	100 m	UAV flight altitude
h	50 m	GS height
V_m	50 m/s	The maximum UAV speed
P_u	0.5 W	The UAV transmit power
P_S	5 W	The GS transmit power
t_p	1 ms	Transmission duration of one packet
β_u, β_S	3 dB	SNR threshold
A_0	-15 dB	Path loss constant
N_0	-50 dBm	Noise power
α_u, α_S	3 dB	Path loss exponent

consider a set of 6 GU and a dedicated GS wireless systems. They are randomly and evenly distributed in a 2D area of $1.5 \times 1.5 \text{ km}^2$. Figure 2 shows the optimized trajectory of Algorithm 1 solved at different times T . According to the trajectory diagram Fig. 2, as the cycle T increases, the drone uses its maneuverability to modify its trajectory to bring it closer to GUS. When $T = 210 \text{ s}$, the UAV remains stationary for a period of time at the apex of the trajectory, flying at maximum speed between the vertices of the trajectory. When $T = 30$ and 90 s , the UAVs fly at maximum speed V_m so as to be as close as possible to each user in each period T to obtain higher communication quality.

In Fig. 3, we show that Algorithm 1 can finally converge when $T = 90 \text{ s}$. According to Fig. 3, the minimized maximum delay of the proposed algorithm is rapidly reduced as the number of iterations increases. After about 20 iterations, the algorithm finally converges. In Fig. 4, we consider the scenario of using single UAVs; (1) Static UAV, where each UAV is placed in the geometric center of the ground users position and GS position; (2) Simple circular trajectory, With the geometric center position of the user and GS position as the center; (3) Optimized trajectory, obtained by Algorithm 1. Compared the performance of three different scenarios in Fig. 4, the benefits of the proposed trajectory are fully demonstrated. For optimized trajectories with large periods T , the UAV can provide higher quality communication for the ground users, and the transmission delay will be smaller.

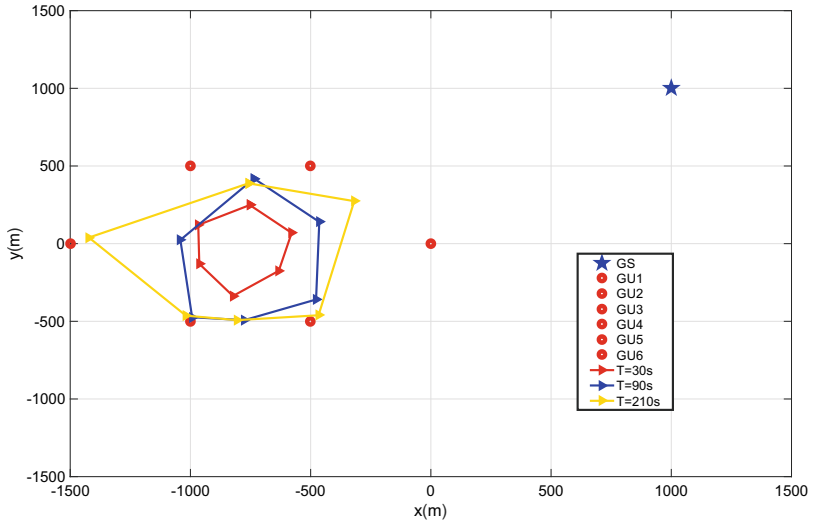


Fig. 2. The optimized trajectory of Algorithm 1 solved at different times T .

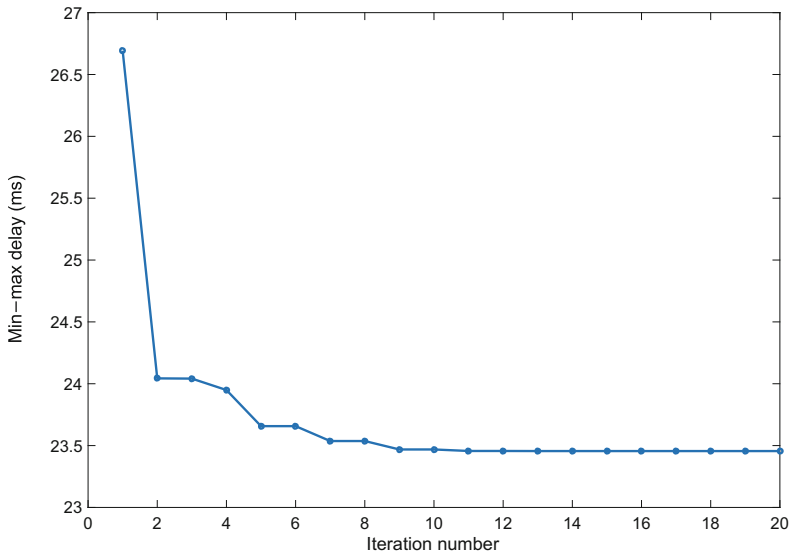


Fig. 3. Convergence performance of the Algorithm 1.

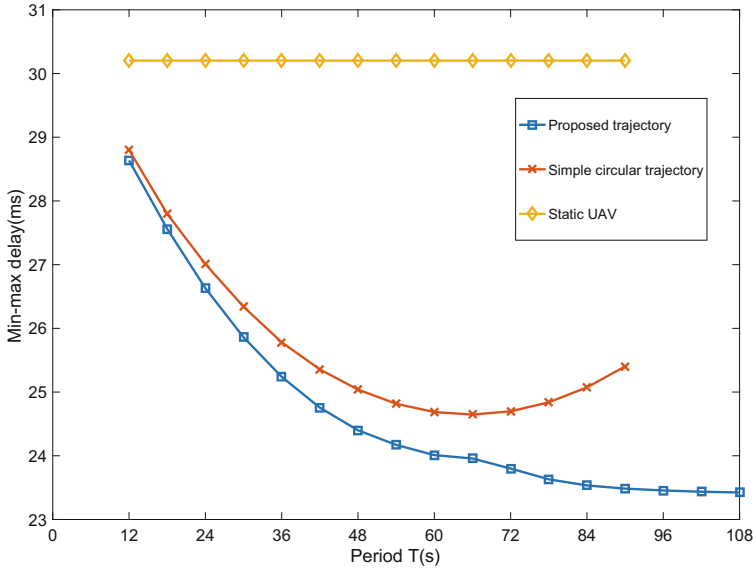


Fig. 4. Min-max delay with different trajectory designs as a function of period T .

6 Conclusions

Reducing transmission delay is one of the main challenges in UAV-enabled communication research. To achieve fairness among users, we minimize the maximum delay by jointly optimizing the UAVs trajectory and communication scheduling. The simulation results show that the algorithm can significantly reduce the total transmission delay of multi-UAV networks. We found a fundamental trade-off between the total transmission delay of multi-UAV communication network model and the UAV flight period T . In the future work, we consider the scenario of using a single UAV, and designing a new scheme caching at the UAV. We aim to improve the performance of this communication network by optimizing the UAVs trajectory and caching design.

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