Journal of Systems Engineering and Electronics
Vol. 33, No. 2, April 2022, pp.312 – 321

Energy efficiency maximization for buffer-aided multi-UAV relaying communications

CAO Dongju[1], YANG Wendong[1,*], CHEN Hui[1], WU Yang[1], and TANG Xuanxuan[2]

1. College of Communications Engineering, Army Engineering University of PLA, Nanjing 210007, China;
2. Radar Non-commissioned Officer School, Air Force Early Warning Academy, Wuhan 430019, China

Abstract: This paper studies a multiple unmanned aerial vehicle (UAV) relaying communication system, where multiple UAV relays assist the blocked communication between a group of ground users (GUs) and a base station (BS). Since the UAVs only have limited-energy in practice, our design aims to maximize the energy efficiency (EE) through jointly designing the communication scheduling, the transmit power allocation, as well as UAV trajectory under the buffer constraint over a given flight period. Actually, the formulated fractional optimization problem is difficult to be solved in general because of non-convexity. To resolve this difficulty, an efficient iterative algorithm is proposed based on the block coordinate descent (BCD) and successive convex approximation (SCA) techniques, as well as the Dinkelbach's algorithm. Specifically, the optimization variables of the formulated problem are divided into three blocks and we alternately optimize each block of the variables over iteration. Numerical results verify the convergence of the proposed iterative algorithm and show that the proposed designs achieve significant EE gain, which outperform other benchmark schemes.

Keywords: unmanned aerial vehicle (UAV) relay, buffer aided, communication scheduling, transmit power allocation, UAV trajectory, energy efficiency (EE).

DOI: 10.23919/JSEE.2022.000032

1. Introduction

Recently, unmanned aerial vehicles (UAVs) have been extensively used in different applications to meet various needs, thanks to their autonomy, flexibility, as well as promising application prospects [1–4]. On the one hand, UAVs can be applied as air service platforms to provide corresponding communication services for ground nodes. For instance, when the ground base stations (BSs) are destroyed or the data to be processed exceeds its computing power, the dynamic UAVs can be used as air BSs to assist wireless communications [5–7]. In [8], the authors studied a three-dimensional (3D) deployment problem of UAV-BS, in order to cover the most users with the smallest transmit power. When the ground BS fails, if the mobility of the UAV is utilized to optimize the position of the UAV-BS, the system throughput can still achieve a greater gain [9]. In addition, UAVs can serve as mobile relays to assist long-distance information transmission or blocked ground communications [10]. In [11], the authors studied the performance of multiple UAV relays in two typical communication applications that form a single multi-hop link or multiple dual-hop links relaying systems. On the other hand, UAVs can be used as mobile nodes for monitoring, emergency rescue, and cargo delivery [12]. Despite the promising future, research on UAVs still face huge challenges. First, the characteristics of UAVs mobility and broadcast communication lead to intermittent connection of communication links, and the safety of communication is vulnerable [13,14]. Besides, the limited on-board energy of UAVs is the most fundamental factor influencing the performance and operation time of UAV systems [15].

In terms of UAV's energy, the energy consumption of UAV systems are mainly made up of two parts [16]. One is defined as communication-related energy that is usually used for signal transmission and processing, and the other is defined as propulsion energy which is used to ensure the motility of the UAVs during the flight period, such as movement and hovering. However, the energy consumption for propulsion was far over the communication-related energy consumption, and the baseline energy consumption models of fixed-wing and rotary-wing UAVs were proposed in [17,18], respectively. For UAV-enabled applications, energy consumption saving is crucial to ensure the performance and stability via reducing unnecessary energy consumption. We usually minimize unnecessary communication-related energy consumption

---

Manuscript received August 28, 2020.

*Corresponding author.

This work was supported by the National Natural Science Foundation of China (61671474).

of the UAVs through rational resource allocation and mission planning. In [19,20], the authors respectively studied the energy efficiency (EE) of a single UAV or multiple UAVs, that is, minimizing the transmit power via optimizing the deployment of UAVs to cover the target area better. Optimizing the scheduling of beaconing periods to improve the EE of UAVs was discussed in [21], where a non-cooperative game theory was considered to search the optimal beaconing periods. We can avoid the unnecessary maneuverability of the UAVs to minimize the propulsion energy consumption via UAV velocity and acceleration optimization. In [22,23], Ahmed et al. jointly considered the communication designs, UAV trajectory, velocity, and acceleration to maximize the EE of single UAV-BS and single UAV relaying system, respectively. In these works, a good compromise was made between the throughput and energy consumption by reasonably optimizing the design.

Motivated by the research above, this paper considers the EE optimization in a multi-UAV relaying system, where half-duplex and buffer-aided UAVs serve as mobile relays to enable the information transmission between a group of ground users (GUs) and a BS because the direct links are blocked. For fairness, it is assumed that one UAV can only communicate with one ground node at most, and one ground node can only transmit information with one UAV at the same time. The main contributions of this paper are summarized as follows.

(i) Buffer-aided UAV relays are considered in this paper which provide feasibility for communication scheduling, because buffers overcome the difficulty that the traditional relaying mode is limited by time. In addition, the store-carry-forward relaying mode is considered in this paper, therefore, UAVs can collect the data and buffer it when they fly near the GUs and forward the data to the BS according to the buffer states and the channel state information (CSI).

(ii) The UAV propulsion energy consumption is investigated, which is a function related to the UAV's velocity and acceleration. To balance the system throughput and energy consumption, we maximize the EE of the considered system via jointly optimizing the communication scheduling, transmit power allocation, as well as the UAV trajectory under the buffer constraint. However, the formulated problem is non-convex and close coupled, which is difficult to be tackled in general. To resolve this issue, an efficient iterative algorithm is proposed through adopting the block coordinate descent (BCD) and successive convex approximation (SCA) techniques, and Dinkelbach's methods. Moreover, the proposed design makes a good compromise between the throughput and energy consumption thanks to the degree of freedom given by buffer and trajectory optimization.

The rest of this paper is organized as follows: Section 2 introduces the system model and formulates the energy efficiency maximization problem for the multi-UAV relaying system under the buffer constraint. In Section 3, an efficient iterative algorithm is proposed based on BCD and SCA techniques, as well as the Dinkelbach's algorithm. Numerical results are presented in Section 4, and the conclusions are summarized in Section 5.

2. System model and problem formulation

2.1 System model

As shown in Fig. 1, a multi-UAV relaying communication system is considered, where K ($K>1$) buffer-aided UAVs serve as mobile relays to assist ground communications between U ($U>1$) GUs and a BS. The UAV relays flying at fixed attitude H apply half-duplex and decode-and-forward (DF) relaying strategies to aid the blocked ground communications. Assume that the UAVs provide services to ground nodes in a time-division multiple access (TDMA) mode during any flight period T ($T>0$), and the buffer Z of UAVs is infinite.

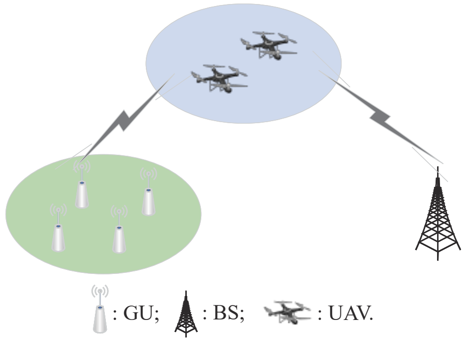


Fig. 1 System model

In this paper, we consider a 3D Cartesian coordinate system, where the horizontal coordinates of GUs and a BS are given by $\boldsymbol{w}_u=[x_u,y_u]^{\mathrm{T}}(u=1,2,\cdots,U)$ and $\boldsymbol{w}_D=[x_D,y_D]^{\mathrm{T}}$, respectively. For convenience of analysis, the given period T is dispersed into N sufficiently small time slots with equal length d_t, i.e., $T=Nd_t$. Therefore, the horizontal coordinate of UAV k can be approximated as $\boldsymbol{q}_k[n]=[x_k[n],y_k[n]]^{\mathrm{T}}$ in the time slot n. The UAV's trajectories should satisfy the following constraints:

$$\|\boldsymbol{q}_k[1]-\boldsymbol{q}_I\|\leqslant D,\ \forall k, \tag{1}$$

$$\|\boldsymbol{q}_k[N]-\boldsymbol{q}_F\|\leqslant D,\ \forall k, \tag{2}$$

$$\|\boldsymbol{v}_k[n]\|<V_{\max},\ \forall k,n, \tag{3}$$

$$\|\boldsymbol{a}_k[n]\|<a_{\max},\ \forall k,n, \tag{4}$$

where $\boldsymbol{q}_I$ and $\boldsymbol{q}_F$ denote the initial and final horizontal coordinate of UAVs, respectively. $D = V_{\max} d_t$ is the maximum instantaneous travel distance of a UAV, where $V_{\max}$ represents the maximum flight velocity of UAVs, and $a_{\max}$ is the maximum acceleration. According to the inherent relationship between the UAV's horizontal coordinate $\boldsymbol{q}_k[n]$ and instantaneous velocity $\boldsymbol{v}_k[n]$ and acceleration $\boldsymbol{a}_k[n]$, we have the following constraints:

$$\boldsymbol{q}_k[n+1] = \boldsymbol{q}_k[n] + \boldsymbol{v}_k[n] d_t + \frac{1}{2}\boldsymbol{a}_k[n] d_t^2, \tag{5}$$

$$\boldsymbol{v}_k[n+1] = \boldsymbol{v}_k[n] + \boldsymbol{a}_k[n] d_t, \tag{6}$$

where $n = 1, 2, \cdots, N-1, \forall k$. Besides, UAV's trajectories should satisfy the collision avoidance constraint in multi-UAV communication systems, thus, we have

$$\left\|\boldsymbol{q}_k[n] - \boldsymbol{q}_j[n]\right\| \geqslant D,\ \forall n, k, j, k \neq j. \tag{7}$$

Consider that the wireless communication channels between the UAV relays and the ground nodes may be influenced by obstacles, the air-to-ground (A2G) channels are modeled as Rician fading channels that are affected by both small-scale fading and large-scale path fading [24–26]. Therefore, the channel power gains from GUs to UAVs and UAVs to BS can be respectively modeled [26] as follows:

$$\begin{aligned} &h_{u,k}[n] = h_{u,k}[n]^{\text{LoS}} + h_{u,k}[n]^{\text{NLoS}} \approx \\ &\sqrt{\frac{\beta}{(G+1)\, d_{u,k}[n]^2}}\left(\sqrt{G}\mathrm{e}^{\mathrm{j}\frac{2\pi}{\lambda} d_{u,k}[n]} + g_{u,k}[n]\right) = \\ &\sqrt{\frac{\beta}{(G+1)\, d_{u,k}[n]^2}}\left(\sqrt{G}\mathrm{e}^{\mathrm{j}\frac{2\pi}{\lambda} \theta_{u,k}[n]} + g_{u,k}[n]\right),\ \forall u, k, n, \end{aligned} \tag{8}$$

$$\begin{aligned} &h_{k,D}[n] = h_{k,D}[n]^{\text{LoS}} + h_{k,D}[n]^{\text{NLoS}} \approx \\ &\sqrt{\frac{\beta}{(G+1)\, d_{k,D}[n]^2}}\left(\sqrt{G}\mathrm{e}^{\mathrm{j}\frac{2\pi}{\lambda} d_{k,D}[n]} + g_{k,D}[n]\right) = \\ &\sqrt{\frac{\beta}{(G+1)\, d_{k,D}[n]^2}}\left(\sqrt{G}\mathrm{e}^{\mathrm{j}\frac{2\pi}{\lambda} \theta_{k,D}[n]} + g_{k,D}[n]\right),\ \forall k, n \end{aligned} \tag{9}$$

where $G \geqslant 0$ represents the Rician factor and β is the reference channel power gain. $d_{u,k}[n] = \sqrt{H^2 + \|\boldsymbol{q}_k[n] - \boldsymbol{w}_u\|^2}$ and $d_{k,D}[n] = \sqrt{H^2 + \|\boldsymbol{q}_k[n] - \boldsymbol{w}_D\|^2}$ are expressed as the instantaneous distance from UAVs to the GUs and the BS, respectively. $2\pi/\lambda d_{u,k}[n]$ ($2\pi/\lambda d_{k,D}[n]$) is the line-of-sight (LoS) component and λ is the wavelength. Since $\theta_{u,k}[n]$ ($\theta_{k,d}[n]$) is influenced by the UAVs locations variation over a fight period, we model it as a uniformly distributed random variable in $[0, 2\pi)$ to facilitate trajectory optimization. Moreover, $g_{u,k}[n]$ ($g_{k,D}[n]$) is non-line-of-sight (NLoS) channel component that obeys complex Gaussian distribution, i.e., $g_{u,k}[n]\,(g_{k,D}[n]) \sim \mathrm{CN}(0,1)$.

In this paper, half-duplex and store-carry-forward relaying strategies are adopted. As a result, a UAV can only serve one ground node at most in each time slot and one ground node can only transmit data to one UAV at most in each time slot. To this end, the binary variables $\{s_{u,k}[n], s_{k,D}[n]\}$ are introduced, which indicate whether the GU u communicates with the UAV k in time slot n. If true, $s_{u,k}[n] = 1$; else, $s_{u,k}[n] = 0$. Then, the communication scheduling constraints are given by

$$\sum_{u=1}^{U} s_{u,k}[n] + s_{k,D}[n] \leqslant 1,\ \forall k, n, \tag{10}$$

$$\sum_{k=1}^{K} s_{u,k}[n] \leqslant 1,\ \forall u, n, \tag{11}$$

$$[n] \leqslant 1,\ \forall n, \tag{12}$$

$$\{s_{u,k}[n], s_{k,D}[n]\} \in \{0, 1\}. \tag{13}$$

Denote $p_{u,k}[n]$ and $p_{k,D}[n]$ as the transmit power of GU u and UAV k in time slot n, respectively. It is assumed that the transmit power should satisfy the average and peak power constraints, which are denoted as P_{mean} and P_{peak}, respectively. Then, we have

$$0 \leqslant p_{u,k}[n] \leqslant P_{\text{peak}},\ \forall u, n, \tag{14}$$

$$\frac{1}{N}\sum_{n=1}^{N} p_{u,k}[n] \leqslant P_{\text{mean}},\ \forall u, n, \tag{15}$$

$$0 \leqslant p_{k,D}[n] \leqslant P_{\text{peak}},\ \forall k, n, \tag{16}$$

$$\frac{1}{N}\sum_{n=1}^{N} p_{k,D}[n] \leqslant P_{\text{mean}},\ \forall k, n. \tag{17}$$

Based on the discussion above, the achievable rate from GU u to UAV k in bps/Hz in time slot n is given by

$$R_{u,k}[n] = s_{u,k}[n] \log_2\left(1 + \frac{p_{u,k}[n] \left\|h_{u,k}[n]\right\|^2}{\sigma^2}\right) \tag{18}$$

where σ^2 is the additive white Gaussian noise power at the receiver. According to the store-carry-forward relaying strategy, the UAVs temporarily store the data sent by the GUs in their buffers, and then forward it to the BS following the "first-in-first-out" principle at any subsequent time slot according to the CSI. At the end of time slot n, the buffer state of UAV k can be written as

$$Z_k[n] = Z_k[n-1] + R_{u,k}[n]. \tag{19}$$

Similarly, the achievable rate from UAV j ($j \neq k$) to the BS, and the buffer state of UAV j in time slot n can be expressed as

$$R_{j,D}[n] = s_{j,D}[n]\log_2\left(1+\frac{p_{j,D}[n]\left\|h_{j,D}[n]\right\|^2}{\sigma^2}\right), \tag{20}$$

$$Z_j[n] = Z_j[n-1] - R_{j,D}[n]. \tag{21}$$

Since the data that UAVs can forward limited by the amount of stored data, $R_{j,D}[n]$ can be reformulated as

$$R_{j,D}[n] = \min\left(s_{j,D}[n]\log_2\left(1+\frac{p_{j,D}[n]\left\|h_{j,D}[n]\right\|^2}{\sigma^2}\right), Z_j[n-1]\right). \tag{22}$$

Actually, the energy consumption of UAVs is mainly composed of two parts. One is the communication-related energy of UAVs such as signal reception and forwarding. The other is the propulsion energy that is used to ensure the maneuverability of the UAVs during the flight period. It is universally acknowledged that the communication-related energy can often be negligible compared to the propulsion energy. According to [17], the propulsion energy consumption of fixed-wing UAVs related to $\boldsymbol{v}_k[n]$ and $\boldsymbol{a}_k[n]$ can be modeled as

$$E_k[n] = d_t\left[c_1\|\boldsymbol{v}_k[n]\|^3 + \frac{c_2}{\|\boldsymbol{v}_k[n]\|}\left(1+\frac{\|\boldsymbol{a}_k[n]\|^2}{g^2}\right) + \varDelta_k\right] \tag{23}$$

where c_1 and c_2 are two constant parameters correlated with the UAV's weight, wing area and air density, etc., g denotes the gravitational acceleration. $\varDelta_k$ is the kinetic energy which can be expressed as $\varDelta_k = 1/2m\left(\|v_k[N]\|^2 - \|v_k[1]\|^2\right)$, where m denotes the total mass of the UAV.

2.2 Problem formulation

For convenience of analysis, we define $S = \{s_{u,k}[n], s_{k,D}[n], \forall u,k,n\}$, $P = \{p_{u,k}[n], p_{k,D}[n], \forall u,k,n\}$, and $Q = \{q_k[n], v_k[n], a_k[n], \forall k,n\}$. Assume that the location of ground nodes and the underlying parameters of UAVs are known, the aim is to maximize the EE of the multi-UAV relaying communication system via jointly designing communication scheduling S, transmit power P, and UAV trajectory Q subject to the buffer constraint. Therefore, the optimization problem can be mathematically formulated as

$$\max_{S,P,Q} \frac{B\sum_{n=1}^{N}\sum_{k=1}^{K} R_{k,D}[n]}{\sum_{n=1}^{N}\sum_{k=1}^{K} d_t\left[c_1\|\boldsymbol{v}_k[n]\|^3 + \frac{c_2}{\|\boldsymbol{v}_k[n]\|}\left(1+\frac{\|\boldsymbol{a}_k[n]\|^2}{g^2}\right)+\varDelta_k\right]} \tag{24a}$$

$$\text{s.t.}\begin{cases} Z_k[n] \geqslant 0, \ \forall k,n, \\ (1)-(7),(10)-(17). \end{cases} \tag{24b}$$

It is easy to notice that problem (24) is non-convex for several reasons. Firstly, the optimization variable S for communication scheduling is related to the binary integer programming in constraint (13). Secondly, UAVs collision avoidance constraint (7) and buffer constraint (24b) are still non-convex concerning transmit power P and UAV trajectory Q. Thirdly, the fractional objective function is non-concave. Therefore, problem (24) is difficult to be worked out in general. Moreover, the buffer constraint (24b) indicates that the UAV relays can only transmit the data that has been stored from GUs, which is also known as the information-causal constraint, so problem (24) can be reformulated as

$$\max_{S,P,Q} \frac{B\sum_{n=1}^{N}\sum_{k=1}^{K} s_{k,D}[n]\log_2\left(1+\frac{p_{k,D}[n]\left\|h_{k,D}[n]\right\|^2}{\sigma^2}\right)}{\sum_{n=1}^{N}\sum_{k=1}^{K} d_t\left[c_1\|\boldsymbol{v}_k[n]\|^3 + \frac{c_2}{\|\boldsymbol{v}_k[n]\|}\left(1+\frac{\|\boldsymbol{a}_k[n]\|^2}{g^2}\right)+\varDelta_k\right]} \tag{25a}$$

$$\text{s.t.}\begin{cases} \sum_{i=1}^{n} s_{k,D}[i]\log_2\left(1+\frac{p_{k,D}[i]\left\|h_{k,D}[i]\right\|^2}{\sigma^2}\right) \leqslant \\ \sum_{i=1}^{n}\sum_{u=1}^{U} s_{u,k}[i]\log_2\left(1+\frac{p_{u,k}[n]\left\|h_{u,k}[i]\right\|^2}{\sigma^2}\right) \\ n = 1,2,\cdots,\mathrm{N}, \ \forall k, \\ (1)-(7),(10)-(17) \end{cases} \tag{25b}$$

3. The proposed algorithm

To make the non-convex problem (25) more tractable, an efficient algorithm by adopting BCD and SCA techniques, as well as the Dinkelbach's method are proposed. Specifically, the optimization variables of problem (25) are divided into three blocks, namely the communication scheduling variables S, the transmit power variables P, as well as UAV trajectory variables Q. Next, these block variables are alternately optimized in an iterative manner until the algorithm converges to a local optimal solution. Generally, the proposed algorithm can only get a local optimal solution of the original problem after a series of mathematical treatments.

3.1 Communication scheduling

For given transmit power allocation P and UAV trajectory Q, the communication scheduling of problem (25) is reduced to

$$\max_{S}\sum_{n=1}^{N}\sum_{k=1}^{K} s_{k,D}[n]\log_2\left(1+\frac{p_{k,D}[n]\left\|h_{k,D}[n]\right\|^2}{\sigma^2}\right)$$
$$\text{s.t. } (10)-(13),(25\text{b}). \tag{26}$$

It is worth noting that the mixed integer programming of problem (26) results in its non-convexity. To make it more tractable, the binary variables in (13) are relaxed to continuous variables, i.e., $0 \leqslant \{s_{m,k}[n], s_{k,d}[n]\} \leqslant 1$. After that, problem (26) can be rephrased as

$$\max_{S} \sum_{n=1}^{N}\sum_{k=1}^{K} s_{k,D}[n]\log_2\left(1+\frac{p_{k,D}[n]\left\|h_{k,D}[n]\right\|^2}{\sigma^2}\right), \tag{27a}$$

$$\text{s.t.}\begin{cases} \displaystyle\sum_{u=1}^{U} s_{u,k}[n]+s_{k,D}[n] \leqslant 1,\ \ \forall k,n, & \text{(27b)}\\ \displaystyle\sum_{k=1}^{K} s_{u,k}[n] \leqslant 1,\ \ \forall u,n, & \text{(27c)}\\ \displaystyle\sum_{k=1}^{K} s_{k,D}[n] \leqslant 1,\ \ \forall n, & \text{(27d)}\\ 0 \leqslant \{s_{u,k}[n], s_{k,d}[n]\} \leqslant 1, & \text{(27e)}\\ \displaystyle\sum_{i=1}^{n} s_{k,D}[i]\log_2\left(1+\frac{p_{k,D}[i]\left\|h_{k,D}[i]\right\|^2}{\sigma^2}\right) \leqslant & \\ \displaystyle\sum_{i=1}^{n}\sum_{u=1}^{U} s_{u,k}[i]\log_2\left(1+\frac{p_{u,k}[i]\left\|h_{u,k}[i]\right\|^2}{\sigma^2}\right) & \text{(27f)}\\ n=1,2,\cdots,N,\ \ \forall k. & \end{cases}$$

Note that problem (27) is linear regarding the communication scheduling variables S for given $\{P,Q\}$. Then, problem (27) can be efficiently solved by convex optimization tools [27]. Obviously, when the equalities in constraints (27b) – (27d) hold, the optimal solution S is achieved.

3.2 Transmit power allocation

Next, the transmit power P at GUs and UAV relays is investigated for given communication scheduling S and UAV trajectory Q. Therefore, the transmit power allocation of problem (25) can be simplified as

$$\max_{P} \sum_{n=1}^{N}\sum_{k=1}^{K} s_{k,D}[n]\log_2(1+p_{k,D}[n]\gamma_{k,D}[n]), \tag{28a}$$

$$\text{s.t.}\begin{cases} \displaystyle\sum_{i=1}^{n} s_{k,D}[i]\log_2(1+p_{k,D}[i]\gamma_{k,D}[i]) \leqslant & \\ \displaystyle\sum_{i=1}^{n}\sum_{u=1}^{U} s_{u,k}[i]\log_2(1+p_{u,k}[i]\gamma_{u,k}[i]), & \text{(28b)}\\ n=1,2,\cdots,N,\ \ \forall k, & \\ (14)-(17), & \end{cases}$$

where $\gamma_{k,D}[n]=\left\|h_{k,D}[n]\right\|^2/\sigma^2$ and $\gamma_{u,k}[n]=\left\|h_{u,k}[n]\right\|^2/\sigma^2$. Since the left hand side of information causality constraints in (28b) is non-convex with regard to $p_{k,D}[n]$, which will lead to the non-convexity of problem (28). To tackle this issue, the slack variables $u=\{u_{k,D}[n],\forall k,n\}$ are introduced, problem (28) can be approximated as

$$\max_{P,u} \sum_{n=1}^{N}\sum_{k=1}^{K} s_{k,d}[n]\,u_{k,D}[n], \tag{29a}$$

$$\text{s.t.}\begin{cases} 0 \leqslant p_{u,k}[n] \leqslant P_{\text{peak}},\ \ \forall u,n, & \text{(29b)}\\ \displaystyle\frac{1}{N}\sum_{n=1}^{N} p_{u,k} \leqslant [n]P_{\text{mean}},\ \ \forall u,n & \text{(29c)}\\ 0 \leqslant p_{k,D}[n] \leqslant P_{\text{peak}},\ \ \forall k,n, & \text{(29d)}\\ \displaystyle\frac{1}{N}\sum_{n=1}^{N} p_{k,D}[n] \leqslant P_{\text{mean}},\ \ \forall k,n, & \text{(29e)}\\ u_{k,D}[n] \leqslant \log_2(1+p_{k,D}[n]\gamma_{k,D}[n]),\ \ \forall k,n, & \text{(29f)}\\ \displaystyle\sum_{i=1}^{n} s_{k,D}[i] \leqslant u_{k,D}[i] & \\ \displaystyle\sum_{i=1}^{n}\sum_{u=1}^{U} s_{u,k}[i]\log_2(1+p_{u,k}[i]\gamma_{u,k}[i]), & \text{(29g)}\\ n=1,2,\cdots,N,\ \ \forall k. & \end{cases}$$

It can be observed that problem (29) is convex and can be efficiently solved. Actually, the optimal solution P to problem (29) is usually the lower bound of problem (28) for given communication scheduling S and UAV trajectory Q, if and only if the equality in constraint (29f) holds, problems (28) and (29) have the same optimal solution P.

3.3 UAV trajectory optimization

In this section, the UAV trajectory Q is discussed for given communication scheduling S and transmit power allocation P. For convenience, we let

$$P_{u,k}[n]=\frac{p_{u,k}[n]\beta}{\sigma^2(G+1)}\left(\sqrt{G}\mathrm{e}^{\mathrm{j}\theta_{u,k}[n]}+g_{u,k}[n]\right)^2,\ \ \forall u,k,n, \tag{30a}$$

$$P_{k,D}[n]=\frac{p_{k,D}[n]\beta}{\sigma^2(G+1)}\left(\sqrt{G}\mathrm{e}^{\mathrm{j}\theta_{k,D}[n]}+g_{k,D}[n]\right)^2,\ \ \forall k,n. \tag{30b}$$

Then, the UAV trajectory of problem (25) can be reduced as

$$\max_{Q}\frac{B\displaystyle\sum_{n=1}^{N}\sum_{k=1}^{K} s_{k,D}[n]\log_2\left(1+\frac{P_{k,D}[n]}{\|\boldsymbol{q}_k[n]-\boldsymbol{w}_D[n]\|^2+H^2}\right)}{\displaystyle\sum_{n=1}^{N}\sum_{k=1}^{K} d_t\left[c_1\|\boldsymbol{v}_k[n]\|^3+\frac{c_2}{\|\boldsymbol{v}_k[n]\|}\left(1+\frac{\|\boldsymbol{a}_k[n]\|^2}{g^2}\right)+\varDelta_k\right]} \tag{31a}$$

$$\text{s.t.}\begin{cases}\sum_{i=1}^{n} s_{k,D}[i]\log_2\left(1+\dfrac{P_{k,D}[i]}{\|\boldsymbol{q}_k[i]-\boldsymbol{w}_D[i]\|^2+H^2}\right)\leqslant \\ \sum_{i=1}^{n}\sum_{u=1}^{U} s_{u,k}[i]\log_2\left(1+\dfrac{P_{u,k}[i]}{\|\boldsymbol{q}_k[i]-\boldsymbol{w}_u[i]\|^2+H^2}\right), \\ n=1,2,\cdots,N,\ \forall k, \\ (1)-(7). \end{cases} \tag{31b}$$

Obviously, problem (33) is still non-convex because of the non-concavity of the fractional objective function of (31a) and the non-convexity of constraints in (7) and (31b) with regard to the trajectory variables Q. To tackle this difficult, the SCA technique and the Dinkelbach's algorithm are applied to obtain an approximate solution of problem (31). Firstly, the slack variables $\varphi=\{\varphi_{k,D}[n], \forall k,n\}$ and $\tau=\{\tau_k[n],\forall k,n\}$ are introduced, problem (31) can be approximated as

$$\max_{Q,\varphi,\tau}\frac{B\sum_{n=1}^{N}\sum_{k=1}^{K}s_{k,D}[n]\varphi_{k,D}[n]}{\sum_{n=1}^{N}\sum_{k=1}^{K}d_t\left[c_1\|\boldsymbol{v}_k[n]\|^3+\dfrac{c_2}{\tau_k[n]}\left(1+\dfrac{\|\boldsymbol{a}_k[n]\|^2}{g^2}\right)+\varDelta_k\right]}, \tag{32a}$$

$$\text{s.t.}\begin{cases}\varphi_{k,D}[n]\leqslant\log_2\left(1+\dfrac{P_{k,D}[n]}{\|\boldsymbol{q}_k[n]-\boldsymbol{w}_D[n]\|^2+H^2}\right),\ \forall k,n, & (32\text{b}) \\ \tau_k^2[n]\,\|\boldsymbol{v}_k[n]\|^2,\ \forall k,n, & (32\text{c}) \\ \sum_{i=1}^{n}s_{k,D}[i]\varphi_{k,D}[i]\leqslant & \\ \sum_{i=1}^{n}\sum_{u=1}^{U}s_{u,k}[i]\log_2\left(1+\dfrac{P_{u,k}[i]}{\|\boldsymbol{q}_k[i]-w_u[i]\|^2+H^2}\right), & (32\text{d}) \\ n=1,2,\cdots,N,\ \forall k, & \\ (1)-(7). & \end{cases}$$

Compare problem (31) and (32), and problem (32) is the lower bound in general. If and only if the equalities in constraints (32c) and (33d) hold, problem (32) achieves an optimal solution and problems (31) and (32) are equivalent. Even though constraint (32b) is convex in terms of $\|\boldsymbol{q}_k[n]-\boldsymbol{w}_D[n]\|^2$, the resulting set of a convex quadratic function is usually non-convex. Similarly, constraints (7), (32c), and (33d) are non-convex. As a result, problem (32) is non-convex.

To resolve the non-convexity of constraints (7) and (32b) – (32d), the SCA technique is applied which maximizes a lower bound of the original function by a more tractable function at any given feasible point [28]. First, since $\log_2\left(1+P_{k,D}[n]/\|\boldsymbol{q}_k[n]-\boldsymbol{w}_D[n]\|^2+H^2\right)$ convex with regard to $\|\boldsymbol{q}_k[n]-\boldsymbol{w}_D[n]\|^2$, its global under-estimator can be obtained by applying the first-order Taylor expansion at the given point $\left\|\boldsymbol{q}_k^f[n]-\boldsymbol{w}_D[n]\right\|^2$,

$$\log_2\left(1+\frac{P_{k,D}[n]}{\|\boldsymbol{q}_k[n]-\boldsymbol{w}_D[n]\|^2+H^2}\right)\geqslant\log_2\left(1+\frac{P_{k,D}[n]}{\psi_{k,D}^f[n]}\right)-$$
$$\frac{P_{k,D}[n]\left(\|\boldsymbol{q}_k[n]-\boldsymbol{w}_D[n]\|^2-\left\|\boldsymbol{q}_k^f[n]-\boldsymbol{w}_D[n]\right\|^2\right)}{\left(\psi_{k,D}^f[n]+P_{k,D}[n]\right)\psi_{k,D}^f[n]}\overset{\varDelta}{=}\phi_{k,D}[n] \tag{34}$$

where $\psi_{k,D}^f[n]=\left\|\boldsymbol{q}_k^f[n]-\boldsymbol{w}_D[n]\right\|^2+H^2$. Similarly, since constraints (32c) and (7) are convex in terms of $\boldsymbol{v}_k[n]$, $\boldsymbol{q}_k[n]$, and $\boldsymbol{q}_j[n]$, the lower bound functions can be achieved at the given points $\boldsymbol{v}_k{}^f[n]$, $\boldsymbol{q}_k{}^f[n]$, and $\boldsymbol{q}_j{}^f[n]$, respectively.

$$\left\|\boldsymbol{q}_k[n]-\boldsymbol{q}_j[n]\right\|^2\geqslant2\left(\boldsymbol{q}_k^f[n]-\boldsymbol{q}_j^f[n]\right)^{\mathrm{T}}$$
$$(\boldsymbol{q}_k[n]-\boldsymbol{q}_j[n])-\left\|\boldsymbol{q}_k^f[n]-\boldsymbol{q}_j^f[n]\right\|^2 \tag{35}$$

$$\|\boldsymbol{v}_k[n]\|^2\geqslant\left\|\boldsymbol{v}_k^f[n]\right\|^2+2\left(\boldsymbol{v}_k^f[n]\right)^{\mathrm{T}}\left(\boldsymbol{v}_k[n]-\boldsymbol{v}_k^f[n]\right) \tag{36}$$

Next, we resolve the non-concavity of the information-causality constraint (32d). It is not difficult to notice that $\log_2\left(1+P_{u,k}[n]/\|\boldsymbol{q}_k[n]-\boldsymbol{w}_u[n]\|^2+H^2\right)$ is convex in terms of $\|\boldsymbol{q}_k[n]-\boldsymbol{w}_u[n]\|^2$ in constraint (32d). Therefore, we can get its lower bound function by the same method as the problem above. Given the feasible point $\left\|\boldsymbol{q}_k^f[n]-\boldsymbol{w}_u[n]\right\|^2$,we have

$$\log_2\left(1+\frac{P_{u,k}[n]}{\|\boldsymbol{q}_k[n]-\boldsymbol{w}_u[n]\|^2+H^2}\right)\geqslant\log_2\left(1+\frac{P_{u,k}[n]}{\psi_{u,k}^f[n]}\right)-$$
$$\frac{P_{u,k}[n]\left(\|\boldsymbol{q}_k[n]-\boldsymbol{w}_u[n]\|^2-\left\|\boldsymbol{q}_k^f[n]-\boldsymbol{w}_u[n]\right\|^2\right)}{\left(\psi_{u,k}^f[n]+P_{u,k}[n]\right)\psi_{u,k}^f[n]}\overset{\Delta}{=}\phi_{u,k}[n] \tag{37}$$

where $\psi_{u,k}^f[n]=\left\|\boldsymbol{q}_k^f[n]-\boldsymbol{w}_u[n]\right\|^2+H^2$. Then, problem (31) can be approximated as

$$\max_{Q,\varphi,\tau}\frac{B\sum_{n=1}^{N}\sum_{k=1}^{K}s_{k,D}[n]\varphi_{k,D}[n]}{\sum_{n=1}^{N}\sum_{k=1}^{K}d_t\left[c_1\|\boldsymbol{v}_k[n]\|^3+\dfrac{c_2}{\tau_k[n]}\left(1+\dfrac{\|\boldsymbol{a}_k[n]\|^2}{g^2}\right)+\varDelta_k\right]} \tag{38a}$$

$$\text{s.t.}\begin{cases} \|\boldsymbol{q}_k[1]-\boldsymbol{q}_I\| \leqslant D,\ \forall k, & \text{(38b)}\\ \|\boldsymbol{q}_k[N]-\boldsymbol{q}_F\| \leqslant D,\ \forall k, & \text{(38c)}\\ \|\boldsymbol{v}_k[n]\| < V_{\max},\ \forall k,n, & \text{(38d)}\\ \|\boldsymbol{a}_k[n]\| < a_{\max},\ \forall k,n, & \text{(38e)}\\ \boldsymbol{q}_k[n+1] = \boldsymbol{q}_k[n]+\boldsymbol{v}_k[n]d_t+\dfrac{1}{2}\boldsymbol{a}_k[n]d_t^2, & \\ \forall k, n=1,2,\cdots,N-1, & \text{(38f)}\\ \boldsymbol{v}_k[n+1]=\boldsymbol{v}_k[n]+\boldsymbol{a}_k[n]d_t,\ \forall k,n=1,2,\cdots,N-1, & \text{(38g)}\\ V_{\max}^2+\|\boldsymbol{q}_k^f[n]-\boldsymbol{q}_j^f[n]\|^2- & \\ 2\left(\boldsymbol{q}_k^f[n]-\boldsymbol{q}_j^f[n]\right)^{\mathrm{T}}(\boldsymbol{q}_k[n]-\boldsymbol{q}_j[n])\leqslant 0,\ \forall k, j\neq k, n & \text{(38h)}\\ \tau_k^2[n]-\left(\|\boldsymbol{v}_k^f[n]\|^2+2(\boldsymbol{v}_k^f[n])^{\mathrm{T}}\left(\boldsymbol{v}_k[n]-\boldsymbol{v}_k^f[n]\right)\right)\leqslant 0, & \\ \forall k,n & \text{(38i)}\\ \varphi_{k,D}[n]\leqslant \phi_{k,D}[n],\ \forall k,n, & \text{(38j)}\\ \displaystyle\sum_{i=1}^{n} s_{k,D}[i]\varphi_{k,D}[i]\leqslant \sum_{i=1}^{n}\sum_{u=1}^{U} s_{u,k}[i]\phi_{k,D}[i], & \\ n=1,2,\cdots,N,\ \forall k. & \text{(38k)} \end{cases}$$

Obviously, the numerator of the objective function (38a) is concave and non-negative. Also, the denominator and the feasible bound are convex. Therefore, problem (38) can be called a concave-convex fractional programming problem. When the numerator, denominator and feasible region meet the above conditions, the fraction function of the form like $F(r)=Z(r)/X(r)$ can be transformed into the function of the form like $F(r)=Z(r)-\alpha X(r)$ by the Dinkelbach's algorithm, where α is a constantly updated value that depends on $\alpha_{i+1}=Z_{r_i}/X_{r_i}$. Moreover, the Dinkelbach's algorithm is guaranteed to converge which has been proved in [29,30]. Therefore, problem (38) can be approximated as

$$\max_{Q,\varphi,\tau}\sum_{n=1}^{N}\sum_{k=1}^{K}(f_{k,D}[n]-\alpha_i h_k[n])$$

$$\text{s.t.}\ (38\text{b})-(38\text{k}) \tag{39}$$

where

$$f_{k,D}[n]=Bs_{k,D}[n]\varphi_{k,D}[n], \tag{40}$$

$$h_k[n]=d_t\left[c_1\|\boldsymbol{v}_k[n]\|^3+\frac{c_2}{\tau_k[n]}\left(1+\frac{\|\boldsymbol{a}_k[n]\|^2}{g^2}\right)+\varDelta_k\right], \tag{41}$$

where α_i depends on $\sum_{n=1}^{N}\sum_{k=1}^{K} f_{k,D}[n]/h_k[n]$. Actually, problem (39) always maximizes the lower bound of problem (31), so the objective value of the original problem should be non-decreasing over iterations.

Algorithm 1 Alternating optimization algorithm for problem (25)

```
1. Initialization: Initialize communication scheduling, transmit power allocation and UAV trajectory $\{S^l, P^l, Q^l\}$. Let the accuracy tolerance $\varepsilon \geqslant 0$ and the iteration number $l = 0$,
2. Repeat
3.     Solve problem (27) with given $P^l$ and $Q^l$, and update the optimal solution $S^{l+1}$.
4.     Solve problem (29) with given $S^{l+1}$ and $Q^l$, and update the optimal solution $P^{l+1}$.
5.     Solve problem (39) with given $S^{l+1}$ and $P^{l+1}$, and update the optimal solution $Q^{l+1}$.
6.     Update $l = l + 1$.
7. Until The objective value of problem (25) converges to the prescribed accuracy $\varepsilon$.
```

3.4 Overall algorithm

Based on the discussion above, the key of proposed alternating is to alternately optimize the communication scheduling S, transmit power allocation P and UAV trajectory Q via employing the BCD and SCA techniques, as well as the Dinkelbach's algorithm, for which the details of the overall algorithm are summarized in Algorithm 1. The bound in (29f) indicates that problem (29) maximizes the lower bound of the original problem (25), and the inequations in (34) – (36) and (38) suggest that the optimal solution of problem (39) is the lower bound of the original problem (25). Therefore, the objective value of problem (25) obtained by solving the optimal solution of problems (27), (29), and (39) is non-decreasing over iterations. Moreover, since the optimal value of problem (25) is finite, Algorithm 1 is guaranteed to converge.

4. Numerical results

In this section, numerical results are provided to demonstrate the validity of the proposed design, which jointly designs the communication scheduling, transmit power allocation as well as UAV trajectory to maximize the EE of a multi-UAV relaying wireless communication system. For comparison, two benchmark schemes are considered as shown below.

(i) Based on the system model of the proposed design, we maximize the EE via only considering communication scheduling and power allocation without trajectory optimization (denoted as ECP). Under this scheme, the UAVs fly in different directions with a semicircle of 500 m radius.

(ii) The other benchmark scheme maximizes the system throughput without considering the UAV's energy consumption via jointly optimizing communication scheduling, power allocation and UAV trajectory (denoted as TCPT).

It is considered that the numbers of GUs and UAVs are $U=4$, $K=2$, respectively. The specific distributions of GUs and BS are shown in Fig. 2, and the two UAVs use semicircles in different directions as initial trajectories where the corresponding initial and final locations are set as $\boldsymbol{q}_I=[500,500]^{\mathrm{T}}$ and $\boldsymbol{q}_F=[500,-500]^{\mathrm{T}}$, respectively. The fixed attitude of UAVs is set as $H=100$ m and, the maximum velocity and acceleration of UAVs are set as $V_{\max}=40\ \mathrm{m/s}$ and $a_{\max}=5\ \mathrm{m/s^2}$, respectively. Referring to [17], we set $c_1=9.26\times10^4$ and $c_2=2\,250$. The communication bandwidth is set as $B=1$ MHz, the noise power is supposed to be $\sigma^2=-110$ dBm and the reference channel power gain is set as $\beta=-50$ dBm. It is assumed that peak power and average power are set as $P_{\max}=0.04\ W$ and $P_{\text{mean}}=P_{\max}/4$, respectively. Moreover, the accuracy of convergence is set as $\varepsilon=10^{-3}$.

Fig. 2 plots the different UAV's trajectories of proposed design and TCPT scheme. In Fig. 2, the GUs are marked with black ●, the BS and the initial/final location are marked with black ▲ and red ★, respectively.

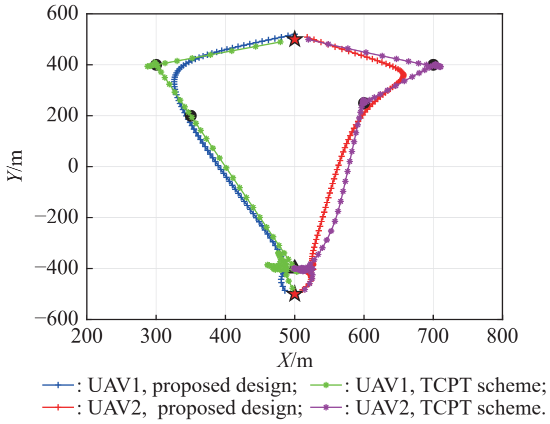
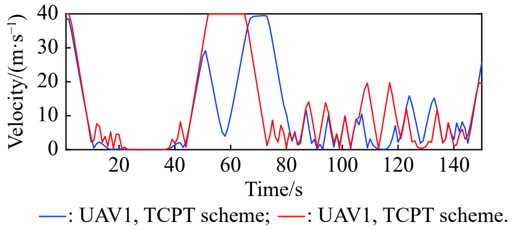


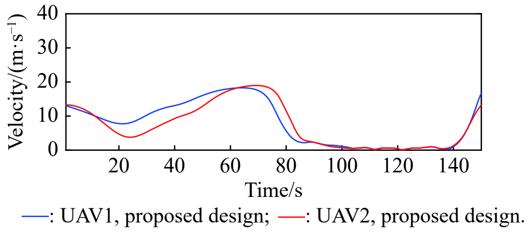
Fig. 2 UAV trajectory by Algorithm 1 with T = 150 s and d_t = 1 s

From Fig. 2, it is observed that the UAVs approach from the initial location to the GUs for both the proposed design and TCPT scheme. In order to collect as much information as possible from the GUs, the velocity of the UAVs are relatively slow at this time. When flying near the BS, the UAVs slow down and hover around the BS for a period of time to facilitate the UAVs to transmit more information to the BS. Finally, the UAVs fly back to the final location. Comparing the trajectories of the proposed design and TCPT scheme, it is not difficult to find that the UAVs flight velocities are higher under the TCPT scheme when the UAVs approach the GUs and BS, which maximizes throughput without considering energy consumption. In addition, UAVs can completely approach all GUs and hover over them for a certain period time to colloect more information. However, the proposed scheme takes the EE as the optimization goal which depends on throughput and energy consumption, so the UAVs trajectories curve is smoother.

In order to illustrate different performances of UAVs better under maximum EE and maximum throughput, Fig. 3 shows the time-varying velocity of the UAVs trajectories in Fig. 2. It is worth noting that the UAVs firstly fly to the GUs with large velocity, then reduce their velocities and hovering around the GUs to improve the throughput for the throughput-maximization trajectories. Similarly, UAVs fly towards the BS with increased velocity, and then reduce their velocities and hover around the BS to forward as much information as possible. In contrast, the UAV's velocity of the proposed design is relatively slower when approaching the GUs and BS. Observing (23), it is not difficult to find that too high velocity will lead to the increase of propulsion energy consumption, which is not conducive to EE.



(a) Velocity of UAV1



(b) Velocity of UAV2

Fig. 3 Corresponding velocity of the UAVs trajectories in Fig. 2

Fig. 4 illustrates the EE of different schemes versus the peak power $P_{\max}$ for given flight period T = 150 s. From Fig. 4, it is obvious that the EE of proposed design and ECP can be improved as expected via increasing the peak power. However, changing the peak power has little effect on the EE of the TCPT scheme. Actually, it is not hard to explain this phenomenon. Since the proposed design and ECP scheme take the EE as the optimization goal which makes a good compromise between throughput and energy consumption, but the TCPT scheme maximizes the throughput without considering the energy which will result in huge propulsion energy consumption at some time slots, as shown in Fig. 3, the high velocity of the UAVs under the TCPT scheme. Obviously, the proposed design always achieves the significant EE gain, because trajectory optimization provides the feasibility of significantly enhancing system performance.

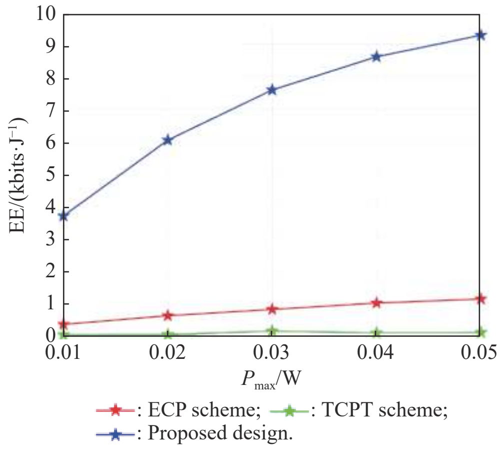


Fig. 4 **EE versus the peak power $P_{\max}$ with $T = 150$ s and $d_t = 1$ s**

From Fig. 5, it is observed that as the number of iterations increases, the EE of the system is also improved, and finally tends towards stability. Therefore, Fig. 5 shows that the proposed algorithm is convergent, which also verifies that the proposed algorithm can efficiently improve the EE of the considered system.

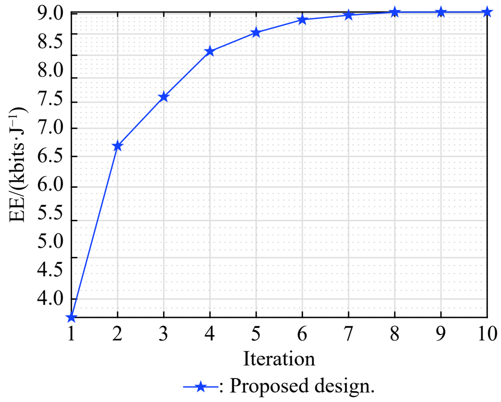


Fig. 5 **Convergence of Algorithm 1**

5. Conclusions

This paper investigates an energy efficient multi-UAV relaying communication system. The objective is to maximize the EE of the UAVs via jointly designing the communication scheduling, transmit power allocation and UAV trajectory under the buffer constraint. To resolve the fractional non-convex optimization problem, an efficient iterative algorithm is proposed by applying the BCD and SCA techniques, and the Dinkelbach's algorithm, and the proposed algorithm converges to a local optimal solution. Moreover, numerical results show that the proposed design makes a good compromise between the throughput and energy consumption as compared to the benchmark schemes. Also, the proposed design can significantly enhance the EE thanks to the degree of freedom given by the buffer and trajectory optimization.

References

[1] HAYAT S, YANMAZ E, MUZAFFAR R. Survey on unmanned aerial vehicle networks for civil applications: a communications viewpoint. IEEE Communications Surveys Tutorials, 2016, 18(4): 2624–2661.

[2] QIANTORI A, SUTIONO A B, HARIYANTO H, et al. An emergency medical communications system by low altitude platform at the early stages of a natural disaster in Indonesia. Journal of Medical Systems, 2012, 36(1): 41–52.

[3] ROGERS J. How drones are helping the Nepal earthquake relief effort. https://www.foxnews.com/tech/how-drones-are-helping-the-nepal-earthquake-relief-effort.

[4] MOZAFFARI M, SAAD W, BENNISN M, et al. A tutorial on UAVs for wireless networks: applications, challenges, and open problems. IEEE Communications Surveys Tutorials, 2019, 21(3): 2334–2360.

[5] BUCAILLE I, HETHUIN S, MUNARI A, et al. Rapidly deployable network for tactical applications: aerial base station with opportunistic links for unattended and temporary events absolute example. Proc. of the IEEE Military Communications Conference, 2013: 1116–1120.

[6] BOR-YALINIZ R I, EL-KEY A, YANIKOMEROGLU H. Efficient 3D placement of an aerial base station in next generation cellular networks. Proc. of the IEEE International Conference on Communications, 2016. DOI: 10.1109/ICC.2016.7510820.

[7] LYU J B, ZENG Y, ZHANG R, et al. Placement optimization of UAV-mounted mobile base stations. IEEE Communications Letters, 2016, 21(3): 604–607.

[8] ALZENAD M, EL-KEYI A, LAGUM F, et al. 3D placement of an unmanned aerial vehicle base station (UAV-BS) for energy-efficient maximal coverage. IEEE Wireless Communications Letters, 2017, 6(4): 434–437.

[9] MERWADAY A, TUNCER A, KUMBHAR A, et al. Improved throughput coverage in natural disasters: unmanned aerial base stations for public-safety communications. IEEE Vehicular Technology Magazine, 2016, 11(4): 53–60.

[10] JIANG X, WU Z L, YIN Z D, et al. Power and trajectory optimization for UAV-enabled amplify-and-forward relay networks. IEEE Access, 2018, 6: 48688–48696.

[11] CHEN Y F, ZHAO N, DING Z G, et al. Multiple UAVs as relays: multi-hop single link versus multiple dual-hop links. IEEE Trans. on Wireless Communications, 2018, 17(9): 6348–6359.

[12] PURI A. A survey of unmanned aerial vehicles (UAV) for traffic surveillance. Proc. of the International Conference on Unmanned Aircraft Systems, 2013: 221–234.

[13] FREW E W, BROWN T X. Airborne communication networks for small unmanned aircraft systems. Proceedings of the IEEE, 2008, 96(12): 2008–2027.

[14] ZENG Y, ZHANG R, LIM T J. Wireless communications with unmanned aerial vehicles: opportunities and challenges. IEEE Communications Magazine, 2016, 54(5): 36–42.

[15] LI B, FEI Z S, ZHANG Y. UAV communications for 5G and beyond: recent advances and future trends. IEEE Internet of

Things Journal, 2018, 6(2): 2241–2263.

[16] FOTOUHI A, QIANG H R, DING M, et al. Survey on UAV cellular communications: practical aspects, standardization advancements, regulation, and security challenges. IEEE Communications Surveys Tutorials, 2019, 21(4): 3417–3442.

[17] ZENG Y, ZHANG R. Energy-efficient UAV communication with trajectory optimization. IEEE Trans. on Wireless Communications, 2017, 16(6): 3747–3760.

[18] ZENG Y, XU J, ZHANG R. Energy minimization for wireless communication with rotary-wing UAV. IEEE Trans. on Wireless Communications, 2019, 18(4): 2329–2345.

[19] MOZAFFARI M, SAAD W, BENNIS M, et al. Drone small cells in the clouds: design, deployment and performance analysis. Proc. of the IEEE Global Communications Conference, 2015. DOI:10.1109/GLOCOM.2015.7417609.

[20] MOZAFFARI M, SAAD W, BENNIS M, et al. Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage. IEEE Communications Letters, 2016, 20(8): 1647–1650.

[21] KOULALI S, SABIR E, TALEB T, et al. A green strategic activity scheduling for UAV networks: a sub-modular game perspective. IEEE Communications Magazine, 2016, 54(5): 58–64.

[22] AHMED S, CHOWDHURY M Z, JANG Y M. Energy-efficient UAV-to-user scheduling to maximize throughput in wireless networks. IEEE Access, 2020, 8: 21215–21225.

[23] AHMED S, CHOWDHURY M Z, JANG Y M. Energy-efficient UAV relaying communications to serve ground nodes. IEEE Communications Letters, 2020, 24(4): 849–852.

[24] KHUWAJA A, CHEN Y F, ZHAO N, et al. A survey of channel modeling for UAV communications. IEEE Communications Surveys Tutorials, 2018, 20(4): 2804–2821.

[25] YOU C S, ZHANG R. 3D trajectory optimization in Rician fading for UAV-enabled data harvesting. IEEE Trans. on Wireless Communications, 2019, 18(6): 3192–3207.

[26] LIU L, ZHANG S W, ZHANG R. CoMP in the sky: UAV placement and movement optimization for multi-user communications. IEEE Trans. on Communications, 2019, 67(8): 5645–5658.

[27] GRANT M, BOYD S. CVX: MATLAB software for disciplined convex programming, 2016. http://cvxr.com/cvx.

[28] BOYD S, BOYD S P, VANDENBERGHE L. Convex optimization. Cambridge: Cambridge University Press, 2004.

[29] PHILLIPS A T. Quadratic fractional programming: Dinkelbach's method. Boston: Springer, 1998.

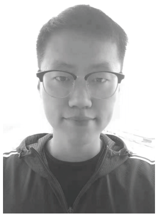
[30] CROUZEIX J P, FERLAND J A. Algorithms for generalized fractional programming. Mathematical Programming, 1991, 52(1/3): 191–207.

Biographies

CAO Dongju was born in 1996. She received her B.S. degree in electronic information engineering from Yancheng Institute of Technology, Yancheng, China, in 2018. She is currently working toward her M.S. degree in College of Communication Engineering, Army Engineering University of PLA, Nanjing, China. Her current research interests include cooperative communications, UAV communications and convex optimization techniques.
E-mail: caodongj@163.com

YANG Wendong was born in 1981. He received his B.S. degree in communications engineering and Ph.D. degree in communications and information systems both from College of Communications Engineering, PLA University of Science and Technology, Nanjing, China in 2004 and 2009 respectively. Since 2009, he has been with the College of Communications Engineering, PLA University of Science and Technology. His current research interests include MIMO systems, OFDM systems, cooperative communications, and cognitive radio.
E-mail: ywd1110@163.com

CHEN Hui was born in 1974. He received his B.S. degree in communications engineering and M.S. degree in communications and information systems both from College of Communications Engineering, Nanjing, China in 1995 and 1999 respectively. Since 2017, he has been with College of Communications Engineering, Army Engineering University of PLA. His current research interests include cloud computing, big data application, information security, and network systems engineering.
E-mail: huiczj@126.com



WU Yang was born in 1989. He received his B.S and M.S. degrees from the PLA University of Science and Technology in 2012 and 2015 respectively. He is currently pursuing his Ph.D. degree in cyberspace security in Institute of Communications Engineering, Army Engineering University of PLA. His research interests include physical layer security, UAV communication and convex optimization.
E-mail: wuyang0710@163.com

TANG Xuanxuan was born in 1991. He received his B.S. degree in communication engineering from the College of Communications Engineering, PLA University of Science and Technology, Nanjing, China, in 2014, and his Ph.D. degree in information and communication engineering from the College of Communications Engineering, Army Engineering University of PLA, Nanjing, China, in 2019. His current research interests include cooperative communications, wireless sensor networks, Internet of Things, physical layer security, and energy harvesting systems.
E-mail: tang_xx@126.com