Trajectory design and resource allocation for UAV energy minimization in a rotary-wing UAV-enabled WPCN☆

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Abstract Due to the low efficiency of energy harvest (EH) for the traditional wireless powered communication network (WPCN), we propose a communication scheme based on unmanned aerial vehicle (UAV)-enabled WPCN, which can greatly improve the EH efficiency problem. In this paper, the UAV trajectory, time allocation, transmit power of UAVs, scheduling of wireless information transfer (WIT) and wireless power transfer (WPT) are jointly optimized to minimize the whole energy consumption. To solve the formulated non-convex problem with multiple constraints and attain locally optimal solution, an iterative algorithm is proposed. Simulations show that our proposed algorithm is superior to other benchmark algorithms.

1. Introduction

Recently, a unmanned aerial vehicle (UAV) which possesses lightweight, swift mobility, and low-altitude flight natures has been widely applied into various fields [1]. For example, in the wireless communication systems, a UAV can acts as an access point (AP) or a relay to provide information and energy transmission services for users [2,3]. Due to the advantage of the UAV, UAV-enabled wireless communications have been received an increasing attention from both academic and industry. Unmanned aerial vehicle (UAVs) are applied to the fifth generation (5G) and beyond 5G (B5G) wireless communication networks, that is promising and can produce great application value and commercial value [4,5].

In UAV-aided wireless communication networks, the research on the trajectory design or optimization and resource allocation can enhance system performance. So there are many investigations focused on the UAV trajectory design or optimization and resource allocation in wireless communication network [6–15]. In a UAV-assisted relay network, the bandwidth resource allocation and the three-dimensional (3D) UAV trajectory were jointly optimized to maximize the system throughput based on UAV's flexibility [6]. A clustered non-orthogonal multiple access system was considered in [7], where the authors presented an iterative algorithm of subslot allocation and UAV trajectory design to maximize mean information rate of IoT terminal devices in the sixth generation (6G) communication work. When the UAV served terrestrial users and was requested to satisfy quality-of-experience (QoE) requirement of each user in [8], the authors aimed to maximize energy-efficiency by optimizing bandwidth and power allocation, as well as UAV trajectory.

A UAV as a hybrid access point of energy and information transmission, another UAV as jammer, and a ground eavesdropper were considered in the UAV-aided communication scenario, where the average secrecy rate was maximized via the optimization of the UAVs' trajectory and their transmit power [9]. The Internet of Remote Things (IoRT) had good application value in rural and suburban zones, and the authors in [10] presented the IoRT computing offloading network with UAVs to minimize sum energy consumption of the system based on the optimization of UAV trajectory, bit resource and devices scheduling. The multicarrier solar-powered UAV can offer sustaining communication service for terrestrial users in [11], where the authors optimized subcarrier allocation and the UAV 3D trajectory so as to maximize total system throughput. In [12], a UAV needed to be recharged regularly to provide service for users in the downlink, and the average rate of users was maximized via the optimization of UAV 3D trajectory and time allocation. According to the limited energy store of UAV, a fly-hover-communicate protocol was put forward to maximize the throughput of terrestrial nodes by searching optimal hovering point and time allocation [13]. In cognitive radio networks, the UAV's power and its trajectory and subcarrier allocation were studied as optimization variables in order to maximize average throughput of the secondary users based on alternating optimization scheme [14]. Under the UAV-aided vehicular network and the establishment of communication link between the UAV and high speed vehicles for maximizing the average rate of vehicles, the radio allocation and the trajectory of UAV were jointly optimized

under the condition of guaranteeing the quality of communication service [15].

Due to the limited battery capacity of UAV, it is of great significance to study the energy consumption minimization of the UAV, which can extend the communication time of the wireless network. In the UAV-assisted wireless network, there are some researches of energy consumption minimization of the UAV [16–24]. A UAV served multiple users located at the ground under the requested timeout of ground users, and total energy consumption minimization of the UAV was studied by optimizing the UAV's trajectory and its velocities [16]. A Internet-of-Things (IoT) system was considered in [17], where a UAV collected information from some devices of IoT and minimized the UAV energy consumption based on its energy budget via power allocation of devices and the optimization of UAV flight path and communication scheduling. In [18], a new communication protocol for the network system composed of multi-antenna UAV was put forward, and the UAV energy consumption and communication time minimization were studied under that protocol and the designs of antenna beamwidth, UAV speed and flight height.

In [19], the UAV not only needed to complete the information collection mission from ground sensors, but also minimized its total flight time based on bisection search and dynamic programming methods, in order to enhance UAV energy efficiency under certain energy storage of the UAV. The authors in [20] used a UAV to disseminate information to ground devices in the IoT wireless communication system, and aimed to minimize mission time for the UAV based on the UAV's energy budget. In wireless sensor networks, the tradeoff problem about the energy consumption of the UAV and all terrestrial sensors was studied via the minimization of the weighted energy consumption for the UAV and the sensors [21]. A UAV was deployed as an aerial base station to send data to terrestrial sensors based on the orthogonal frequency division multiple access (OFDMA) protocol, in order to minimize the sum energy consumption of the UAV by the design of iterative algorithm [22]. The UAVs were used to quickly restore and support communication in no communication coverage areas where natural disasters had damaged wireless communications. Because UAVs' the limited battery capacity leaded to their flight time to be also limited, the author in [23] applied the genetic algorithm and trajectory design to minimize UAV energy consumption, so as to prolong communication time. The energy consumption model of rotary-wing UAV was considered in [24], where the UAV needed to perform given mission of information transmission for terrestrial nodes to minimize its propulsion and communication energy consumption. Although the above literatures had done some research on UAV energy consumption, their research was not involved in the WPCN network.

In a UAV-aided wireless powered communication network (WPCN), the UAV is a power provider for downlink users. Therefore, the research of UAV energy consumption is more practical significance and application value in WPCN [25–30]. The scenario of a UAV as information access point (AP) and other UAV as energy AP and other scenario of a UAV as hybrid AP were considered in UAV-enabled WPCN, where the UAVs trajectory and terminals power as optimization variables were studied so as to maximize the throughput of terminals [25]. In a UAV-enabled WPCN, users on the ground need

the UAV to recharge them, which sent data to the UAV after harvesting certain energy, in order to study the system throughput maximization problem based on the optimization of transmit power of users and the UAV trajectory [26]. In [27], the objective of the task completion time minimization was considered in UAV-enabled WPCN, where authors adopted the subgradient algorithm and bisection search method to solve original optimization problem. A harvest and transmit protocol was presented to tackle near-far problem in UAV-enabled WPCN, where the throughput maximization of each node and time allocation problem were studied by using convex optimization techniques [28].

In multiple UAVs-enabled WPCN system, the author in [29] studied multiple UAVs collaboration scheme for charging IoT devices and collecting information from the devices in order to enhance the uplink throughput efficiency based on Work-Gain algorithm. Based on the energy causality constraint, the UAV speed constraint and its initial and final positions constraint, the users scheduling and time slot allocation were considered and optimized to minimize the energy consumption of a rotary-wing UAV in WPCN [30]. According to the research contents of literatures [25–30], it is observed that there are not relevant research on the optimization of the UAV transmit power as a variable in UAV-enabled WPCN. In this paper, Our works are different from those works in [6–15]. We focus on design of UAV trajectory and resource allocation schemes which include time slot allocation and power allocation to optimize UAV energy consumption under meeting the communication throughput requirements in the WPCN. In our presented system solution, the UAV trajectory, the UAV transmit power, the total communication time and the time slot as optimization variables are considered, which are jointly optimized to minimize the UAV energy consumption. In order to deal with hard non-convex problem, we put forward an efficient iteration algorithm to attain optimal solution of the problem based on taylor expansion and convex approximation method.

In this paper, the rest contents are arranged as follows. In Section 2, a system model consisting of a UAV, terrestrial users, uplink and downlink is put forward and the optimization problem with the UAV trajectory, the transmit power, as well as the time slot variables is formulated in the WPCN. Because the formulated primal problem is non-convex problem, it needs to be tackled and be transformed to convex problem through the associated convex processing method in Section 3. We attain the optimal solution of the disposed convex problem and obtain lots of simulations to show the superiority of our scheme in Section 4. We sum up our work and contribution for this paper in Section 5.

2. System model

As shown in Fig. 1, we consider a rotary-wing UAV-enabled WPCN, where the K terrestrial users communicate with a UAV. In the downlink, every terrestrial user $k \in \mathcal{K}, \mathcal{K} \triangleq = \{1, \cdots, K\}$ without any energy storage first needs to harvest energy via wireless power transfer (WPT) from the rotary-wing UAV. Considering the characteristics of long-distance transmission of radio frequency (RF) signals [31], the UAV adopts RF signal to charge users in the WPT. In the uplink, the user k transmits information to the UAV
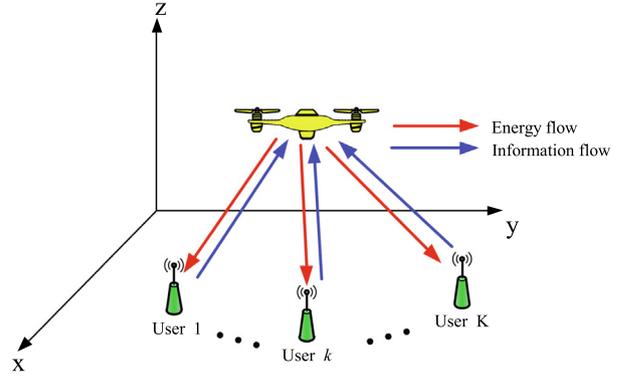

Fig. 1 The system model.

by utilizing the harvested energy. The location of each user k fixed at ground is $w_k = (x_k, y_k), k \in \mathcal{K}$, with the three-dimensional (3D) Cartesian coordinate. Suppose that the specific location of each terrestrial user is stored in the UAV's memory in advance, and is known by the UAV before carrying out missions. Suppose that the flight velocity of the UAV flying at certain height H can not exceed the maximum speed V_{max} during total mission time θ_t. Although the flight trajectory of the UAV is dynamically changing, its horizontal position at a any time $t, t \in [0, \theta_t]$, can still be expressed as $q(t) = (x(t), y(t))$. For ease of exposition, we discretize θ_t into N time slots with very small slot length. Let $\theta[n]$ represents the duration of each small time slot. The duration $\theta[n]$ is uncertain and needs to be optimized as a variable, due to uncertain mission completion time of the UAV. Considering the uplink and downlink communication at different time slots for noninterference with each other, the $\theta[n]$ is divided into $K + 1$ subslots. The subslot $\tau_0[n]$ denotes small time duration for the UAV charging to the terrestrial users at the nth time slot. Similarly, the subslot $\tau_k[n], k \in \mathcal{K}$ denotes small time duration of information transmission from user k to the UAV. A time-division multiple access (TDMA) transmission protocol is considered in our system model. Therefore, the communication between the UAV and each user should follow TDMA protocol. In every time slot n, the sum of each subslot can not exceed the time duration $\theta[n]$, and this constraint is given by

$$\sum_{k=0}^{K} \tau_k[n] \leqslant \theta[n], \forall n \in \mathcal{N} = \{1, 2, \cdots, N\}. \tag{1}$$

Similarly, we discretize the UAV path into $N - 1$ small enough segment, that are represented by N waypoints $\{q[n]\}_{n=1}^{n=N}$. Let $q[1]$ represents the UAV's initial point, and $q[N]$ represents the UAV's final point. Although the UAV's position in the air is not fixed, the distance from user k to the UAV at any time slot n can be calculated as follows.

$$d_k[n] = \sqrt{\|q[n] - w_k\|^2 + H^2}, \forall k, n. \tag{2}$$

Suppose that the line-of-sight (LoS) link is considered for the communication channels of uplink and downlink in the UAV-enabled WPCN system. According to the speciality of the LoS links, we can easily model the power gain of communication channel between terrestrial user k and the UAV, which is written as

$$h_k[n] = \beta_0 d_k^{-2}[n] = \frac{\beta_0}{\|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2 + H^2}, \tag{3}$$

where β_0 represents the reference channel power gain when the reference distance is set one meter. According to Shannon theorem and channel gain, we can calculate the achievable information rate of the uplink from user k to the UAV, which in Bits/s/Hz is expressed as

$$R_k[n] = B\log_2\left(1 + \frac{P_k h_k(n)}{\sigma^2}\right) = B\log_2\left(1 + \frac{\phi_k}{\|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2 + H^2}\right), \tag{4}$$

where P_k represents the transmit power of the kth user, B on behalf of the channel bandwidth, σ^2 represents the noise power at the users and $\phi_k = \frac{P_k \beta_0}{\sigma^2}$ is defined as the signal-to-noise ratio (SNR) of reference channel in uplink from the users to the UAV. Based on the achievable information rate of the uplink, we can calculate sum amount of information of the uplink from user k to the UAV. Hence, this sum uplink amount of information of the user k over N time slots is given by

$$Q_k(\boldsymbol{q}[n], \tau_k[n]) = B\sum_{n=1}^{N}\tau_k[n]\log_2\left(1 + \frac{\phi_k}{\|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2 + H^2}\right). \tag{5}$$

At $\tau_0[n]$ subslot, all users can simultaneously harvest the wireless energy signals broadcasted by the UAV and convert them into energy with the linear conversion efficiency $\eta \in (0, 1]$ based on a simplified constant RF-to-DC energy conversion model. At the nth time slot, the harvested energy of the kth user from the UAV is formulated as

$$\tilde{E}_k[n] = \frac{\eta\beta_0 P_u[n]\tau_0[n]}{\|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2 + H^2}, \tag{6}$$

where $P_u[n]$ is behalf on the transmit power of the UAV which can charge terrestrial users in the nth time slot. All users without stored energy first harvest energy from the UAV at the nth time slot, and then they can utilize the harvested energy to transmit information to the UAV at next time slot due to the energy processing delay of one time slot. In each time slot, the energy consumption of each user for uplink data transmission can not be greater than its harvested energy. Thus, the energy causality constraint for each user k is given by

$$\sum_{i=1}^{n} P_k \tau_k[i] \leqslant \sum_{i=1}^{n-1} \frac{\eta\beta_0 P_u[i]\tau_0[i]}{\|\boldsymbol{q}[i] - \boldsymbol{w}_k\|^2 + H^2}, \forall k, n \in \hat{\mathcal{N}}, \tag{7}$$

where we define $\hat{\mathcal{N}} = \{2, 3 \cdots, N\}$. According to the power consumption model of the rotary-wing UAV in [24], it includes the blade profile power consumption, the induced power consumption and the parasite power consumption. The rotary-wing UAV makes use of its propulsion power consumption to keep it hovering or moving. In this paper, we adopt this power consumption model of the rotary-wing UAV to calculate its propulsion energy consumption in the UAV-enable WPCN. The power consumption function of the rotary-wing UAV with speed V is expressed as

$$P(V) = P_0\left(1 + \frac{3V^2}{U_{tip}^2}\right) + P_i\left(\sqrt{1 + \frac{V^4}{4v_0^4}} - \frac{V^2}{2v_0^2}\right)^{1/2} + \frac{1}{2}d_0\rho s A V^3, \tag{8}$$

where U_{tip} and v_0 denote the rotor blade speed and mean rotor induced velocity of a rotary-wing UAV, respectively. ρ represents air density. s and A denote rotor solidity and disc area of UAV, respectively. P_0 is behalf on the blade profile power constant and P_i represents the induced power constant. For the setting value of every parameter in (8), we can obtain it from [24].

The total consuming energy of the rotary-wing UAV is composed of communication energy and propulsion energy. The communication energy consumption of the rotary-wing UAV is written as $E_c[n] = \sum_{n=1}^{N}\tau_0[n]P_u[n]$. The propulsion energy consumption of the rotary-wing UAV is expressed as $E_p[n] = \sum_{n=1}^{N}\theta[n]P(V[n])$, where $V[n] = \frac{\|\boldsymbol{q}[n+1]-\boldsymbol{q}[n]\|}{\theta[n]}$ denotes the flight velocity of the rotary-wing UAV in the nth time slot duration. Therefore, the total energy consumption of the rotary-wing UAV is formulated as

$$E_{tot}(\boldsymbol{q}[n], P_u[n], \tau_0[n], \theta[n]) = \sum_{n=1}^{N}\tau_0[n]P_u[n]$$
$$+ \sum_{n=1}^{N}\theta[n]P\left(\frac{\|\boldsymbol{q}[n+1]-\boldsymbol{q}[n]\|}{\theta[n]}\right)$$
$$= \sum_{n=1}^{N}\tau_0[n]P_u[n] + \sum_{n=1}^{N}P_0\left(\theta[n] + \frac{3\omega[n]^2}{\theta[n]U_{tip}^2}\right) \tag{9}$$
$$+ P_i\sum_{n=1}^{N}\left(\sqrt{\theta[n]^4 + \frac{\omega[n]^4}{4v_0^4}} - \frac{\omega[n]^2}{2v_0^2}\right)^{1/2}$$
$$+ \frac{1}{2}d_0\rho s A\sum_{n=1}^{N}\frac{\omega[n]^3}{\theta[n]^2},$$

where $\omega[n] \triangleq \|\boldsymbol{q}[n+1] - \boldsymbol{q}[n]\|$ represents the flight length of a line segment for the rotary-wing UAV at the nth time slot when the rotary-wing UAV flies from the nth location point to the $n+1$th location point. The UAV energy minimization problem with some constraint conditions is formulated as

$$(P1): \min_{\substack{\boldsymbol{q}[n], P_u[n], \\ \tau_0[n], \tau_k[n], \theta[n]}} E_{tot}(\boldsymbol{q}[n], P_u[n], \tau_0[n], \theta[n]) \tag{10a}$$

$$\text{s.t. } Q_k(\boldsymbol{q}[n], \tau_k[n]) \geqslant Q_{\min}, \forall k, \forall n, \tag{10b}$$

$$\|\boldsymbol{q}[n+1] - \boldsymbol{q}[n]\| \leqslant \min\{\omega_{\max}, \theta[n]V_{\max}\}, \forall n, \tag{10c}$$

$$\boldsymbol{q}[1] = \boldsymbol{q}[N], \tag{10d}$$

$$\tau_k[n] \geqslant 0, \forall k, \forall n, \tag{10e}$$

$$0 \leqslant P_u[n] \leqslant P_u^{\max}, \forall n, \tag{10f}$$

$$(1) \text{ and } (7). \tag{10g}$$

From problem (P1), we can observe that the objective function of (P1) is the minimization function of the sum energy consumption for the rotary-wing UAV. (10b) denotes the minimum throughput requirement for each user transmitting information. (10c) indicates the flight distance constraint of the rotary-wing UAV from the nth location point to the $n+1$th location point at the nth time slot. (10d) indicates that the rotary-wing UAV flies back to its starting point which is same point with final point after the UAV accomplishing mission, and (10f) indicates maximum transmit power constraint of the rotary-wing UAV at any n time slot. Although the constraints (1) and (10c)-(10f) are all convex, problem (P1) still is a non-convex problem due to non-convex objective function E_{tot} and non-convex constraints (10b) and (7). Therefore, we need to do some relevant convex processing for the non-convex function and constraints in order to convert the non-convex problem into convex problem.

3. Proposed solution to problem (P1)

In this section, we first transform the non-convex function and constraints into the convex ones by the Taylor expansion and the successive convex approximation methods. Then, we can solve the transformed convex problem to attain optimal solution via the presented efficient algorithm. From the objective function (10a) or (9), we can observe that the second term and the fourth term of the formula (9) are convex in regard to variables $q[n]$ and $\theta[n]$. Nevertheless, the first term in the formula (9) is non-convex with regard to variables $P_u[n]$ and $\tau_0[n]$, since it is a coupling function multiplied by $P_u[n]$ and $\tau_0[n]$. The third term of the formula (9) is non-convex in regard to variables $q[n]$ and $\theta[n]$ and needs to be dealt with. We introduce a slack variable $\mu[n]$ and let the square of it to replace the third term of formula (9). And one has

$$\mu[n]^2 = \sqrt{\theta[n]^4 + \frac{\omega[n]^4}{4v_0^4} - \frac{\omega[n]^2}{2v_0^2}}. \tag{11}$$

By moving some terms on both sides of the Eq. (11), we can obtain a new equation.

$$\frac{\theta[n]^4}{\mu[n]^2} = \mu[n]^2 + \frac{\omega[n]^2}{v_0^2}. \tag{12}$$

In order to deal with the non-convex function of the first term in the formula (9), we introduce slack variable $Z[n]$ to transform the coupling function to a linear function which is convex.

$$Z[n] = \tau_0[n]P_u[n]. \tag{13}$$

By introducing multiple relaxation variables and transforming non-convex function into convex function for the first term and the third term of the objective function (10a) or (9), the objective function of problem (P1) with relaxation variables can be rewritten as

$$\hat{E}_{tot}(q[n], Z[n], \mu[n], \theta[n]) = \sum_{n=1}^{N} Z[n]$$
$$+ \sum_{n=1}^{N} P_0 \left(\theta[n] + \frac{3\omega[n]^2}{\theta[n]U_{tip}^2} \right) + P_i \sum_{n=1}^{N} \mu[n] \tag{14}$$
$$+ \frac{1}{2} d_0 \rho s A \sum_{n=1}^{N} \frac{\omega[n]^3}{\theta[n]^2}.$$

In (14), we can observe that each term of equality is convex via convex processing. Because the non-convex constraint (10b) needs to be dealt with, a slack variable $S_k[n]$ is introduced. In order to tackle the non-convex constraint (7), we introduce slack variables $A_k[i]$. Thus

$$S_k[n]^2 = B\tau_k[n]\log_2 \left(1 + \frac{\phi_k}{\|q[n] - w_k\|^2 + H^2} \right), \tag{15}$$

$$A_k[i]^2 = \frac{\eta\beta_0 Z[i]}{\|q[i] - w_k\|^2 + H^2}. \tag{16}$$

Based on the equality (15), we put the square of slack variable $S_k[n]$ into the left part of the constraint (10b). Therefore, the constraint (10b) becomes $\sum_{n=1}^{N} S_k[n]^2 \geqslant Q_{\min}$. Similarly, we put the square of slack variable $A_k[i]$ into the right part of the constraint (7) based on the equality (16). So, the constraint (7) is rewritten as $\sum_{i=1}^{n} P_k\tau_k[i] \leqslant \sum_{i=1}^{n-1} A_k[i]^2$. Based on the above processing, (P1) can be reformulated as

$$(P1.1): \min_{\substack{q[n],\tau_k[n],\theta[n],Z[n] \\ \mu[n],S_k[n],A_k[n],\tau_0[n]}} \hat{E}_{tot}(q[n], Z[n], \mu[n], \theta[n]) \tag{17a}$$

$$\text{s.t.} \sum_{n=1}^{N} S_k[n]^2 \geqslant Q_{\min}, \forall k, \tag{17b}$$

$$\frac{S_k[n]^2}{\tau_k[n]} \leqslant B\log_2 \left(1 + \frac{\phi_k}{\|q[n] - w_k\|^2 + H^2} \right),$$
$$\forall k, \forall n, \tag{17c}$$

$$\sum_{i=1}^{n} P_k\tau_k[i] \leqslant \sum_{i=1}^{n-1} A_k[i]^2, \forall k, n \in \hat{\mathcal{N}}, \tag{17d}$$

$$\frac{A_k[n]^2}{Z[n]} \leqslant \frac{\eta\beta_0}{\|q[n] - w_k\|^2 + H^2}, \forall k, \forall n, \tag{17e}$$

$$\frac{\theta[n]^4}{\mu[n]^2} \leqslant \mu[n]^2 + \frac{\|q[n+1] - q[n]\|^2}{v_0^2}, \forall n, \tag{17f}$$

$$\mu[n] \geqslant 0, \forall n, \tag{17g}$$

$$0 \leqslant Z[n] \leqslant P_u^{\max}\tau_0[n], \forall n, \tag{17h}$$

$$(1), (10c) - (10e). \tag{17i}$$

Notice that the inequality constraints (17c), (17e) and (17f) in (P1.1) are obtained from (15), (16) and (12). Although the constraint (10b) of problem (P1) is introduced the slack variable $S_k[n]$ to tackle its non-convexity, the equivalence between the convex tackled inequality constraint with the slack variable and the original inequality should also be considered. By adding the constraint condition (17c) in problem (P1.1), the constraint conditions of the combination of (17b) and (17c) is equivalent to the constraint (10a) of problem (P1). By introducing the inequality (17e) in problem (P1.1), the combination of the inequality (17d) and (17e) is equivalent to the inequality (7). Due to minimize the objective function, the constraint condition (17f) is introduced to attain the lower boundary value of the objective function. The constraint condition (17h) of problem (P1.1) is obtained from the inequality (10f) of problem (P1.1) and the Eq. (13). Therefore, problem (P1.1) is equivalent to problem (P1). Due to the non-convex constraints (17b)-(17f), (P1.1) is still a non-convex problem. By utilizing the first-order Taylor expansion to tackle the non-convex constraint (17b), we have

$$S_k[n]^2 \geqslant S_k^{(f)}[n]^2 + 2S_k^{(f)}[n]\left(S_k[n] - S_k^{(f)}[n] \right), \tag{18}$$

where $S_k^{(f)}[n]$ denotes the value of $S_k[n]$ at the fth iteration. For the convex disposal of $A_k[i]^2$ in (17d), we adopt same processing method which is the first-order Taylor expansion to attain lower bounded. Thus, the convex disposal of $A_k[i]^2$ is as follows.

$$A_k[i]^2 \geqslant A_k^{(f)}[i]^2 + 2A_k^{(f)}[i]\left(A_k[i] - A_k^{(f)}[i] \right), \tag{19}$$

where $A_k^{(f)}[i]$ denotes the value of $A_k[i]$ at the fth iteration. The right hand side (RHS) of inequality (17c) is not a concave function in regard to variable $q[n]$. Via using the first-order Taylor expansion, the global lower bound for the RHS of (17c) can be given as

$$B\log_2\left(1 + \frac{\phi_k}{\|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2 + H^2}\right)$$

$$\geqslant G_k^{(f)}[n] - \lambda_k^{(f)}[n]\left(\|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2 - \|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2\right) \triangleq$$

$$R_k^{(f)}(\boldsymbol{q}[n]), \tag{20}$$

where $G_k^{(f)}[n] = B\log_2\left(1 + \frac{\phi_k}{H^2 + \|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2}\right)$ and $\lambda_k^{(f)}[n] = \frac{B(\log_2 e)\phi_k}{\left(H^2 + \|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2\right)\left(H^2 + \|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2 + \phi_k\right)}$. $\boldsymbol{q}^{(f)}[n]$ denotes the value of $\boldsymbol{q}[n]$ at the fth iteration.

Because the RHS of inequality (17e) is not a concave function with respect to $\boldsymbol{q}[n]$, we need to convert the RHS of inequality (17e) into the first order linear function with variable $\boldsymbol{q}[n]$ by applying the first-order Taylor expansion method. So, the lower bound for the RHS of (17e) is written as

$$\frac{\eta\beta_0}{\|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2 + H^2}$$

$$\geqslant \frac{\eta\beta_0\left(2\|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2 + H^2 - \|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2\right)}{\left(\|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2 + H^2\right)^2}. \tag{21}$$

Because the RHS of inequality (17f) is not a concave function, it needs to be tackled by applying the first-order Taylor expansion. Therefore, the global concave lower bound of the RHS in (17f) can be given as

$$\mu[n]^2 + \frac{\|\boldsymbol{q}[n+1] - \boldsymbol{q}[n]\|^2}{v_0^2} \geqslant \mu^{(f)}[n]^2$$

$$+ 2\mu^{(f)}[n]\left(\mu[n] - \mu^{(f)}[n]\right) - \frac{\|\boldsymbol{q}^{(f)}[n+1] - \boldsymbol{q}^{(f)}[n]\|^2}{v_0^2}$$

$$+ \frac{2}{v_0^2}\left(\boldsymbol{q}^{(f)}[n+1] - \boldsymbol{q}^{(f)}[n]\right)^T\left(\boldsymbol{q}[n+1] - \boldsymbol{q}[n]\right) \tag{22}$$

$$\triangleq F^{(f)}(\mu[n], \boldsymbol{q}[n]),$$

where $\mu^{(f)}[n]$ and $\boldsymbol{q}^{(f)}[n]$ are the fth iteration value of $\mu[n]$ and $\boldsymbol{q}[n]$, respectively. By dealing with non-convex constraints (17b)-(17f) of (P1.1) and obtaining their corresponding lower bound, new optimization problem can be reformulated as

$$(P1.2): \min_{\substack{\boldsymbol{q}[n], \tau_k[n], \theta[n], Z[n] \\ \mu[n], S_k[n], A_k[n], \tau_0[n]}} \hat{E}_{tot}(\boldsymbol{q}[n], Z[n], \mu[n], \theta[n]) \tag{23a}$$

$$\text{s.t. } \sum_{n=1}^{N} S_k^{(f)}[n]^2 + \sum_{n=1}^{N} 2S_k^{(f)}[n]\left(S_k[n] - S_k^{(f)}[n]\right) \geqslant Q_{\min}, \tag{23b}$$
$$\forall k, \forall n,$$

$$\frac{S_k[n]^2}{\tau_k[n]} \leqslant R_k^{(f)}(\boldsymbol{q}[n]), \forall k, \forall n, \tag{23c}$$

$$\sum_{i=1}^{n} \tau_k[i]P_k \leqslant \sum_{i=1}^{n-1} A_k^{(f)}[i]^2$$
$$+ \sum_{i=1}^{n-1} 2A_k^{(f)}[i]\left(A_k[i] - A_k^{(f)}[i]\right), \forall k, n \in \hat{\mathcal{N}}, \tag{23d}$$

$$\frac{A_k[n]^2}{Z[n]}$$
$$\leqslant \frac{\eta\beta_0\left(2\|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2 + H^2 - \|\boldsymbol{q}[n] - \boldsymbol{w}_k\|^2\right)}{\left(\|\boldsymbol{q}^{(f)}[n] - \boldsymbol{w}_k\|^2 + H^2\right)^2}, \tag{23e}$$
$$\forall k, \forall n,$$

$$\frac{\theta[n]^4}{\mu[n]^2} \leqslant F^{(f)}(\mu[n], \boldsymbol{q}[n]), \forall n, \tag{23f}$$

$$(1), (10c) - (10e), (17g), (17h). \tag{23g}$$

(P1.2) can be verified to be a convex optimization problem according to the convex disposal of the objective function and all constraints. Problem (P1.2) can be effectively solved by applying standard convex optimization techniques and CVX [32]. If the constraints of problem (P1.2) are satisfied based on global lower bounds in (20)–(22), then it can also ensure to satisfy problem (P1.1). The original problem (P1) is a non-convex problem, which is hard to be solved. In order to find the solution efficiently, the original problem (P1) needs to be disposed into a convex problem. The problem (P1.2) is obtained by applying the convex optimization technique to dispose the non-convex original problem. Due to the global lower bounds in (18)–(22), when the constraints (23b)-(23f) of the problem (P1.2) are satisfied, then, those for the original problem (P1) are also guaranteed to be satisfied. The feasible region of the problem (P1.2) is generally a subset region of the original problem (P1). Therefore, the optimum solution of the problem (P1.2) is the sub-optimum solution of the original problem. In order to solve (P1.2), we present an efficient algorithm which is summarized as Algorithm 1. According to [32,33], the total complexity of Algorithm 1 is calculated as $O\left(L\ln(\varepsilon^{-1})K^{\frac{7}{2}}N^{\frac{7}{2}}\right)$, where L represents the iteration number of continuous convex approximation and ε represents the accuracy threshold. K and N denote the number of terrestrial users and time slots, respectively.
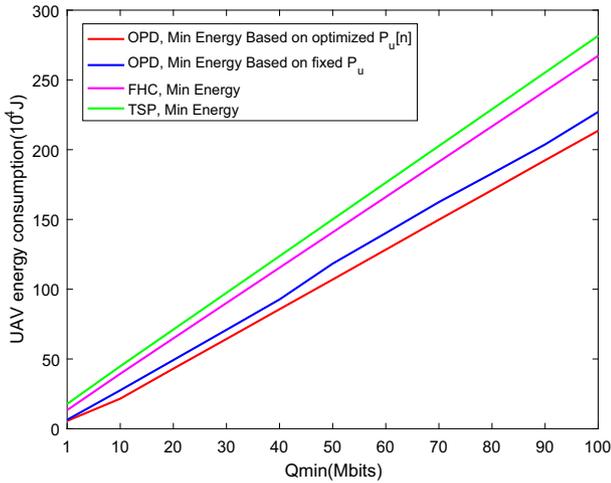
4. Simulation results

In the simulation, the flight altitude of the rotary-wing UAV is fixed at certain altitude $H = 5$ m. Considering the stability of the air-to-ground communication link, the rotary-wing UAV's flight speed cannot exceed its maximum flying speed $V_{\max} = 5$ m/s. The transmit power of user k is set as $P_k = 10$ dBm, $\forall k \in \mathcal{K}$. There is the existence of noise interference in the communication channel of the uplink and downlink and the value of noise power is set as $\delta^2 = -90$ dBm. When the reference distance is set one meter, we define the value of the reference channel power gain as $\beta_0 = -30$ dB. The sum bandwidth of communication channel is set as $B = 1$ MHz in the rotary-wing UAV-enabled WPCN. When the terrestrial users harvest energy from the rotary-wing UAV in the air, their energy conversion efficiency is set as $\beta_0 = -30$ dB. Furthermore, the simulation setting value for parameters of (8) is obtained from [24]. We consider $K = 7$ terrestrial users and use the pink squares to make marks about their horizontal positions in Figs. 3 and 4. Suppose that the collecting information throughput of the rotary-wing UAV from each user has same and minimum throughput requirement as $Q_{\min}$.
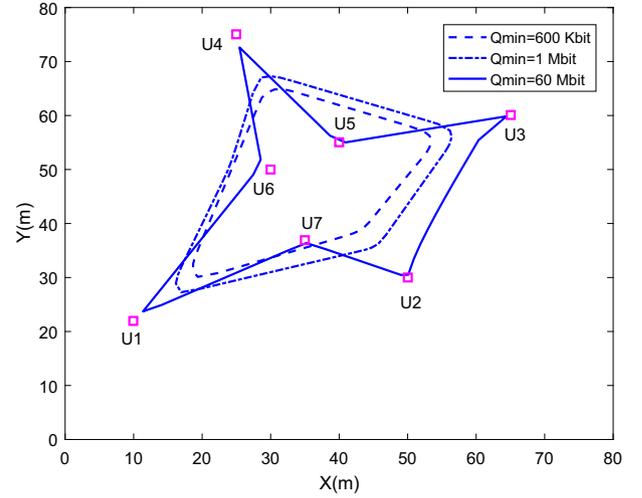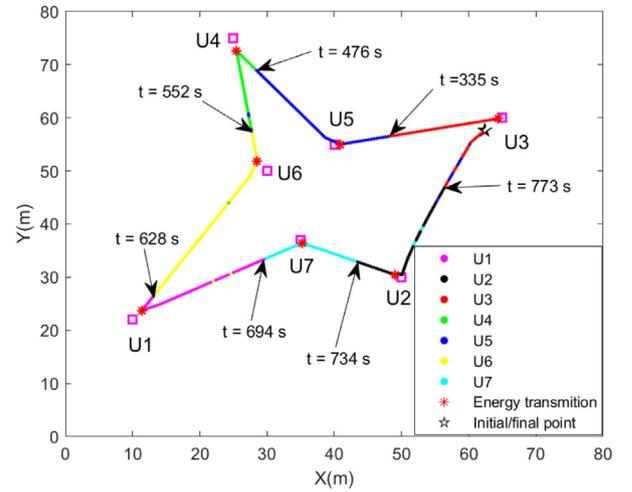
Fig. 2, shows the energy consumption curves of the rotary-wing UAV under different minimum throughput requirements $Q_{\min}$ for the four design schemes, which are the optimized path discretization (OPD) design with the variable $P_u[n]$, the optimized path discretization (OPD) design with the fixed P_u, the flying and hovering communication (FHC) design and the traveling salesman problem (TSP) design, respectively. As shown in Fig. 2, when the $Q_{\min}$ increases, it is observed that UAV energy consumption all increases for the four schemes. When the throughput requirement $Q_{\min}$ is very small, the gaps among the four curves are also very small. As the throughput requirement $Q_{\min}$ increase, the gaps between the curves based

Table 1 The iterative optimization algorithm.

Algorithm 1: The iterative algorithm for (P1)

1: **Initialization**: Find a feasible $q^{(0)}[n], \theta^{(0)}[n], P_u^{(0)}[n], \tau_0^{(0)}[n],$

   $\tau_k^{(0)}[n]$ and set accuracy threshold $\varepsilon, \varepsilon > 0$ and $l = 0$.

2: **repeat**

3:    Calculate the current values of slack variables

$\mu^{(f)}[n], Z^{(f)}[n],$

   $S_k^{(f)}[n]$ and $A_k^{(f)}[i]$, based on (11), (13), (14) and (16).

4:    Solve $P1.2$ for given $q^{(f)}[n], \mu^{(f)}[n], \theta^{(f)}[n], S_k^{(f)}[n], A_k^{(f)}[i]$

   and $\tau_k^{(f)}[n]$ by using the CVX, and denote the optimal

solution

   as $q^{opt}[n], \theta^{opt}[n], P_u^{opt}[n], \tau_0^{opt}[n]$ and $\tau_k^{opt}[n]$.

5:    Update the local value $q^{(f+1)}[n] = q^{opt}[n],$

   $P_u^{(f+1)}[n] = P_u^{opt}[n], \theta^{(f+1)}[n] = \theta^{opt}[n],$

   $\tau_0^{(f+1)}[n] = \tau_0^{opt}[n]$ and $\tau_k^{(f+1)}[n] = \tau_k^{opt}[n]$.

6:    Update $l = f + 1$.

7: **until** convergence.

Fig. 3 UAV optimization trajectories under three different throughput requirements.

Fig. 2 Energy consumption of the UAV based on four different designs.

Fig. 4 Energy and information transmission scheduling for the UAV and users.

on the OPD design and the curves based on the FHC design and the TSP design become more larger. It indicates that the energy consumption of the rotary-wing UAV based on the OPD design is less than that of the rotary-wing UAV based on the FHC and the TSP design. In Fig. 2, notice that the UAV energy consumption based on ODP design with variable $P_u[n]$ scheme is lower than those of ODP design with fixed P_u scheme. This because the UAV sends power at every time slot and transmits energy inefficiently at some time slots so as to increase the communication energy consumption of the UAV under the OPD design with fixed P_u. However, based on OPD design with variable $P_u[n]$, the UAV flies above each user on the ground and transmits energy efficiently to every user so as to reduce the communication energy consumption of the UAV. From Fig. 2 and above statement, it can show that the scheme of the UAV energy consumption based on ODP design with variable $P_u[n]$ is an optimal scheme among those four schemes.

As shown in Fig. 3, it can be seen that three optimized trajectories of the UAV based on the OPD and optimized $P_u[n]$ under three different throughputs $Q_{\min} = 600$ Kbit, $Q_{\min} = 1$ Mbit and $Q_{\min} = 60$ Mbit are analyzed. When there is high throughput requirement in Fig. 2, such as $Q_{\min} = 60$ Mbit, we can clearly observe that the UAV needs to detour its trajectory towards each user in order to accomplish the higher throughput mission. However, when there is low throughput requirement, such as $Q_{\min} = 600$ Kbit, the UAV flies around the geometric centroid of all users in order to reduce its energy consumption for the lower throughput mission.

Fig. 4 shows the energy and information transmission scheduling for the UAV and users under throughput $Q_{\min} = 60$ Mbit. We can observe that the UAV flies to the nearest position directly above each user and delivers energy to users. That is because the distance between the UAV and user k is the shortest as the UAV closing to above user k, and the UAV can deliver more power to user k quickly. It is

observed that each user is scheduled to send information to the UAV mainly in some time slots after it harvests large energy. In Fig. 4, we can observe that a user and the UAV are scheduled to transmit their information and broadcast energy within a schedule interval, respectively. For instance, the user 5 is scheduled to transmit its information to the UAV and the UAV is scheduled to broadcast energy to all users from $t = 335$ s to $t = 476$ s. When the UAV leaves from its initial point, the schedule time of schedule interval for each user gradually decreases in turn. This is because the UAV is scheduled every time to broadcast energy signal to all users and the later scheduled users have harvested sufficient energy previously. Therefore, the later scheduled users will spend less time or not need to spend time to harvest energy. Then the total schedule time will decrease in the later schedule interval.

According to the energy causality inequality (7), the total energy consumption of each user should be less than or equal to the total harvested energy of each user. As shown in Fig. 5, the total energy consumption of each user is almost equal to the total harvested energy of each user. This indicates that the harvested energy of each user is fully used to transmit information. It also indicates that energy utilization of users is very high.

Fig. 6 shows the change of transmit power for the UAV with optimized $P_u[n]$ and fixed P_u based on $Q_{min} = 60$ Mbit. We can observe that the transmit power for the UAV with optimized $P_u[n]$ suddenly increases to the large value from zero at certain times. That is because the UAV is scheduled at certain times to deliver energy to users quickly. It is clearly observed that the mean transmit power of the UAV with optimized $P_u[n]$ is less than the constant transmit power of it with fixed P_u. Therefore, the sum energy consumption of the UAV based on the optimized $P_u[n]$ is lower than that based on fixed P_u under the same throughput requirements.

In Fig. 7, the convergence of Algorithm 1 is shown. We randomly enumerate three throughput requirements which are $Q_{min} = 60$M, $Q_{min} = 40$M, and $Q_{min} = 20$M in order to observe the convergence of Algorithm 1. The simulation of algorithm convergence for three throughput requirements is
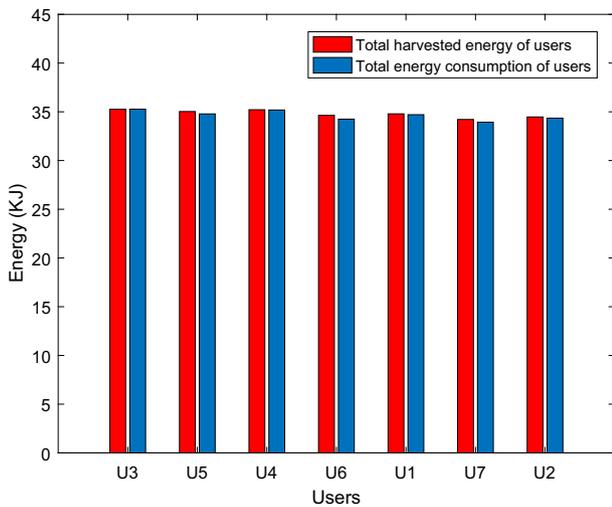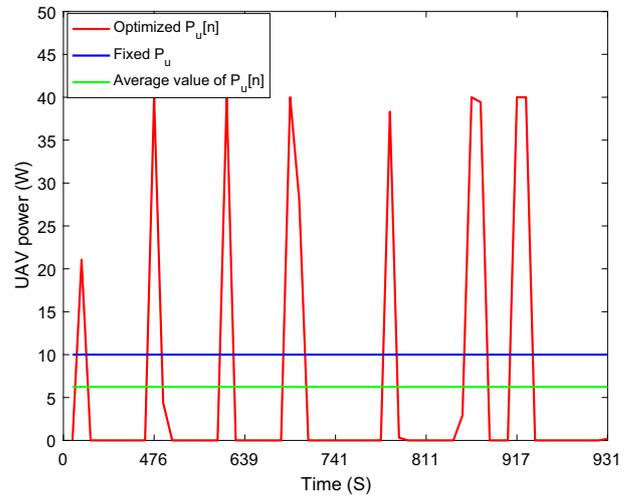

Fig. 6 Change of transmit power for the UAV versus time under optimized $P_u[n]$ and fixed P_u.
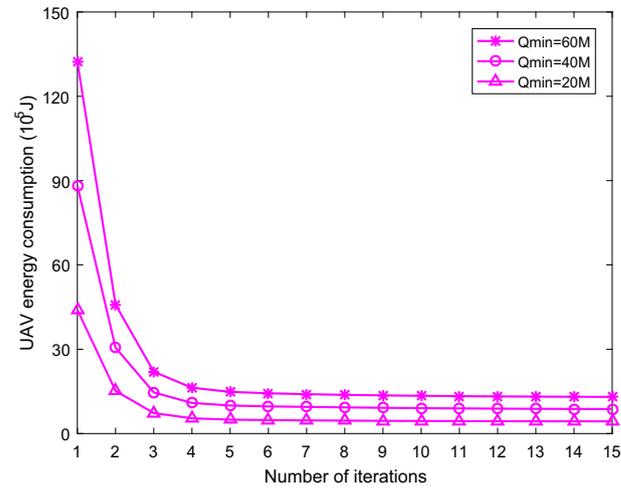

Fig. 7 Convergence of Algorithm 1 with three different throughput requirements.

based on the given total discrete point N or total time slot numbers $N - 1$ previously. As the number of iteration increase, the rotary-wing UAV's energy consumptions are rapidly close to a certain value based on random three throughput requirements. It indicates that Algorithm 1 can converge quickly by a few iterations. It is also proved that our presented algorithm is an efficient algorithm based on the trajectory optimization and resource allocation.

5. Conclusions

In this paper, we study a rotary-wing UAV-enabled WPCN system. In the WPCN system, the rotary-wing UAV played the role of the hybrid access point, where the UAV charged the terrestrial users in downlink and collected information from them in uplink. During communication tasks being carried out in uplink and downlink, we studied the energy consumption model of the UAV, which included the

Fig. 5 The causality of the total harvested energy and energy consumption for users.

communication energy consumption and the propulsion energy consumption. We aimed to minimize sum energy consumption of the rotary-wing UAV by jointly optimizing the UAV trajectory, the power allocation of the UAV, the scheduling strategy, and the time allocation. An efficient iterative algorithm was presented to achieve the minimum energy consumption of the UAV. Simulation results showed that our presented scheme is better than other benchmark schemes in the aspect of energy consumption.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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