Trajectory and Resource Optimization in OFDM based UAV-Powered IoT Network

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***Abstract*—The Internet of Things (IoT) is playing an increasingly vital role in multiple industries and our everyday life. A pressing practical problem of IoT devices (IoT-Ds) is their explosive growth of connectivity which leads to large energy consumption. One of the most promising solutions to achieve a sustainable green IoT network is unmanned aerial vehicle (UAV) enabled wireless power transfer (WPT) due to its flexibility, mobility and cost advantage. In this paper, we propose an UAV-powered IoT network based on Orthogonal Frequency Division Multiplexing (OFDM). In the proposed network, two ground nodes (GNs) are powered by two UAVs through down link WPT. In the uplink, the data collected by GNs are transmitted to the corresponding UAVs with the harvested energy by utilizing orthogonal subcarriers, which can effectively avoid the interference. UAVs' trajectories and resource allocation are optimized to maximize the sum average transmission rate of two GNs while ensuring the minimum average transmission rate of each GN. In this paper, we utilize successive convex programming (SCP) technique to solve the proposed optimization problem. Simulation results show that our proposed scheme achieves larger sum average transmission rate than the benchmark schemes.**

***Index Terms*—Green IoT network, UAV, OFDM, trajectory and resource optimization**

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I. Introduction

Internet of Things (IoT) is an emerging technology which has been bringing transformative changes to industry, agriculture and all aspects of our daily lifes. A majority of IoT-based visions, e.g. smart city, smart home and tactile Internet are progressively being realized [1]- [6]. The development of IoT technology motivate researchers to explore a vast range of novel applications [7]- [13], which are accompanied with vigorous increment of IoT connections. According to Ericsson, 28 billion IoT nodes will be connected around the world by 2021, among which more than 15 billion IoT nodes will be used to support machine-to-machine communication [14].

The huge number of IoT nodes and massive information transmission required for future IoT applications lead to tremendous amount of energy consumption. Most IoT nodes are currently powered by various of batteries with different sizes and capacities [15]. These batteries may need to be replaced periodically due to their limited battery life. Energy harvesting (EH) is considered as a possible solution to realize self-sustainable IoT-Ds. By harvesting energy from the environment, the batteries of IoT-Ds can be recharged, helping prolong the lifetime of IoT network. Several works have been devoted to harvesting and managing environmental energy, e.g., kinetic, solar and wind, to make IoT nodes sustainable [16]- [18].

In spite of these advantages, EH suffers from the uncertainty of the environment and hence the unstable performance. Wireless power transfer (WPT) provides a more reliable and controlable solution for energy supply of IoT nodes through harvesting energy from radio frequency (RF) signal, which provides an effective way to provide energy supply to these IoT nodes deployed underground or remote places, in which the battery of IoT nodes cannot be changed [19]- [23]. Achieving a high energy efficiency is a challenge of WPT due to the path loss and the power attenuation of electro-magnetic waves [23]. In view of this, UAV is regarded as a promising platform of WPT to improve the energy efficiency as low-cost UAVs can fly close to IoT-Ds [24]- [27], where the trajectories of UAVs can be optimized to improve the system performance [28]. In addition, UAVs can also exchange information with IoT-Ds [30]. Several studies have investigated how to improve the system performance by exploiting the mobility of UAVs [27]- [32].

The aforementioned studies on UAV-powered IoT networks mainly focus on improving energy efficiency by optimizing UAV trajectory. However, interference exists when multiple

IoT nodes simultaneously transmit their information to UAVs. Orthogonal frequency division multiplexing (OFDM), a mature technology which has been widely adopted in many communication standards including LTE and 5G New Radio, can enable high-rate and robust information transmission with orthogonal subcarriers to avoid the interference. [33]. Enhanced system performance can be achieved by optimizing subcarrier and power allocation in OFDM based networks [34]- [35]. Motivated by the above advantages, there have been several studies on OFDM based IoT networks [33], [36].

This paper focus on OFDM based UAV-powered IoT network, which is a feasible solution to cope with the problem of interference and energy supply. Specifically, we utilize OFDM technology to avoid interference in UAV-powered IoT network, in which two ground IoT nodes (GNs) simultaneously transmit their collected information to UAVs over orthogonal OFDM subcarriers. We investigate the resource and trajectory optimization to maximize the sum average transmission rate of GNs. Our main contributions in this work are summarized as follows.

- An OFDM based UAV-powered IoT network is proposed to avoid interference, in which two GNs simultaneously transmit their information to UAVs over orthogonal subcarriers by utilizing the harvested energy from the UAVs.
- To maximize the sum average transmission rate of GNs, we optimize the UAV trajectory and resources including transmit time, power and OFDM subcarrier allocation. We propose a SCP based algorithm to solve the corresponding non-convex optimization problem.
- Simulation results indicate that our proposed scheme outperforms two benchmark schemes in terms of the sum average transmission rate due to the interference avoidance. Besides, we study the impact of the inter-GN distance, energy transfer power and minimum average transmission rate.

The remainder of this work is organized as follows. Related works is presented in Section II. Then, we introduce the system model and problem formulation Section III. Section IV presents the solution of the optimization problem and our algorithm design. Simulation results are presented in Section V. Finally, we summarize the paper in Section VI.

II. Related Works

- Novel IoT applications: [6] proposed a dynamic resource allocation scheme for Tactile Internet of Things based on quality of experience. [7] proposed a smart home implementation with five sensors to control the priorities of different missions. Minimum energy consumption of household appliances for sustainable smart home is investigated in [8]. [9] presented a survey on blueprint and current concept of smart city, in which large number of IoT-D sensors monitor and gather information from the environment to support various services. Applications designed modularly can be reused by other cities and this has been tested in three Danish cities [10]. The deployment of large number of IoT nodes in smart city provides possibilities for the realization of Tactile Internet of Things [11]. [12] introduced a heterogeneous network model and a new cache replacement scheme for Tactile Internet of Things with three layers to achieve higher energy efficiency. A queue control problem of delay and reliability in energy-constrained tactile communication is formulated and addressed in [13].

- Energy supply technologies for IoT: [16] utilized human kinetic energy for EH, and proposed a power management scenario to improve the energy efficiency. [17] developed an energy-harvesting-aware routing protocol to improve energy efficiency and quality of service for IoT networks. In order to maximize the utilization of harvested energy, a graphene-based energy management EH network is proposed in [18]. A three-stage method is proposed to solve the minimization problem for less energy cost of wireless powered IoT network in [19]. [20] investigated the long distance WPT, and designed a repeater circuit for multiple loads. Beamforming WPT is able to achieve higher energy efficiency and to transfer power in long distance [21]. A WPT beam scheduling scheme is proposed in [22], in which the channel information is obtained through contextual learning. [23] proposed three novel beamforming schemes to improve the energy efficiency of wireless powered IoT networks.

- UAV-powered IoT: A multilayer distributed UAV-enabled wireless network architecture is proposed in [27]. [28] proposed a magnetic resonance-coupled WPT model for UAV-powered IoT networks, which studied the optimization problems of energy utilization maximization and trajectory deviation minimization. In [29], multiple devices are charged by an UAV with energy transmitter, whose three-dimensional location is optimized to maximize the received energy. UAV trajectory optimization has attracted increasing research attention because it is an important factor which determines the system performance. Wireless resource allocation and UAV trajectory are optimized jointly to maximize the throughput of wireless powered IoT nodes in [30]. The UAV route is designed to prolong the lifetime of sensors under data gathering and energy constraint in [31]. [32] proposed an UAV trajectory scenario for communication networks, in which multiple ground nodes are powered by single UAV.

- OFDM based IoT: [33] utilized frequency diversity to reduce the BER of OFDM based IoT system under the spectral efficiency constraint. [36] proposed a low complexity scheme of narrowband OFDM transmitter for IoT nodes based on lookup tables. [37] investigated sparse index OFDM modulation based IoT networks, and proposed an energy efficient scheme to reduce PARA. [38] proposed a novel OFDM scheme for massive information transmission of IoT network, which is able to improve the energy efficiency and information security. A new decoding algorithm for OFDM is proposed to enable low-power transmission under the IoT Wi-Fi standards in [39].

III. System Model and Problem Formulation

A. System Model

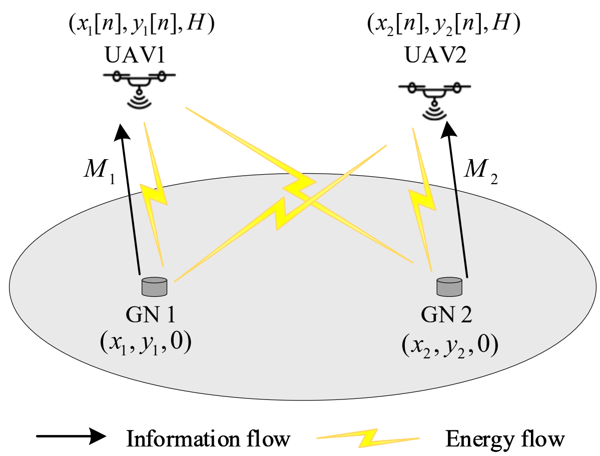

Fig. 1. System model

The proposed system model of UAV-powered IoT network is shown in Fig. 1. Two GNs are deployed on the ground for IoT services. Two UAVs are deployed to transfer power for GNs and receive information of the corresponding GNs, i.e., UAV 1 and UAV 2 receive information from GN 1 and GN 2, respectively.

The flight time of UAVs T is equally divided into N time slots whose index and length are denoted as n and δ, respectively. The location of UAV i in time slot n is denoted as $q_i[n]$. Two UAVs fly from the given start points $q_i[0]$ to the end points $q_i[N]$ at a fixed altitude H. GN j is deployed at w_j, and the distance between GNs is denoted as D_{GN}. We assume that UAVs hover at certain locations $q_i[n]$ in each time slot n, which consists of a power transferring phase $\delta_E[n]$ and an information transmission phase $\delta_I[n], \delta_E[n] + \delta_I[n] = \delta$, due to the half-duplex characteristic of antenna deployed on UAVs. Two UAVs simultaneously transfer power or receive information in each time slot, in which two UAVs have the same time allocation $\delta_E[n]$ and $\delta_I[n]$. Environmental information is collected by GNs, which are transmitted to UAVs in the uplink. In the down link, UAVs transfer power to GNs by broadcasting the signals utilizing all the OFDM subcarriers. To avoid the interference, information of two GNs are transmitted over orthogonal and complementary OFDM subcarrier sets M_1 and M_2, respectively, i.e., $M_1 \cap M_2 = \emptyset$, $M_1 \cup M_2 = M$, where M is the whole OFDM subcarrier set which contains U subcarriers. The detailed notations are shown in Table 1.

B. Problem Formulation

The channel power gain of the uplink from GN j to UAV i in the n-th time slot over k-th subcarrier is given by [43]

$$h_{q_i,w_j}[n][k]{=}\beta_0\left|g_{q_i,w_j}[k]\right|^2 d_{q_i,w_j}^{-\alpha}[n], i,j \in \{1,2\}, \tag{1}$$

where $\alpha = 2$ denotes the path loss exponent, $\beta_0 = 10^{-3}$ denotes the average channel power gain at the reference

TABLE I
NOTATIONS

Symbol	Description
T	UAVs' flight time
N	Number of time slots
P	Transmission power of UAVs
U	Number of subcarriers
H	Fling height of UAV
D_{GN}	The distance between GNs
$q_i[n]$	Location of UAV i
$q_i^{(t)}[n]$	Location of UAV i at t-th iteration
w_j	Location of GN j
$\delta_E[n]$	Length of power transferring phase
$\delta_I[n]$	Length of information transmission phase
δ	Length of each time slot
M	OFDM subcarrier set
M_j	OFDM subcarrier set occupied by GN j
h_{q_i,w_j}	Channel power gain of the uplink from GN j to UAV i
d_{q_i,w_j}	Distance between GN j and UAV i
d_{min}	Minimum distance between UAVs
S_{max}	Maximum speed of UAVs
g_{q_i,w_j}	Small-scale fading coefficient of the k-th subcarrier
β_0	Average channel power gain at the reference distance of d_0= 1m
α	Path loss exponent
$\tilde{g}$	Deterministic LoS channel component
$\hat{g}$	Rayleigh fading factor
K	Rician factor of the uplink channel
$Q_j[n]$	Energy consumption of GN j in time slot n
$Q_j[n][k]$	The information transmission power of GN j in time slot n over the k-th subcarrier
Q_j^{total}	Total energy consumption of GN j
$E_j[n][k]$	Harvested energy of GN j in time slot n and subcarrier k
E_j^{total}	Total harvested energy of GN j
$r_j[n][k]$	Uplink transmission rate in time slot n over subcarrier k
η	Energy conversion efficiency
p_k	Transmission power over subcarrier k
σ_i^2	Noise power at UAV i
R	Auxiliary variable
R_j	Average transmission rate of GN j
R_{th}^j	Minimum information transmission rate of GN j
$R_{current}^j$	Current average transmission rate of GN j in the subcarrier allocation
$R_{current}^{j}{}'$	Average transmission rate of GN j if subcarrier k' will be assigned to M_j
ΔR	Increment of average transmission rate
$P_j^{avg\prime}$	Transmission power of GN j over each subcarrier if subcarrier k' will be assigned to M_j

distance of $d_0 = 1m$, $d_{q_i,w_j}[n]$ denotes the distance between UAV i and GN j in time slot n, which is given by

$$d_{q_i,w_j}[n] = \sqrt{||q_i[n] - w_j||^2 + H^2}, i, j \in \{1, 2\}, \quad (2)$$

where $q_i[n]$ denotes the UAV location in time slot n, w_j denotes the location of GN j. Thus, the channel power gain is written as

$$h_{q_i,w_j}[n][k] = \frac{\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{||q_i[n] - w_j||^2 + H^2}, i, j \in \{1, 2\}. \quad (3)$$

The small-scale fading coefficient $g_{q_i,w_j}[k]$ in equation (1) is given by [42]

$$g_{q_i,w_j}[k] = \sqrt{\frac{K}{K+1}}\tilde{g} + \sqrt{\frac{1}{K+1}}\hat{g}[k], i, j \in \{1, 2\}, \quad (4)$$

where $\tilde{g}$ and $\hat{g}$ denote the deterministic LoS channel component and Rayleigh fading factor, respectively. K denotes the Rician factor of the uplink channel between UAVs and GNs.

The energy consumption of GN j in time slot n for information transmission is given by

$$Q_j[n] = \delta_I[n] \sum_{k \in M_j} Q_j[n][k], j \in \{1, 2\}, \quad (5)$$

where $Q_j[n][k]$ denotes the information transmission power of GN j in time slot n over subcarrier k. The total energy consumption of GN j is given by

$$Q_j^{total} = \sum_{n=1}^{N} Q_j[n] = \delta_I[n] \sum_{n=1}^{N} \sum_{k \in M_j} Q_j[n][k], j \in \{1, 2\}. \quad (6)$$

As UAVs provide energy for GNs with fixed power P by broadcasting, each GN is able to harvest energy from both UAVs. In the downlink, the harvested energy of GN j in time slot n and subcarrier k is given by

$$E_j[n][k] = \eta p_k \delta_E[n] \sum_{i=1}^{2} h_{q_i,w_j}[n][k], j \in \{1, 2\} \quad (7)$$

where η denotes the energy conversion efficiency, and $p_k = \frac{P}{U}$ denotes the transmission power over subcarrier k, where P and U denote the transmission power of UAVs and number of subcarriers, respectively.

Therefore, the total harvested energy of GN j is given by

$$E_j^{total} = \sum_{n=1}^{N} \sum_{k \in M} E_j[n][k], j \in \{1, 2\}. \quad (8)$$

The transmission rate of link GN $j \rightarrow$ UAV i in time slot n over subcarrier k is given by [30]

$$r_j[n][k] = \frac{\delta_I[n]}{\delta} \log_2 \left(1 + \frac{Q_j[n][k] h_{q_i,w_j}[n][k]}{\sigma_i^2}\right), \quad (9)$$

where $k \in M_j, n \in N, i = j, j \in \{1, 2\}$, and σ_i^2 denotes the noise power at UAV i.

The average transmission rate of GN j over flight time T is given by [30]

$$R_j = \frac{1}{N} \sum_{n=1}^{N} \sum_{k \in M_j} r_j[n][k], j \in \{1, 2\}. \quad (10)$$

With the target to maximize the sum average transmission rate of two GNs by optimizing UAVs' trajectories, transmission time, subcarrier and transmit power allocation under the constraints of energy, minimum distance between UAVs and minimum average transmission rate of each GN, the optimization problem is formulated as

$$(P1): \max_{\{A,B,C,D\}} \frac{1}{N} \sum_{j=1}^{2} \sum_{n=1}^{N} \sum_{k \in M_j} r_j[n][k] \quad (11)$$

subject to

$$\begin{aligned}
&C1: Q_j^{total} \leq E_j^{total}, j \in \{1, 2\} \\
&C2: \delta_E[n] + \delta_I[n] \leq \delta, \forall n \in N \\
&C3: 0 \leq \delta_I[n] \leq \delta, 0 \leq \delta_E[n] \leq \delta, \forall n \in N \\
&C4: ||q_i[n] - q_i[n-1]||^2 \leq S_{\max}^2, \forall n \in N, i \in \{1, 2\} \\
&C5: ||q_1[n] - q_2[n]||^2 \geq d_{\min}^2, \forall n \in N \\
&C6: \frac{1}{N} \sum_{n=1}^{N} \sum_{k \in M_j} r_j[n][k] \geq R_{th}^j, j \in \{1, 2\}
\end{aligned}$$

where A, B, C, D denote the transmit power allocation, UAVs' trajectories, time allocation and subcarrier allocation, respectively, in which $A = \{Q_1[n][k], Q_2[n][k]\}$, $B = \{q_1[n], q_2[n]\}$, $C = \{\delta_E[n], \delta_I[n]\}$, $D = \{M_1, M_2\}$, $k \in M, n \in N$.

Constraint $C1$ means that the total energy consumption of GNs should not exceed their harvested energy. Constraint $C2$ and $C3$ limit the time allocation $\delta_I[n]$ and $\delta_E[n]$ to a reasonable range. Constraint $C4$ ensures that the velocities of UAVs are limited by the maximum velocity S_{max}. Constraint $C5$ means that the minimum distance between two UAVs should not be closer than $d_{\min}$ to prevent collision. Constraint $C6$ ensures that both GNs achieve their minimum average transmission rate R_{th}^j.

IV. Problem Solution

Substituting (6), (8), (9), (10) into $C1$ and $C6$, optimization problem $P1$ is written as

$$(P2): \max_{\{A,B,C,D\}}$$
$$\sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M_j} \frac{\delta_I[n]}{N\delta} \log_2 \left(1 + \frac{Q_j[n][k] \beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \quad (12)$$

subject to

$$C1: \delta_I[n] \sum_{n=1}^{N} \sum_{k \in M_j} Q_j[n][k]$$
$$\leq \eta p_k \delta_E[n] \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M} \frac{\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right)}, j \in \{1, 2\}$$

$$C2: \delta_E[n] + \delta_I[n] \le \delta, \forall n \in N$$
$$C3: 0 \le \delta_I[n] \le \delta, 0 \le \delta_E[n] \le \delta, \forall n \in N$$
$$C4: ||q_i[n] - q_i[n-1]||^2 \le S_{\max}^2, \forall n \in N, i \in \{1,2\}$$
$$C5: ||q_1[n] - q_2[n]||^2 \ge d_{\min}^2, \forall n \in N$$
$$C6: \sum_{n=1}^{N} \sum_{k \in M_j} \frac{\delta_I[n]}{N\delta} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) {\sigma_i}^2}\right) \ge R_{th}^j, i = j, j \in \{1,2\}$$

It is easy to find that constraints of $C1$, $C5$ and $C6$ are non-convex. Thus, the optimization problem (P2) is non-convex, which is difficult to obtain the optimal solution.

By introducing an auxiliary variable R, the optimization problem (P2) can be equivalently reformulated as

$$(P3): \max_{\{A,B,C,D\}} R \tag{13}$$

subject to

$$C7: \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M_j} \frac{\delta_I[n]}{N\delta} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \ge R, i = j, j \in \{1,2\}$$
$$C1 - C6$$

Although the optimization problem (P3) is still non-convex, it can be solved iteratively by applying the SCP techniques [30], which is an approximation algorithm locating Kuhn-Tucker solutions to non-convex mathematical programs [41]. The optimal transmit power allocation $A = \{Q_1[n][k], Q_2[n][k]\}$, UAVs' trajectories $B = \{q_1[n], q_2[n]\}$, time allocation $C = \{\delta_E[n], \delta_I[n]\}$ and subcarrier allocation $D = \{M_1, M_2\}$ can be obtained by considering the others as given in an alternating manner.

A. Transmit power allocation

With given time allocation , subcarrier allocation and UAVs' trajectories, the transmit power allocation optimization problem is formulated as

$$(P4): \max_{\{A\}} R \tag{14}$$

subject to

$$C8: \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M_j} \frac{\delta_I[n]}{N\delta} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \ge R, i = j, j \in \{1,2\}$$
$$C9: \eta p_k \delta_E[n] \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M} h_{q_i,w_j}[n][k] - \sum_{n=1}^{N} \sum_{k \in M_j} \delta_I[n] Q_j[n][k] \ge 0, j \in \{1,2\}$$
$$C10: \frac{\delta_I[n]}{N\delta} \sum_{n=1}^{N} \sum_{k \in M_j} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \ge R_{th}^j, i = j, j \in \{1,2\}$$

Problem (P4) is a typical convex problem, which can be solved by standard optimization techniques such as CVX.

B. Time allocation

With given transmit power allocation, subcarrier allocation and UAVs' trajectories, the time allocation optimization problem is formulated as

$$(P5): \max_{\{C\}} R \tag{15}$$

subject to

$$C11: \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M_j} \frac{\delta_I[n]}{N\delta} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \ge R, i = j, j \in \{1,2\}$$
$$C12: \eta p_k \delta_E[n] \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M} h_{q_i,w_j}[n][k] - \sum_{n=1}^{N} \sum_{k \in M_j} \delta_I[n] Q_j[n][k] \ge 0, j \in \{1,2\}$$
$$C13: \frac{\delta_I[n]}{N\delta} \sum_{n=1}^{N} \sum_{k \in M_j} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \ge R_{th}^j, i = j, j \in \{1,2\}$$
$$C14: \delta_E[n] + \delta_I[n] \le \delta, \forall n \in N$$
$$C15: 0 \le \delta_I[n] \le \delta, 0 \le \delta_E[n] \le \delta, \forall n \in N$$

Problem (P5) can be solved by standard optimization techniques such as CVX as it is a linear program.

C. Trajectory optimization

With given transmit power allocation, subcarrier allocation and time allocation, the optimization problem of UAVs' trajectories is formulated as

$$(P6): \max_{\{B\}} R \tag{16}$$

subject to

$$C16: \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M_j} \frac{\delta_I[n]}{N\delta} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \ge R, i = j, j \in \{1,2\}$$
$$C17: \delta_I[n] \sum_{n=1}^{N} \sum_{k \in M_j} Q_j[n][k] \le \eta p_k \delta_E[n] \sum_{n=1}^{N} \sum_{i=1}^{2} \sum_{k \in M} \frac{\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right)}, j \in \{1,2\}$$
$$C18: ||q_i[n] - q_i[n-1]||^2 \le S_{\max}^2, \forall n \in N, i \in \{1,2\}$$
$$C19: ||q_1[n] - q_2[n]||^2 \ge d_{\max}^2, \forall n \in N$$
$$C20: \frac{\delta_I[n]}{N\delta} \sum_{n=1}^{N} \sum_{k \in M_j} \log_2 \left(1 + \frac{Q_j[n][k]\beta_0 \left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n] - w_j||^2 + H^2\right) \sigma_i^2}\right) \ge R_{th}^j, i = j, j \in \{1,2\}$$

Since the constraints of $C16$, $C17$, $C18$ and $C19$ are non-convex, the optimization problem (P6) is non-convex, which is difficult to obtain the optimal solution. SCP technique can be utilized to solve the optimization problem (P6), in which the trajectory optimization problem is approximated into a convex problem at each iteration [41]. Then, the optimal UAVs trajectories can be obtained by updating it in an iterative manner.

Assuming the initial trajectory of UAV i is denoted as $q_i^{(0)}[n] = \left(x_i^{(0)}[n], y_i^{(0)}[n], H\right)$, and the trajectory of UAV i after t-th iteration is denoted as $q_i^{(t)}[n] = \left(x_i^{(t)}[n], y_i^{(t)}[n], H\right)$. Any convex function can be globally lower bounded with its first-order Taylor expansion. Thus, with any given UAVs trajectories $q_i^{(t)}[n]$, we can obtain

$$\begin{aligned}
&r_j[n][k]\\
=&\frac{\delta_I[n]}{\delta}\log_2\left(1+\frac{Q_j[n][k]\beta_0\left|g_{q_i,w_j}[k]\right|^2}{\left(||q_i[n]-w_j||^2+H^2\right)\sigma_i^2}\right)\\
\geq&\frac{\delta_I[n]}{\delta}\log_2\left(\left(||q_i[n]-w_j||^2+H^2\right)\sigma_i^2+Q_j[n][k]\beta_0\left|g_{q_i,w_j}[k]\right|^2\right)\\
-&\frac{\delta_I[n]}{\delta}r_j^{ub}[n]\\
\triangleq&r_j^{lb}[n][k], \qquad (17)
\end{aligned}$$

where $r_j^{ub}[n]$ is the upper bound of $\log_2\left(\left(||q_i^{(t)}[n]-w_j||^2+H^2\right)\sigma_i^2\right)$, and $r_j^{lb}[n][k]$ is the lower bound of $r_j[n][k]$.

$$\begin{aligned}
r_j^{ub}[n] \triangleq& \log_2\left(\left(||q_i^{(t)}[n]-w_j||^2+H^2\right)\sigma_i^2\right)\\
&+\frac{\log_2(e)\left(||q_i[n]-w_j||^2-||q_i^{(t)}[n]-w_j||^2\right)}{\left(||q_i^{(t)}[n]-w_j||^2+H^2\right)}. \qquad (18)
\end{aligned}$$

We can obtain from constraints of $C17$ that

$$\begin{aligned}
&\sum_{i=1}^{2}\frac{\eta p_k\delta_E[n]\beta_0\left|g_{q_i,w_j}[k]\right|^2}{\|q_i[n]-w_j\|^2+H^2}\\
\geq&\sum_{i=1}^{2}\frac{2\eta p_k\delta_E[n]\beta_0\left|g_{q_i,w_j}[k]\right|^2}{\left\|q_i^{(t)}[n]-w_j\right\|^2+H^2}\\
-&\sum_{i=1}^{2}\frac{\eta p_k\delta_E[n]\beta_0\left|g_{q_i,w_j}[k]\right|^2\left(H^2+\|q_i[n]-w_j\|^2\right)}{\left(\left\|q_i^{(t)}[n]-w_j\right\|^2+H^2\right)^2}\\
\triangleq&\mathrm{E}_j^{lb}[n][k], \qquad (19)
\end{aligned}$$

where $\mathrm{E}_j^{lb}[n][k]$ is the lower bound of $\sum\limits_{i=1}^{2}\frac{\eta p_k\delta_E[n]\beta_0\left|g_{q_i,w_j}[k]\right|^2}{\|q_i[n]-w_j\|^2+H^2}$

The lower bound of constraint $C19$ is given by

$$\begin{aligned}
||q_1[n]-q_2[n]||^2 \geq& -||q_1^{(t)}[n]-q_2^{(t)}[n]||^2\\
&+2\left(q_1^{(t)}[n]-q_2^{(t)}[n]\right)^T\left(q_1[n]-q_2[n]\right). \qquad (20)
\end{aligned}$$

With lower bounds in (17), (19), (20) and any given $q_i^{(t)}[n]$, problem (P6) can be approximated as

$$(P7):\max_{\{B\}} R \qquad (21)$$

subject to

$$C21:\frac{\delta_I[n]}{N\delta}\sum_{n=1}^{N}\sum_{j=1}^{2}\sum_{k\in M_j}r_j^{lb}[n][k]\geq R$$

$$C22:\sum_{n=1}^{N}\sum_{k\in M}E_j^{lb}[n][k]-\sum_{n=1}^{N}\sum_{k\in M_j}\delta_I[n]Q_j[n][k]\geq 0, j\in\{1,2\}$$

$$C23:||q_i[n]-q_i[n-1]||^2\leq S_{\max}^2, \forall n\in N, i\in\{1,2\}$$

$$\begin{aligned}
C24:&-||q_1^{(t)}[n]-q_2^{(t)}[n]||^2+2\left(q_1^{(t)}[n]-q_2^{(t)}[n]\right)^T\left(q_1[n]-q_2[n]\right)\\
&\geq d_{\min}^2, \forall n\in N
\end{aligned}$$

$$C25:\frac{\delta_I[n]}{N\delta}\sum_{n=1}^{N}\sum_{k\in M_j}r_j^{lb}[n][k]\geq R_{th}^j, j\in\{1,2\}$$

It is easy to find that constraints of $C21$, $C22$, $C24$ and $C25$ are convex. Thus, the optimization problem P7 at t-th iteration is convex optimization problem, which can be solved by standard optimization techniques such as CVX.

D. Subcarrier allocation

With given time allocation, transmit power allocation and UAVs' trajectories, subcarrier allocation can be obtained by utilizing greedy strategy with the following four steps.

1) Initialization: Divide the OFDM subcarriers set M into two subsets F_1 and F_2 according to the channel power gain $h_{q_i,w_j}[n][k]$. Specifically, subcarrier k is assigned to F_1 if $h_{q_1,w_1}[n][k] \geq h_{q_2,w_2}[n][k]$, otherwise subcarrier k will be assigned to F_2. The subcarriers in F_1 and $F2$ are arranged in descending order of the channel power gain.

2) Preallocation: Assign the subcarriers in F_1 and F_2 one by one to M_1 and M_2 respectively in descending order of the channel power gain until the current average transmission rate $R_{current}^j$ achieves R_{th}^j or F_1 and F_2 are empty. $R_{current}^j$ is updated by

$$R_{current}^j=\frac{\delta_I[n]}{N\delta}\sum_{n=1}^{N}\sum_{k\in M_j}\log_2\left(1+\frac{P_j^{avg}h_{q_i,w_j}[n][k]}{\sigma_i^2}\right), \qquad (22)$$

where power allocated in each subcarrier is given by

$$P_j^{avg}=\frac{E_j^{total}}{N|M_j|}. \qquad (23)$$

3) R_{th}^j guarantee allocation: Firstly, assign the remaining subcarriers in F_1 and F_2 to subcarrier set F'. Then, check the current average transmission rate of GN 1. If $R_{current}^1 < R_{th}^1$, assign subcarriers in F' one by one to M_1 in descending order of $h_{q_1,w_1}[n][k]$ until the minimum average transmission rate R_{th}^1 is achieved. Finally, check the current transmission rate of GN 2. If $R_{current}^2 < R_{th}^2$, assign the remaining subcarriers in F' one by one to M_2 in descending order of $h_{q_2,w_2}[n][k]$

until R_{th}^2 is achieved. Update $R_{current}^j$ according to equation (22).

Algorithm 1 Proposed Algorithm for Subcarrier Allocation

Input: $Q_j[n][k], q_i[n], \delta_E[n], \delta_I[n]$
Repeat:
For each subcarrier $k \in M$
If $h_{q_1,w_1}[n][k] \geq h_{q_2,w_2}[n][k]$
Assign subcarrier k to F_1
Else
Assign subcarrier k to F_2
Until: All the subcarriers in M are assigned to F_1 or F_2
Repeat:
Assign the subcarrier with the largest channel power gain $h_{q_i,w_j}[n][k]$ in F_i one by one to M_i
Update $R_{current}^j$ according to equation (22)
Until: $R_{current}^j \geq R_{th}^j$ or $F_j = \varnothing$
Assign the remaining subcarriers in F_1 and F_2 to F'
Repeat:
If $R_{current}^j < R_{th}^j$
Assign the subcarrier with the largest channel power gain $h_{q_i,w_j}[n][k]$ in F' one by one to M_j
Update $R_{current}^j$ according to equation (22)
Until: $R_{current}^j \geq R_{th}^j$ or $F' = \varnothing$
Repeat:
Calculate ΔR_j of the subcarrier k' with the largest index in F'
If $\Delta R_1 \geq \Delta R_2$
Assign subcarrier k' to M_1
Else
Assign subcarrier k' to M_2
Until: $F' = \varnothing$
Output: M_1, M_2

4) Final allocation: Traverse the remaining subcarriers in F' in ascending order of the subcarrier index. For each subcarrier k' in F', calculate the increment of average transmission rate ΔR_j if k' will be assigned to M_j, which is given by

$$\Delta R_j = R_{current'}^j - R_{current}^j, \tag{24}$$

where

$${R_{current}^j}' = \frac{\delta_I[n]}{N\delta} \sum_{n=1}^{N} \sum_{k \in \{M_j \cup k'\}} \log_2 \left(1 + \frac{P_j^{avg'} h_{q_i,w_j}[n][k]}{\sigma_i^2} \right), \tag{25}$$

$$P_j^{avg'} = \frac{E_j^{total}}{N\left(|M_j| + 1\right)}. \tag{26}$$

If $\Delta R_1 \geq \Delta R_2$, assign subcarrier k' to M_1, otherwise assign subcarrier k' to M_2. The proposed subcarrier allocation algorithm is concluded in **Algorithm 1**.

In summary, subproblems (P4), (P5), (P7) and the subcarrier allocation problem are solved in a alternating manner by SCP method. Finally, a feasible solution to (P3) is obtained by the proposed resource and trajectory joint optimization algorithm, which is presented in **Algorithm 2**.

Algorithm 2 Proposed Algorithm for Resource and Trajectory Joint Optimization

Input: $w_j, q_i[0], q_i[N], T, P, S_{max}, d_{min}$
Initialize: $q_i^{(0)}[n], Q_j^{(0)}[n][k], \delta_I^{(0)}[n], \delta_E^{(0)}[n], M_1^{(0)}, M_2^{(0)}$
Let $\tilde{\delta}_E[n] = \delta_E^{(0)}[n], \tilde{\delta}_I[n] = \delta_I^{(0)}[n], \tilde{q}_i[n] = q_i^{(0)}[n], \tilde{Q}_j[n][k] = Q_j^{(0)}[n][k], \tilde{M}_1 = M_1^{(0)}, \tilde{M}_2 = M_2^{(0)}$
Repeat:
Solve problem P4 by using CVX for given $\{\tilde{\delta}_E[n], \tilde{\delta}_I[n], \tilde{q}_i[n], \tilde{M}_1, \tilde{M}_2\}$, and denote the obtained power allocation as $\{Q_j^{(t)}[n][k]\}$.
Solve problem P5 by using CVX for given $\{\tilde{q}_i[n], \tilde{Q}_j[n][k], \tilde{M}_1, \tilde{M}_2\}$, and denote the obtained time allocation as $\{\delta_E^{(t)}[n], \delta_I^{(t)}[n]\}$.
Solve problem P7 by using CVX for given $\{\tilde{\delta}_E[n], \tilde{\delta}_I[n], \tilde{Q}_j[n][k], \tilde{M}_1, \tilde{M}_2\}$, and denote the obtained UAV trajectory as $q_i^{(t)}[n]$.
Solve the subcarrier allocation problem through **Algorithm 1** for given $\{\tilde{q}_i[n], \tilde{\delta}_E[n], \tilde{\delta}_I[n], \tilde{Q}_j[n][k]\}$, and denote the obtained subcarrier allocation as $\{M_1^{(t)}, M_2^{(t)}\}$.
Update $\tilde{\delta}_E[n] = \delta_E^{(t)}[n], \tilde{\delta}_I[n] = \delta_I^{(t)}[n], \tilde{q}_i[n] = q_i^{(t)}[n], \tilde{Q}_j[n][k] = Q_j^{(t)}[n][k], \tilde{M}_1 = M_1^{(t)}, \tilde{M}_2 = M_2^{(t)}$.
Update the sum average transmission rate of GNs $R_{sum} = R^1 + R^2$ according to $\{\tilde{\delta}_E[n], \tilde{\delta}_I[n], \tilde{q}_i[n], \tilde{Q}_j[n][k], \tilde{M}_1, \tilde{M}_2\}$.
Until: the fractional increase of the objective value is below a threshold ϵ>0.
Update $\delta_E[n] = \tilde{\delta}_E[n], \delta_I[n] = \tilde{\delta}_I[n], q_i[n] = \tilde{q}_i[n], Q_j[n][k] = \tilde{Q}_j[n][k], M_1 = \tilde{M}_1, M_2 = \tilde{M}_2$
Output: $R_{sum}, \delta_E[n], \delta_I[n], q_i[n], Q_j[n][k], M_1, M_2$

V. Simulation Results

In this section, numerical results are presented to validate the performance of our proposed scheme. In the simulation, we set the UAVs' flying altitude $H = 5$m, the minimum distance between UAVs $d_{min} = 1$m, energy conversion efficiency $\eta = 0.6$, noise power $\sigma_i^2 = 10^{-5}$, the Rician factor of the uplink channel $K = 3$, deterministic LoS channel component $|\tilde{g}|^2 = -40$dB and the number of subcarriers $U = 32$. Rayleigh fading factor follows Gaussian distribution $\hat{g}[k] \sim CN(0, -40\text{dB})$. The start points and end points of two UAVs are $(2, -2)$, $(-2, -2)$, $(2, 2)$ and $(-2, 2)$, respectively. Two benchmark schemes are introduced into the performance comparison:

Scheme 1: Two UAVs simultaneously transmit energy to two GNs. Two GNs also simultaneously transmit their information to two UAVs with the harvested energy, which caused serious interference to each other [40].

Scheme 2: Two UAVs transfer power for two GNs, and GNs transmit information to UAVs with broadcasting. To reduce interference at the receiver of UAVs, GN 1 and GN 2 transmit their information to UAVs in different time slots.

The convergence performance of the proposed algorithm with different distances between GNs D_{GN} is shown in Fig.

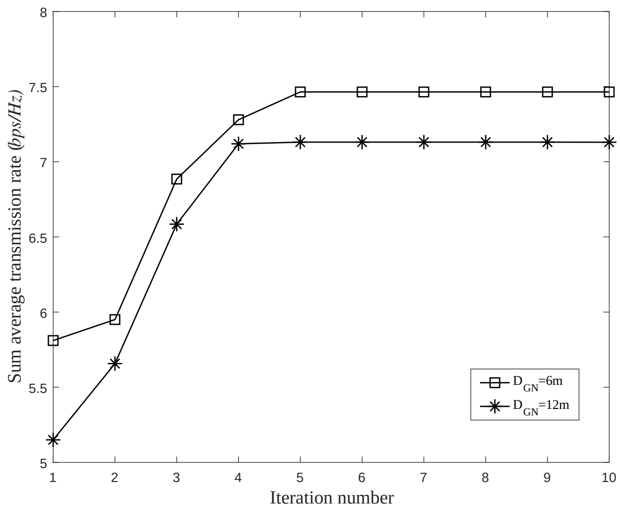

Fig. 2. Convergence procedure of the proposed algorithm

2. It is shown in Fig. 2 that the proposed algorithm converges within 5 iterations regardless of the distance between GNs. We can also observe from Fig. 2 that the system's performance becomes better with smaller distance between GNs due to better channel condition.

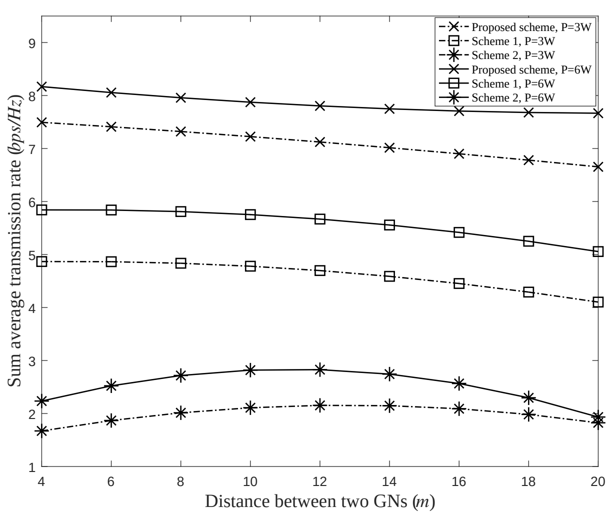

Fig. 3. Sum average transmission rate versus the distance between two GNs

Fig. 3 shows the sum average transmission rate of the proposed scheme and two benchmark schemes versus the distance between two GNs where $R_{th}^{j} = 2.5(\mathrm{bps/Hz})$, $T = 30\mathrm{s}$. We can observe from Fig. 3 that the proposed scheme always outperforms two benchmark schemes, which is because that in our proposed scheme the interference is avoided. The sum average transmission rate of scheme 1 increases when the distance between two GNs is relative small, i.e., smaller than $12\mathrm{m}$, which is because that the interference will become smaller when the distance between two GNs becomes larger. With the distance between two GNs increases, the channel between GNs and UAVs becomes worse, which results in the decrease of sum average transmission rate in the proposed scheme and two benchmark schemes.

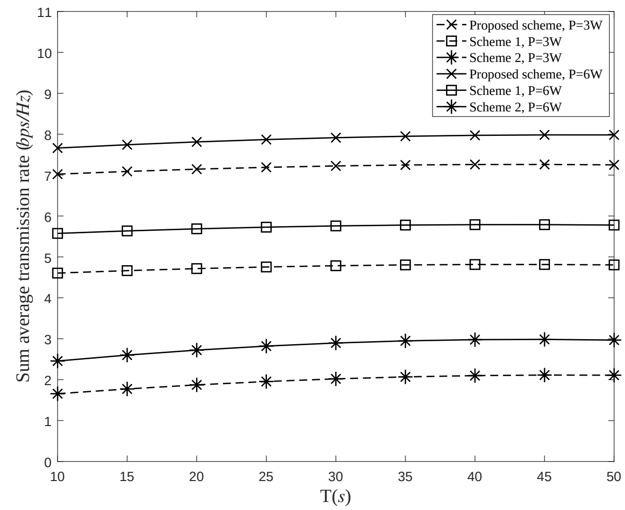

Fig. 4. Sum average transmission rate versus the UAV flight time T

Fig. 4 shows the influence of flight time T on the sum average transmission rate of three schemes when the distance between GNs is $D_{GN} = 10\mathrm{m}$. It is easy to find that longer flight time results in larger sum average transmission rate, which is because that UAVs will spend a larger proportion of flight time at the optimal position. Both Fig. 3 and Fig. 4 indicate that larger UAVs' transmission power P leads to larger sum average transmission rate, which is because that GNs are able to harvest larger power to transmit their information with larger P.

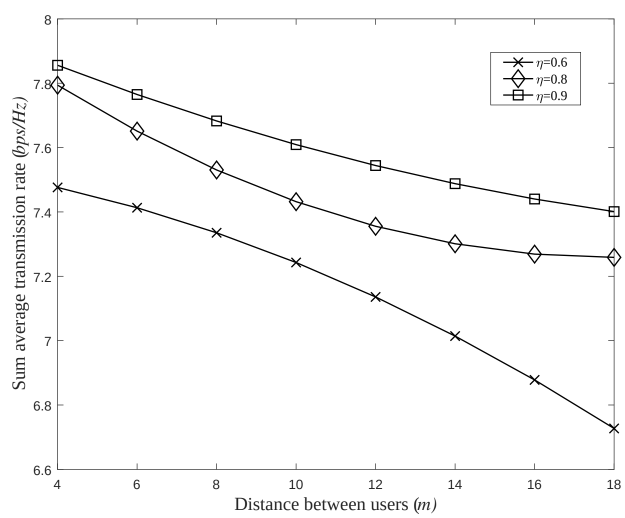

Fig. 5. Sum average transmission rate versus the distance between GNs under different energy conversion efficiency

Fig. 5 shows the sum average transmission rate versus the distance between GNs under different energy conversion efficiency, where $P = 3\text{W}$, $T = 30\text{s}$. We can observe from Fig. 5 that higher energy conversion efficiency results to larger sum average transmission rate. We can also find that with the increase of distance between GNs, the sum average transmission rate gets smaller due to worse channel condition.

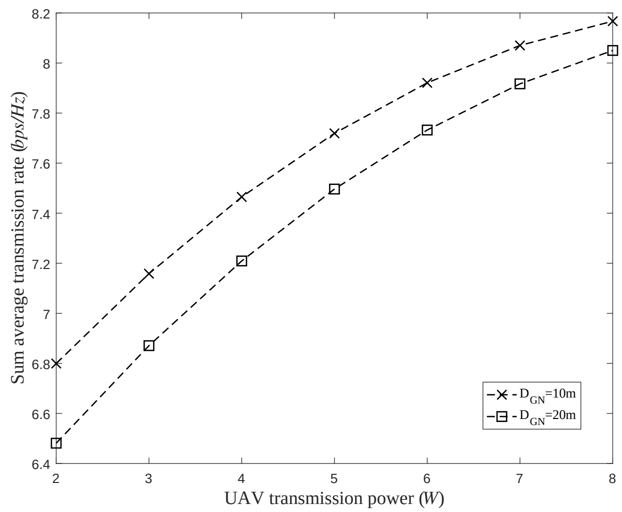

Fig. 6. Sum average transmission rate versus the UAVs' transmission power

Fig. 6 demonstrates this phenomenon more detailedly, which shows the sum average transmission rate versus the UAVs' transmission power P when the distances between two GNs are $D_{GN} = 10\text{m}$ and $D_{GN} = 20\text{m}$.

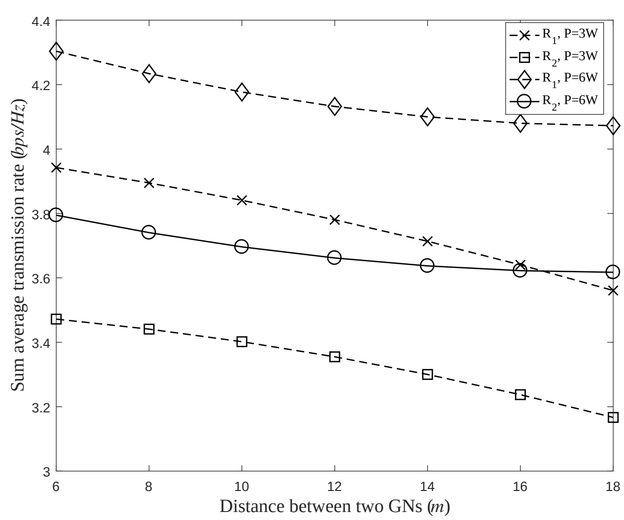

Fig. 7. Average transmission rate of each GN with same R_{th}^{j}

Fig. 7 shows the average transmission rates of each GN, i.e., R_1 and R_2 versus the distance between them, where $R_{th}^{j} = 2.5(bps/Hz)$ and $T = 30\text{s}$. In Fig. 7, we can find that the average transmission rates of both two GNs decrease with the distance due to that the uplink channel become worse when the distance between two GNs becomes larger.

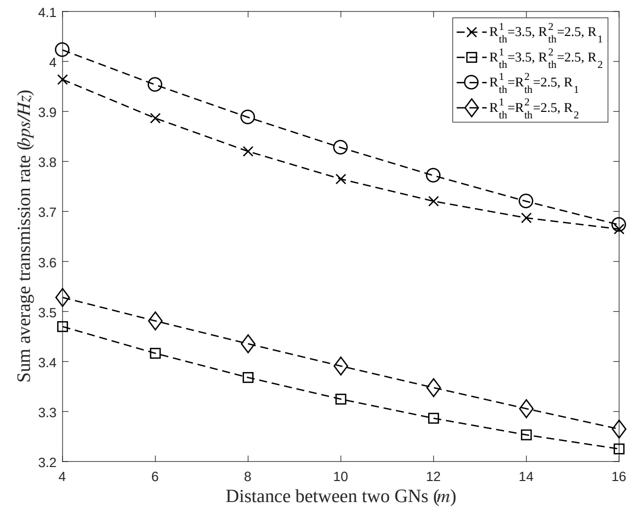

Fig. 8. Average transmission rate of each GN with different R_{th}^{j}

Fig. 8 shows the average transmission rates of each GN when two GNs have different minimum average transmission rate, i.e., $R_{th}^{1} = 3.5(\text{bps/Hz})$, $R_{th}^{2} = 2.5(\text{bps/Hz})$, where $P = 3\text{W}$, $T = 30\text{s}$. In Fig. 8, it is easy to find that the variation tendency of sum average transmission rate is not influenced by the difference of R_{th}^{j}. However, larger R_{th}^{j} leads to the reduction of sum average transmission rate, which is because that more subcarriers are assigned through step (1)-(3) to achieve R_{th}^{j}, in which subcarriers are assigned according to channel power gain. Consequently, less subcarriers are assigned through step (4), in which subcarriers are assigned according to the ΔR, which is able to achieve larger sum average transmission rate than step (1)-(3).

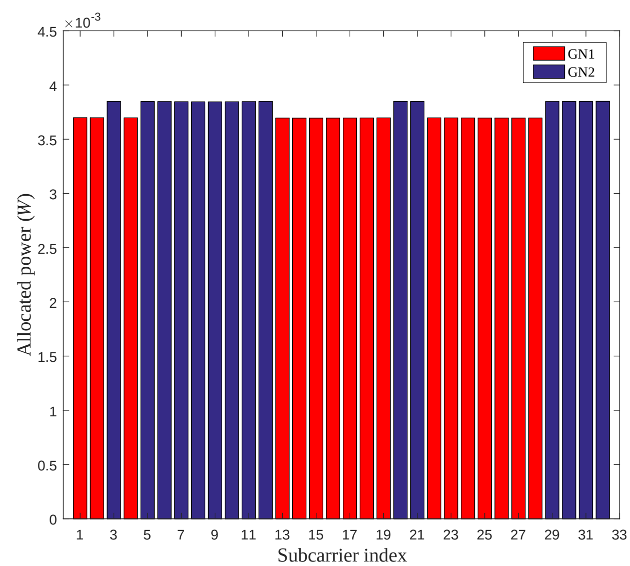

Fig. 9. Power allocated in OFDM subcarriers

Fig. 9 shows the power allocated over OFDM subcarriers, where $R_{th}^{j} = 2.5(\text{bps/Hz})$, $P = 3\text{W}$, $D_{GN} = 10\text{m}$, $T = 30\text{s}$.

We can observe from Fig. 9 that 17 subcarriers are assigned to GN 1 while 15 subcarriers are assigned to GN 2. The difference of subcarriers assigned to two GNs is very small. It is because that the proposed subcarrier allocation algorithm guarantees fairness of the two GNs to some extent.

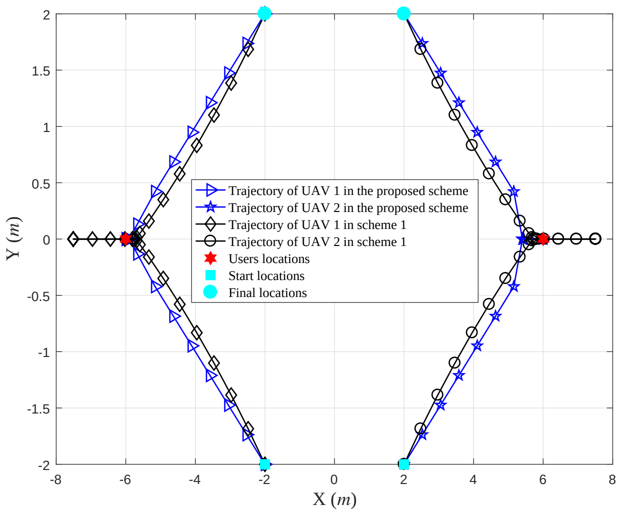

Fig. 10. UAVs' trajectories of the proposed scheme and benchmark scheme 1

Fig. 10 shows the UAVs' trajectories of the proposed scheme and scheme 2. We can observe from Fig. 10 that UAVs in the scheme 2 tends to keep away from the interference source, i.e., UAV 1 flies away from GN 2 and UAV 2 flies away from GN 1, respectively, while the UAVs in the proposed scheme fly toward GNs directly to hover over them. This difference in trajectories is caused by the severe interference in scheme 1, which is avoided in the proposed scheme. In Fig. 10, we can also find that when UAVs fly near to the GNs' locations, they will hover near these places for a quite long time because shorter distance between UAVs and GNs means higher energy transfer efficiency and better channel condition, which will improve the sum average transmission rate. Fig. 11 shows the UAVs' trajectories under different R_{th}^{j}, i.e., $R_{th}^{1} = 3.5(\text{bps/Hz})$, $R_{th}^{2} = 2.5(\text{bps/Hz})$. UAV 1 flies directly towards GN 1 while the trajectory of UAV 2 is biased towards GN 1 to assist it in achieving the minimum average transmission rate.

Fig. 12 shows the subcarriers allocation ratio assigned to GNs with different R_{th}^{j}, i.e., $R_{th}^{1} = 4.5(\text{bps/Hz})$, $R_{th}^{2} = 1.5(\text{bps/Hz})$, where $T = 30\text{s}$ and $D_{GN} = 10\text{m}$. It is easy to find that GN 1 occupies much more subcarriers with low UAVs' transmission power P to achieve the minimum average transmission rate, which is because that it needs more subcarriers to achieve its minimum transmission rate. As the transmission power of UAVs increases, less subcarriers are needed to achieve R_{th}^{1} and R_{th}^{2}. As a result, the difference in subcarriers allocation ratio becomes smaller, which is because that more subcarriers are allocated by step (4).

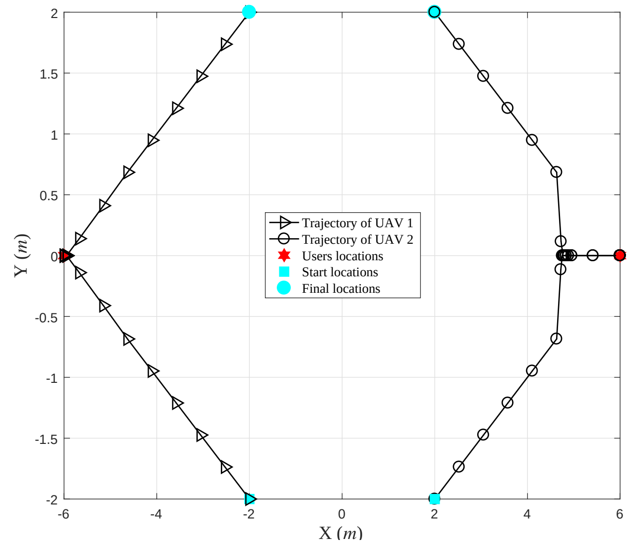

Fig. 11. UAVs' trajectories under different R_{th}^{j}

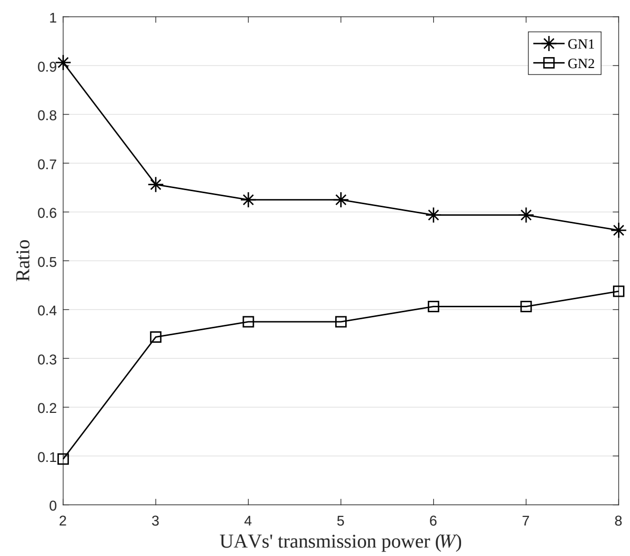

Fig. 12. Subcarriers allocation ratio assigned to GNs with different R_{th}^{j}

VI. Conclusions

In this paper, we investigate an UAV-powered IoT network based on OFDM. The key to avoid interference is transmitting information of different GNs over orthogonal subcarriers. To maximize the sum average transmission rate of GNs, we optimize UAVs' trajectories and resources including transmission time, power and subcarrier allocation, under the constraints of minimum average transmission rate, UAVs' collision avoidance and maximum speed. To cope with the complex and non-convex optimization problem, we approximate the non-convex constraints to their lower bounds to formulate the convex optimization problems, which are then solved by SCP technique. Simulation results show that the proposed scheme is able to achieve larger sum average transmission rate than two benchmark schemes.

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