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UAV-Assisted SWIPT in Internet of Things With Power Splitting: Trajectory Design and Power Allocation

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ABSTRACT Simultaneous wireless information and power transfer (SWIPT) is a promising technology to provide energy and information supplies at the same time in emerging Internet of Things (IoT) systems. In this paper, we focus on leveraging unmanned aerial vehicles (UAVs) to realize energy-transferring and information-transmitting simultaneously in the IoT. This paper investigates the joint optimization of power allocation and trajectory design of the UAV to support infrastructure-starved IoT services. The objective is to maximize the minimum energy harvested among the multiple ground dispersed IoT devices during a finite operating period while guaranteeing the average data rate requirement of each device. Specifically, we study the UAV-assisted SWIPT for the IoT with power splitting, which is mathematically modeled by a variate coupling optimization problem including the UAV's transmit power budget and speed constraint, which is intractable to be directly solved using the existing algorithms. To deal with the problem, this paper develops an efficient iterative algorithm via tactfully constructing the framework of alternating optimization and concave-convex procedure. As a result, it is transformed into settling a series of convex problems. Since the objective function is monotonically increasing and has an upper bound, the convergence can be guaranteed. The simulation results under various parameter configurations indicate our design enhances the efficiency and fairness of power transferred and information transmitted to the IoT devices on the ground over other benchmark schemes.

INDEX TERMS Simultaneous wireless information and power transfer, unmanned aerial vehicle, power allocation, trajectory design, power splitting.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Currently, with the innovation of wireless communication technologies, IoT system attracts increasing research attention [1], [2]. On one hand, IoT devices on the ground have information instruction demand to implement diverse infrastructure-less IoT services [3]. On the other hand, IoT devices are usually energy-constrained. Conventionally, wireless terminals are powered with batteries, which have to be replaced or recharged manually for prolonging the lifetime of the network. It generally incurs high costs and inconvenience, let alone hazardous (e.g. in toxic environments), or even infeasible (e.g. for sensors embedded inside the buildings or medical devices implanted in human bodies) [4].

The emerging technologies of unmanned aerial vehicle (UAV) have been considered as an innovative method to complement for existing IoT systems [5]. Compared with conventional terrestrial wireless communications networks, UAVs that serve as aerial transceivers have several advantages [6]. On one hand, they have highly controllable mobility and low cost. On the other hand, the UAV-assisted system is more swift and flexible for deployment and reconfiguration [7]. Moreover, UAVs usually have relatively good channel state with the ground devices to enhance the

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system capacity because of higher probability of having a line-of-sight (LOS) link [8]. In addition, UAVs can dynamically move towards IoT devices, which can thus improve the efficiency of energy-transferring and information-transmitting [9]. However, in many practical scenarios, just information-transmitting or energy-transferring is not enough for IoT systems. As mentioned above, the IoT devices have both energy and information needs. Due to the low efficiency of energy-transferring and the relatively less energy demand of IoT devices, energy-transferring is promising for many IoT systems. Considering the fact that an IoT terminal usually does not have an external power supply, energy-transferring is typically exploited to enable the long-term operation. Therefore, simultaneous wireless information and power transfer (SWIPT) technology holds significant promise in IoT systems and has led to an upsurge of research recently [10]–[13].

B. RELATED WORK

The study on UAV-assisted IoT systems is still in a very infancy stage. Majority of the existing studies have focused on studying a UAV transmits/receives information to/from ground IoT devices [3], [14]–[17]. Specifically, Xue *et al.* [3] and Zhang *et al.* [15], Wang *et al.* [16], Feng *et al.* [17] investigate the UAV-assisted data dissemination among IoT devices. The work [14] presents a study that mobile UAVs are used as aerial base stations to collect data from ground IoT devices. Notably, in the past couple of years, there are a few emerging work on either UAV-enabled information transmission or energy transfer, however, not specified for IoT scenarios. Specifically, Xu *et al.* [18], [19], study a UAV transfers energy to ground nodes. The work in [20]–[23] investigate the case that a UAV transmits information to ground nodes. Li *et al.* [24], Zhou *et al.* [25] study that a UAV transmits confidential information to multiple information receivers maximizing the minimum secrecy rate to ensure the fairness among ground terminals. In [26], Yang *et al.* study that ground nodes transmit information to a flying UAV. The work in [27] investigates the case that a source node transmits information to a UAV, then the UAV transmits the information to destination node. In [28], Xie *et al.* investigate that a UAV first charges the ground nodes by transferring the wireless energy signals in the downlink, then the ground nodes send their uplink wireless information signals to the UAVs. The work in [29] studies the resource allocation problem in UAV-enabled wireless powered mobile edge computing systems, where a UAV transmits energy signals to charge multiple mobile users and provides computation services for them.

Furthermore, although the topic of SWIPT in wireless networks has been extensively studied in recent years, most of the results cannot be directly applied to UAV-assisted IoT systems [4], [30]–[34]. On one hand, the characteristics of UAVs are not considered, such as the mobility and limitation of energy consumption. On the other hand, there is limited consideration of IoT devices characteristics, such as low energy consumption and diverse deployment in both urban and rural areas, etc. In addition, some related researches on UAV-assisted SWIPT are reported in [35] and [36]. Yin *et al.* [35] present a study on the UAV-assisted SWIPT system with time switching, in which the source node first charges the UAV, then the UAV transmits the information to the destination node. The work in [36] investigates a UAV-assisted SWIPT system consisting of an information receiving node and multiple energy harvesting nodes, where each single ground node does not receive information and harvest energy simultaneously. Differently, in this paper, we study the UAV-assisted SWIPT in IoT with power splitting where the UAV transfers energy and transmits information to all of the ground IoT devices at the same time and each device is equipped with a power splitter. Under this circumstance, the joint optimization of UAV's power allocation and trajectory design is still a fundamental open issue. It is worth noting that theoretically, time switching can be regarded as a special form of power splitting with only binary splitting power ratios [4]. Furthermore, there will be additional time delays with time switching over power splitting schemes.

C. CONTRIBUTIONS

In this paper, we investigate the power allocation and trajectory optimization problem for UAV-assisted SWIPT with power splitting in IoT. With power splitting applied to the devices equipped with receivers, the received signal is split into two signal streams by a power splitter with a fixed power ratio, in which one stream to the energy receiver and the other one to the information receiver. In general, the variation of channel state between the UAV and ground devices could be significantly affected by two important design aspects, the trajectory and transmit power of the UAV. Specifically, the major contributions of this paper are summarized as follows:

- We present a problem formulation of the joint optimization of UAV's transmit power and trajectory for UAV-assisted SWIPT in IoT system with power splitting. The target is to maximize the minimum energy harvested among all of the ground nodes, subject to a minimum average data rate requirement constraint on each node and a maximum budget of transmission power constraint of the UAV. Furthermore, we also take the UAV's maximum speed limit into account. According to the formulation, this problem is a non-convex optimization with mutual coupled variables and it's difficult to be solved directly.
- We provide the feasibility analysis of the formulated problem under different average data rate thresholds of each IoT device. Also, we analyze the variation tendency of the objective function value with the growth of the threshold. As a result, two bounds of the threshold are obtained. The value of objective function begins to be affected as it passes through each bound. Through the feasibility analysis, we can reasonably set the threshold value.

- We develop an efficient algorithm for the maximization of minimum power harvested problem. We derive a more tractable form for the formulated problem by decoupling the non-convex objective function and relaxing the strict average data rate requirement constraint. Particularly, we deal with the derived problem and decompose it into two subproblems. For the subproblem of UAV's transmit power allocation, we handle the standard convex optimization problem with existing efficient methods. While for the subproblem of UAV's trajectory design, we iteratively optimize this problem with the lower bounds of objective function and average data rate requirement constraint. Finally, we propose a joint optimization algorithm by conducting the alternating optimization and concave-convex procedure (CCCP).
- We provide in-depth simulations under various parameter configurations. The results show the convergence behaviors of the proposed algorithm, which is consistent with the theoretical analysis as expected. Moreover, the performance by the proposed scheme outperforms other benchmark schemes based on simulation results.

The rest of this paper is organized as follows. In the next section, we introduce the system model and state the problem formulation. Feasibility analysis of the problem is presented in Section III. The proposed algorithm design is illustrated in Section IV. Simulation results are provided in Section V and the conclusions are drawn in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider a UAV-assisted downlink IoT system, in which a UAV is equipped with a transmitter. The UAV transfers energy and transmits information simultaneously to multiple separated nodes on the ground with power splitting.

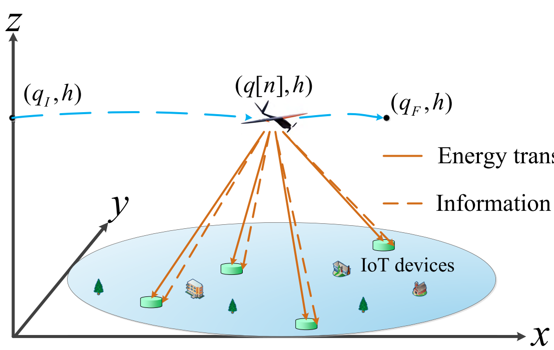


FIGURE 1. Scenario illustration of UAV-assisted SWIPT for IoT.

Denote $\mathcal{K} \triangleq \{1, ..., K\}$ as the set of the ground nodes. Each node $k \in \mathcal{K}$ has fixed location on the ground, denoted by $(x_k, y_k, 0)$, where $\mathbf{w}_k = (x_k, y_k)$ is the k-th node's corresponding location projected onto the horizontal plane. To guarantee the efficiency of energy-harvesting and the reliability of information-receiving, we consider a finite operating duration T, denoted by $\mathcal{T} \triangleq (0, T]$. For the sake of analysis, we divide equally the total time period T into N time slots, where the elemental slot length is denoted as $\delta = T/N$. The number of time slots N is chosen as a sufficiently large number to the extent that the UAV can be regarded approximately as static within each time slot, as well as taking the balance between computational complexity and appropriate accuracy into consideration. Each slot n is contained in a set of $\mathcal{N} \triangleq \{1, ..., N\}$. In practice, in order to avoid a UAV's frequent ascending or descending due to various building and diverse terrain, we consider that the UAV is deployed at a fixed altitude h, just as [8]. Therefore, the location of the UAV at n-th slot is denoted by $(x_U[n], y_U[n], h)$, in which $\mathbf{q}[n] = (x_U[n], y_U[n])$ is the 2D coordinates projected onto the horizontal plane. For convenience, the initial and final locations of the UAV projected onto the horizontal plane are given as $q_I = q[0]$ and $q_F = q[N]$, respectively. Regarding the UAV's maximum flight speed limited by $V_{\max}$, there should be constraints on the UAV's locations as follows:

$$\|q[n] - q[n-1]\| \leq V_{\max}\delta, \quad \forall n \in \mathcal{N}. \tag{1}$$

Next, the UAV-installed transmitter and all nodes are equipped with one antenna to transmit or receive wireless signals. The total bandwidth of the system is equally divided into K subcarriers allocated to K nodes respectively, where the total bandwidth is denoted as B. We consider the case of energy-transferring and information-transmitting with a power-splitter applied to each node, in which the ratio ρ of power is split to the energy receiver and the rest ratio 1-ρ of the power is split to the information receiver, as shown in Fig. 2.

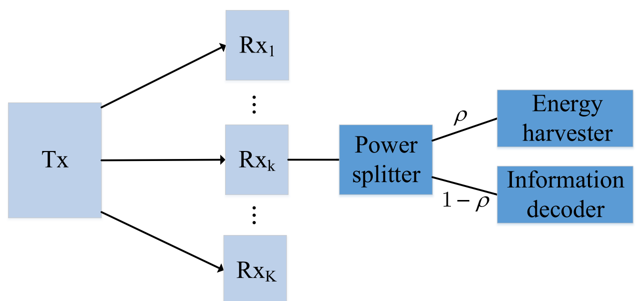


FIGURE 2. The system design of power splitting.

Consider that the maximum budget of power transmitted to all ground nodes is set as P_0 during the whole duration T. Thus, it's expressed as

$$\sum_{k=1}^{K}\sum_{n=1}^{N} p_k[n] \leq P_0, \tag{2}$$

where $p_k[n]$ is the transmit power from the UAV to k-th node at n-th slot.

As the air-to-ground channel between the UAV and the nodes on the ground is normally LOS-dominated, the deterministic propagation model is adopted in this paper which is widely used in the literature [22]. The average power channel gain from the UAV to k-th node at n-th slot can be modeled as

$$h_k[n] = \beta_0 d_k^{-\alpha}[n], \quad \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N}, \tag{3}$$

where

$$d_k[n] = \sqrt{\|\mathbf{q}[n] - \mathbf{w}_k\|^2 + H^2} \tag{4}$$

is the distance between the UAV and the k-th node at n-th slot. β_0 is the channel power gain at the unit reference distance and α is environmental attenuation factor. The instantaneous harvested power by k-th node at n-th slot is thus given by

$$Q_k[n] = \eta\rho p_k[n] h_k[n], \quad \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N}, \tag{5}$$

where $0 \leq \eta \leq 1$ denotes the energy conversion efficiency of the rectifier at each node. Therefore, the total energy harvested by each node $k \in \mathcal{K}$ over the whole period is written as

$$E_k = \delta \sum_{n=1}^{N} \frac{\eta\beta_0\rho p_k[n]}{\left(\sqrt{\|q[n] - w_k\|^2 + h^2}\right)^{\alpha}}, \quad \forall k \in \mathcal{K}. \tag{6}$$

The instantaneous data rate received by k-th node at n-th slot is expressed by

$$r_k[n] = \frac{B}{K}\log_2\left(1 + \frac{(1-\rho)\, p_k[n]\, h_k[n]}{B/K\sigma^2}\right), \ \forall k \in \mathcal{K}, \ n \in \mathcal{N}, \tag{7}$$

where σ^2 is the noise power spectrum density. Therefore, the average data rate received by each node $k \in \mathcal{K}$ over the whole period is written as

$$R_k = \frac{\delta}{T}\sum_{n=1}^{N}\frac{B}{K}\log_2\left(1 + \frac{\beta_0(1-\rho)p_k[n]K}{B\sigma^2\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}}\right), \quad \forall k \in \mathcal{K}. \tag{8}$$

In order to ensure that each ground node has the relatively fair opportunity to harvest power other than the winners-take-all objective, maximizing the minimum power harvested among all the nodes is considered via allocating the transmit power and optimizing the UAV's trajectory. Besides, all the ground nodes have their own tasks receiving information. Then, we consider the average data rate threshold of each node is denoted by γ_{th}.

The investigated problem can be formulated mathematically as

$$
\begin{aligned}
(\text{P1}): \quad & \max_{\{p_k[n], q[n]\}} \ \min_k E_k && \text{(9a)}\\
& s.t.\ R_k \geq \gamma_{th}, \quad \forall k \in \mathcal{K}, && \text{(9b)}\\
& \sum_{k=1}^{K}\sum_{n=1}^{N} p_k[n] \leq P_0, && \text{(9c)}\\
& p_k[n] \geq 0, \quad \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N}, && \text{(9d)}\\
& q[0] = q_I, \quad q[N] = q_F, && \text{(9e)}\\
& \|q[n] - q[n-1]\| \leq V_{\max}\delta_t, \ \forall n \in \mathcal{N}, && \text{(9f)}
\end{aligned}
$$

where constraint (9b) specifies that the average data rate requirement of each node is satisfied. Constraints (9c) and (9d) represent the feasibility of the UAV's transmitted power. Additionally, constraint (9e) ensures that the trajectory range of the UAV does not exceed its hardware limit, and constraint (9f) indicates that the launching and landing point of the UAV. It is observed from the problem formulation above that in the objective function, E_k is not convex with respect to the joint variables $p_k[n]$ and $q[n]$. Similarly, R_k is also not convex towards the joint variables $p_k[n]$ and $q[n]$ in the constraint (9b) [37]. Therefore, problem (P1) is a non-convex optimization problem, which is intratable to be directly solved with existing convex optimization techniques.

III. FEASIBILITY ANALYSIS

Since SWIPT is studied in this system model, we need to consider both energy-transferring and information-transmitting. The objective function is to maximize the minimum power harvested among all of the ground nodes and constraint (9b) indicates that each node meets the average data rate requirement. To coordinate the average data rate received and energy harvested among all of the ground nodes, the tradeoff between objective function and constraint (9b) needs to be dealt with. As a result, the relationship between objective function and constraint (9b) has significant effect on problem (P1). Thus, in this section, we present the analysis of model feasibility.

It is observed that the constraint (9b) means the minimum average data rate received by all the nodes is not less than the threshold γ_{th}, so the constraint (9b) is transformed into

$$\min R_k \geq \gamma_{th}, \quad \forall k \in \mathcal{K}. \tag{10}$$

As a result, it's transformed into analyzing the relationship between the minimum power harvested and the minimum average data rate received among all ground nodes. Next, the minimum power harvested and the minimum average data rate received of each node are denoted as

$$\min E_k = \delta\sum_{n=1}^{N}\frac{\eta\beta_0\rho p_k[n]}{\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}}, \quad \forall k \in \mathcal{K}, \tag{11}$$

$$\min R_k = \frac{\delta}{T}\sum_{n=1}^{N}\frac{B}{K}\log\left(1+\frac{\beta_0(1-\rho)K}{B\sigma^2} \times \frac{p_k[n]}{\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}}\right), \quad k \in \mathcal{K}, \tag{12}$$

respectively.

Theorem 1: The decision region about the optimal objective function value of problem (P1) and the solution set to the target value, where γ_{th}^1 and γ_{th}^{bound} are the lower bound and upper bound of the threshold γ_{th}, respectively, are given as follows:

- *Case 1: When the threshold $\gamma_{th} \leq \gamma_{th}^{1}$, the constraint (9b) has no effect on the objective function, that is to say, the optimal objective function value is the same with or without the constraint (9b) in problem (P1).*
- *Case 2: As the threshold γ_{th} grows from γ_{th}^{1} to γ_{th}^{bound}, the range of the solution sets satisfying constraints (9b-9f) shrinks. So the constraint (9b) will affect the optimal objective function value and the solution set to the target value in problem (P1).*
- *Case 3: When the threshold γ_{th} keeps increasing beyond γ_{th}^{bound}, problem (P1) will have no solution. This value γ_{th}^{bound} mentioned above is the upper bound of the threshold γ_{th} in problem (P1) that we want.*

Proof: Denote $\psi = \eta\beta_0\rho$, $\eta = \frac{\beta_0(1-\rho)K}{B\sigma^2}$ and $x_{k,n} = \frac{p_k[n]}{\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}}$, so (11) and (12) are turned to

$$\min E_k = \delta \sum_{n=1}^{N} \psi x_{k,n} = \delta\psi\left(x_{k,1} + x_{k,2} + \ldots + x_{k,N}\right), \quad \forall k \in \mathcal{K}, \tag{13}$$

$$\begin{aligned} \min R_k &= \frac{\delta}{T}\sum_{n=1}^{N}\frac{B}{K}\log_2\left(1+\eta x_{k,n}\right) \\ &= \frac{\delta}{T}\times\frac{B}{K}\left\{\log_2\left(1+\eta x_{k,1}\right)+\log_2\left(1+\eta x_{k,2}\right)+\ldots\right. \\ &\quad \left.+\log_2\left(1+\eta x_{k,N}\right)\right\}, \quad \forall k \in \mathcal{K}. \end{aligned} \tag{14}$$

The set of solution of the formula (13) is N dimensional space, and the growth in the slope of each space is $\delta\psi$. Comparatively, the set of solution of the formula (14) is also N dimensional space, and the growth in the slope of each space is $\delta\frac{B\eta}{K\ln 2(1+\eta x_{k,n})}$, which depends on the value of $x_{k,n}$, namely the value of the set of $\{p_k[n], q[n]\}$. As a result, the growth trend of the formula (11) is inconsistent with the one of the formula (12).

- When there is no constraint (9b), the set satisfying constraints (9c-9f) is denoted by A. The solution set of formula (11) meeting constraints (9c-9f) is $\left\{p_k^*[n], q^*[n]\right\}$. When there is constraint (9b), as the threshold γ_{th} goes up from 0, the range of the solution set A satisfying constraints (9b-9f) shrinks to another set denoted by B. Nonetheless, as long as $\left\{p_k^*[n], q^*[n]\right\}$ is still contained in set B, the formula (11), namely the optimal objective function value is the same with or without the constraint (9b) in problem (P1).
- When the threshold γ_{th} continues to increase to the value γ_{th}^{1}, $\left\{p_k^*[n], q^*[n]\right\}$ is on the boundary of set B. So γ_{th}^{1} is the lower bound of the threshold γ_{th}. As threshold γ_{th} continues to goes up, the range of the solution set B satisfying constraints (9b-9f) also continues to shrink, $\left\{p_k^*[n], q^*[n]\right\}$ is not included in set B. Therefore, the optimal objective function value in problem (P1) will decrease.
- When the threshold γ_{th} keeps increasing beyond a certain value, there is no set satisfying constraints (9b-9f) at the same time. The value is the upper bound of the threshold γ_{th}, denoted by γ_{th}^{bound}.

■

Now, we can come to a conclusion that the upper bound γ_{th}^{bound} is the maximum of minimum average data rate received among all ground nodes satisfying constraints (9c-9f).

So the upper bound γ_{th}^{bound} can be obtained by solving the mathematical expression in the following

$$\text{(P2)}: \max_{\{p_k[n], q[n]\}} \min_k R_k \tag{15a}$$

$$s.t. \sum_{k=1}^{K}\sum_{n=1}^{N} p_k[n] \leq P_0, \tag{15b}$$

$$p_k[n] \geq 0, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \tag{15c}$$

$$q[0] = q_I, q[N] = q_F, \tag{15d}$$

$$\|q[n] - q[n-1]\| \leq V_{\max}\delta_t, \quad \forall n \in \mathcal{N}. \tag{15e}$$

Consequently, the optimal objective function value of problem (P2) is the upper bound of the threshold γ_{th} in problem (P1).

In addition to what's mentioned above, there is another situation. When the average data rate threshold of each node is different, we set the average data rate requirement of each node separately as the information requirement constraints. Therefore, in the same way, the feasibility analysis is the same as the condition where each node has the same threshold.

IV. JOINT TRANSMIT POWER AND TRAJECTORY OPTIMIZATION

Based on the theoretical analysis results in the Section III, the algorithm is designed for the case that the system model satisfies the feasibility conditions.

By introducing an auxiliary variable on behalf of the lower bound of the initial objective function in problem (P1), denoted by E, the original problem (P1) can be reformulated as follows

$$\text{(P3)}: \max_{\{p_k[n], q[n]\}, E} E \tag{16a}$$

$$s.t. E_k \geq E, \quad \forall k \in \mathcal{K}, \tag{16b}$$

$$R_k \geq \gamma_{th}, \quad \forall k \in \mathcal{K}, \tag{16c}$$

$$\sum_{k=1}^{K}\sum_{n=1}^{N} p_k[n] \leq P_0, \tag{16d}$$

$$p_k[n] \geq 0, \quad \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \tag{16e}$$

$$q[0] = q_I, \quad q[N] = q_F, \tag{16f}$$

$$\|q[n] - q[n-1]\| \leq V_{\max}\delta_t, \quad \forall n \in \mathcal{N}. \tag{16g}$$

It is still a non-convex optimization problem with inequality constraints [37]. In general, there are no existing effective methods that can be directly applied to this problem, so we need to carry out alternating with optimizing variables and utilizing the concave-convex procedure (CCCP) to iteratively approximate the non-convex problem into a series of convex ones. As a result, problem (P3) is first divided into two subproblems. Then, a joint transmit power and trajectory optimization algorithm is developed.

A. TRANSMIT POWER OPTIMIZATION WITH GIVEN TRAJECTORY

Giving some of circumstances where the UAV has to execute some prearranged missions or services, such as surveillance or cargo transportation along a fixed route, the UAV's trajectory is given in those cases. With given trajectory, the only transmit power allocation problem is given as follows:

$$(\mathrm{P4}): \max_{\{p_k[n]\},E} \; E \tag{17a}$$

$$s.t.\ \delta \sum_{n=1}^{N} \frac{\eta\rho\beta_0 p_k[n]}{\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}} \geq E, \quad \forall k \in \mathcal{K}, \tag{17b}$$

$$\frac{\delta}{T}\sum_{n=1}^{N}\frac{B}{K}\log_2 \times \left(1+\frac{\beta_0(1-\rho)p_k[n]K}{B\sigma^2\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}}\right) \geq \gamma_{th}, \quad \forall k \in \mathcal{K}, \tag{17c}$$

$$\sum_{k=1}^{K}\sum_{n=1}^{N} p_k[n] \leq P_0, \tag{17d}$$

$$p_k[n] \geq 0, \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}. \tag{17e}$$

$\log(1+x)$ is a concave function of x, so constraint (17c) is convex. Since the constraint (17b) is a linear programming, the expression above is a standard convex optimization problem and some existing algorithms can be used directly, such as the interior point method.

B. TRAJECTORY OPTIMIZATION WITH GIVEN TRANSMIT POWER

For some cases, due to hardware limitations or specified requirements, the transmit power is required to be fixed. With given transmit power, the trajectory optimization problem is reformulated as

$$(\mathrm{P5}): \max_{\{q[n]\},E} \; E \tag{18a}$$

$$s.t.\ \delta \sum_{n=1}^{N} \frac{\eta\rho\beta_0 p_k[n]}{\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}} \geq E, \quad \forall k \in \mathcal{K}, \tag{18b}$$

$$\frac{\delta}{T}\sum_{n=1}^{N}\frac{B}{K}\log_2 \times \left(1+\frac{\beta_0(1-\rho)p_k[n]K}{B\sigma^2\left(\sqrt{\|q[n]-w_k\|^2+h^2}\right)^{\alpha}}\right) \geq \gamma_{th}, \forall k \in \mathcal{K}, \tag{18c}$$

$$q[0]=q_I,\ q[N]=q_F, \tag{18d}$$

$$\|q[n]-q[n-1]\| \leq V_{\max}\delta_t, \forall n \in \mathcal{N}. \tag{18e}$$

In constraint (18b) and (18c), it is observed that E_k and R_k is not convex with respect to variable $q[n]$. Firstly, to deal with the non-convex set of constraint (18b), we iteratively approximate it into convex set. By using the first-order Taylor expansion, we obtain the lower bound $E_{k,lb}^{i+1}[n]$ for $E_k^{i+1}[n]$ with given $q^i[n]$ at the i-th iteration, so

$$E_k^{i+1}[n] \geq E_{k,lb}^{i+1}[n]. \tag{19}$$

Since function $\frac{a}{(x+b)^{\alpha/2}}$ is a convex function of x, there is

$$\frac{a}{(x+b)^{\alpha/2}} \geq \frac{a}{(x_0+b)^{\alpha/2}} - \frac{\alpha}{2}\frac{a}{(x_0+b)^{\alpha/2+1}}(x-x_0). \tag{20}$$

Let operate $a=\rho\eta\beta_0 p_k[n]$ and $b=h^2$, we have

$$E_{k,lb}^{i+1}[n] \triangleq \frac{\rho\eta\beta_0 p_k[n]}{\left(\left\|q^i[n]-w_k\right\|^2+h^2\right)^{\alpha/2}} - \frac{\alpha}{2}\frac{\rho\eta\beta_0 p_k[n]\left(\left\|q^{i+1}[n]-w_k\right\|^2-\left\|q^i[n]-w_k\right\|^2\right)}{\left(\left\|q^i[n]-w_k\right\|^2+h^2\right)^{\alpha/2+1}}. \tag{21}$$

Next, since $\log_2\left(1+\frac{a}{(b+x)^{\alpha/2}}\right)$ is a convex function of x, which results from the first order condition of convex functions, there is

$$\log_2\left(1+\frac{a}{(b+x)^{\alpha/2}}\right) \geq \log_2\left(1+\frac{a}{b^{\alpha/2}}\right) - \frac{\frac{\alpha}{2}a}{\ln 2(b)\left(b^{\alpha/2}+a\right)}x. \tag{22}$$

Denote that $x=\left\|q^{i+1}[n]-w_k\right\|^2-\left\|q^i[n]-w_k\right\|^2$, $b=\left\|q^i[n]-w_k\right\|^2+h^2$, $a=\frac{\beta_0(1-\rho)p_k[n]K}{B\sigma^2}$. Based on the inequality (22), we obtain

$$r_k^{i+1}[n] \geq r_{k,lb}^{i+1}[n], \tag{23}$$

where

$$r_{k,lb}^{i+1}[n] \triangleq \frac{B}{K}\left\{\log_2\left(\frac{\beta_0(1-\rho)p_k[n]K}{B\sigma^2\left(\left\|q^i[n]-w_k\right\|^2+h^2\right)^{\alpha/2}}\right)\right.$$

Algorithm 1 Joint Transmit Power Allocation and Trajectory Design Optimization

1: Initialize the UAV's transmit power $p_k^i[n]$ and trajectory $q^i[n]$, the iteration number $i = 0$. Set the tolerance of accuracy ε.
2: **Repeat.**
3: Fix the trajectory $q^i[n]$, find the optimal solution $p_k^*[n]$ at the i-th iteration to problem (P4) by standard convex optimization techniques, and let $p_k^{i+1}[n] \leftarrow p_k^*[n]$.
4: Fix the transmit power $p_k^*[n]$, find the optimal solution $q^*[n]$ to problem (P5) at the i-th iteraion, and let $q^{i+1}[n] \leftarrow q^*[n]$.
5: Update $\{p[n], q[n]\}^{i+1} \leftarrow \{p[n], q[n]\}^i$, and $i+1 \leftarrow i$.
6: **Until** $\frac{E^{i+1}-E^i}{E^i} \leq \varepsilon$
7: Return the optimal solution of trajectory $q^*[n]$ and transmit power $p_k^*[n]$ to problem (P1).

$$-\frac{\left(\left\|q^{i+1}[n]-w_k\right\|^2-\left\|q^i[n]-w_k\right\|^2\right)}{\ln 2\left(\left\|q^i[n]-w_k\right\|^2+h^2\right)} \times \frac{\frac{\alpha}{2}p_k[n]}{\left[\frac{B\sigma^2\left(\left\|q^i[n]-w_k\right\|^2+h^2\right)^{\frac{\alpha}{2}}}{\beta_0(1-\rho)K}+p_k[n]\right]}\Bigg\} \tag{24}$$

is the lower bound for $r_k^{i+1}[n]$.

Given the trajectory at i-th iteration, the trajectory at $i+1$-th iteration can be obtained by solving the following optimization problem, denoted as

$$(\text{P6}): \max_{\{q[n]\},E} \; E \tag{25a}$$
$$s.t.\ \delta\sum_{n=1}^{N} E_{k,lb}^{i+1}[n] \geq E,\ \forall k \in \mathcal{K}, \tag{25b}$$
$$\frac{\delta}{T}\sum_{n=1}^{N} r_{k,lb}^{i+1}[n] \geq \gamma_{th}, \forall k \in \mathcal{K}, \tag{25c}$$
$$q[0] = q_I, q[N] = q_F, \tag{25d}$$
$$\|q[n]-q[n-1]\| \leq V_{\max}\delta_t, \quad \forall n \in \mathcal{N}, \tag{25e}$$

which is a convex optimization problem and can be solved using standard convex optimization techniques [37].

C. JOINT TRANSMIT POWER AND TRAJECTORY OPTIMIZATION

The joint power allocation and trajectory optimization problem studied is non-convex, so that it is extremely difficult to find the globe optimal solution. Nevertheless, the suboptimal solution is required to be acceptable at an appropriate accuracy. Based on the two subproblems abovementioned, we propose an efficient algorithm summarized in Algorithm 1. For the UAV with large computing capacity, the UAV can fisrt collect information from the ground and then implement the proposed algorithm onboard to accomplish its tasks. Besides, for the UAV with small computing capacity, the center controller on the ground implements the algorithm and transmits the computing results to the UAV, then the UAV can perform its service according to the information received.

1) CONVERGENCE ANALYSIS OF ALGORITHM 1

On one hand, we can note that the lower bound E exists because of constraint (16d) of problem (P3). As the transmit power limit of the UAV prevents unlimited growth of E, the value of E is the upper bound of a finite value. On the other hand, it's verified that the lower bound E is non-decreasing after each iteration. In step 3 of Algorithm 1, given the optimized trajectory $q^i[n]$, it can be first obtained that $E\left(p_k^i[n], q^i[n]\right) \leq E\left(p_k^{i+1}[n], q^i[n]\right)$. In step 4 of Algorithm 1, it's obtained that $E\left(p_k^{i+1}[n], q^i[n]\right) \leq E\left(p_k^{i+1}[n], q^{i+1}[n]\right)$. So, the conclusion can be drawn that $E\left(p_k^i[n], q^i[n]\right) \leq E\left(p_k^{i+1}[n], q^{i+1}[n]\right)$. According to the discussion above, the convergence of the algorithm proposed is guaranteed. Since E is non-decreasing during the iterations and E is upper bounded [38].

2) COMPUTATION COMPLEXITY ANALYSIS OF ALGORITHM 1

We can see from Algorithm 1 that the main factor of the proposed algorithm is to optimize the transmit power and the trajectory alternately. In each iteration, the main complexity of the proposed algorithm lies in the steps 3 and 4. They use the interior point method with the worst-case complexity of $O(n)^{3.5}\log(1/\varepsilon)$ where n is the number of optimization variables and ε is a given solution accuracy. According to the complexity of the interior point method, the computational costs of steps 3 and 4 are about $O\left((KN)^{3.5}\right)\log(1/\varepsilon)$ and $O\left((N)^{3.5}\right)\log(1/\varepsilon)$, respectively [39], where K and N are the numbers of nodes and time slots. As a result, the total computation complexity of Algorithm 1 is $O\left((KN)^{3.5}\right)\log(1/\varepsilon)$.

V. SIMULATIONS AND DISCUSSION

In this section, we perform a series of experiments to evaluate the performance of our proposed algorithm.

A. BASIC SETUP

For simulations, we consider a 100×100 m^2 area, in which $K = 4$ IoT devices are randomly distributed on the ground. The UAV flies at the altitude $h = 10$ m. The initial and final locations of the UAV are set as (0, 0, 10) and (100, 100, 10), respectively. Furthermore, other system parameters are as follows: $B = 1$ MHz, $\sigma^2 = -169$ dBm/Hz, $P_0 = 1$ W, $T = 30$ s, $N = 60$, $\eta = 0.5$, and $\alpha = 2$. So that the time slot length is $\delta = 0.5$ s. $\beta_0 = 10^{-3}$ is the channel power at the reference distance $d_0 = 1$ m. Alternate iterative optimization is solved by the Matlab optimization toolbox function "fmincon",

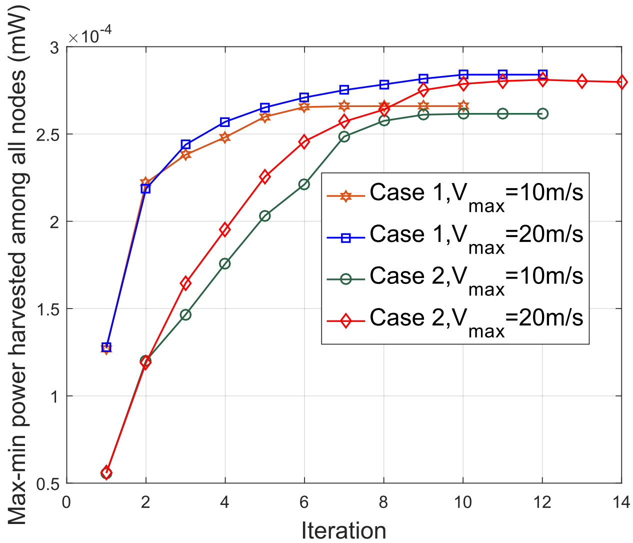


FIGURE 3. Maximization of minimum power harvested among *K* nodes versus iteration in case 1 and case 2.

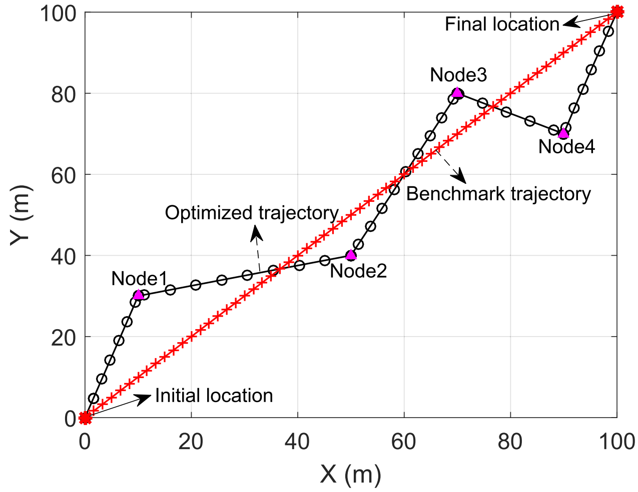
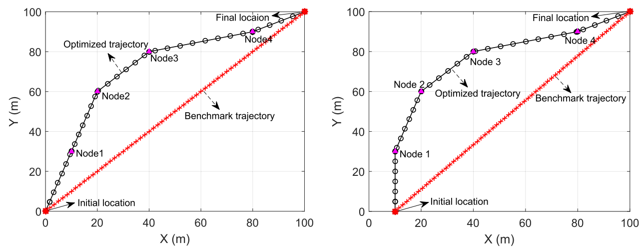
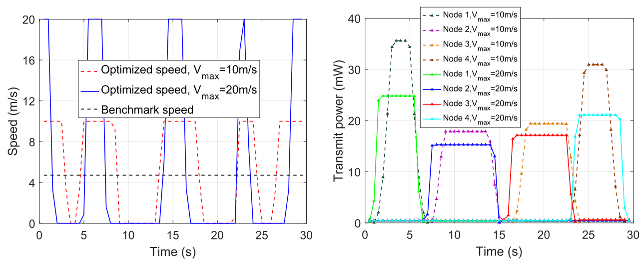


FIGURE 4. Trajectory in case 1.



(a) (b)

FIGURE 5. Trajectory in Case 2, where (a) and (b) represent the UAV has different initial location. (a) Trajectory 1 in case 2. (b) Trajectory 2 in case 2.



(a) (b)

FIGURE 6. The UAV's speed and transmit power in case 1. (a) Speed in case 1. (b) Transmit power in case 1.

where the accuracy tolerance for the proposed algorithms is set as $\varepsilon = 10^{-4}$. The original trajectory is defined as the straight line connecting the initial and final locations of the UAV. To validate the effectiveness of the proposed algorithm, two scenarios are investigated as follows:

- Case 1: The ground IoT devices are randomly distributed on two sides of the original trajectory, where the original trajectory of the UAV flies at a uniform speed along the line of initial and final locations.
- Case 2: The ground IoT devices are randomly distributed on one side of the original trajectory, in which the original trajectory is the same as case 1.

In both cases, two setup of the maximum flight speeds of the UAV are considered, that is, 10 m/s and 20 m/s, respectively.

B. SYSTEM PERFORMANCE

We start by evaluating the convergence behavior of the proposed algorithm proved above. Fig. 3 presents the convergence tendencies of the maximization of minimum power harvested among all nodes on the ground with the number of iterations in case 1 and case 2, where $\gamma_{th} = 2$ Mbps. It verifies the convergence of the proposed algorithm. It can be observed that the maximization of minimum power power harvested is monotonically increasing through iterations until convergence, which is consistent with the theoretical conclusion in Section IV-C. Moreover, we can also figure out that the higher the maximum speed of the UAV is limited, the more the maximization of minimum energy the ground nodes harvest.

Fig. 4 and Fig. 5(a) are the UAV's optimized flight trajectories of the two cases, respectively, where $V_{\max} = 10$ m/s and $\gamma_{th} = 2$ Mbps. It can be seen that whatever the nodes are distributed on the ground, such as one side or two sides of the benchmark trajectory, the optimized trajectories all pass directly above each node. Moreover, no matter where the starting point of the UAV is, the UAV will pass directly above each ground node shown in Fig. 5(b).

Furthermore, the UAV's speed slows down to 0 m/s at some moments as shown in Fig. 6(a) and Fig. 7(a), which indicates that the UAV will hover over the nodes during a period of time. Moreover, the higher the maximum speed of the UAV, the longer the UAV will hover. Combined with Fig. 6(b) and Fig. 7(b), we can observe the longer the UAV hovers over a node, the less power is allocated to that node, and vice versa. Furthermore, when the UAV hovers any node, the higher the maximum speed of the UAV, the less power

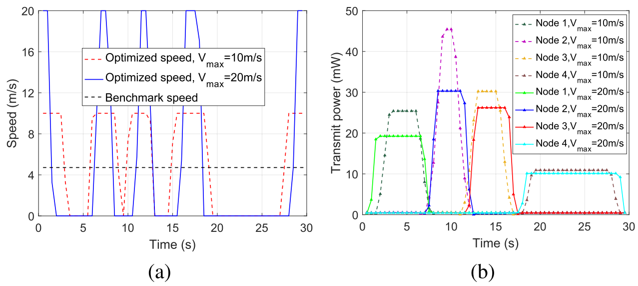


FIGURE 7. The UAV's speed and transmit power in case 2. (a) Speed in case 2. (b) Transmit power in case 2.

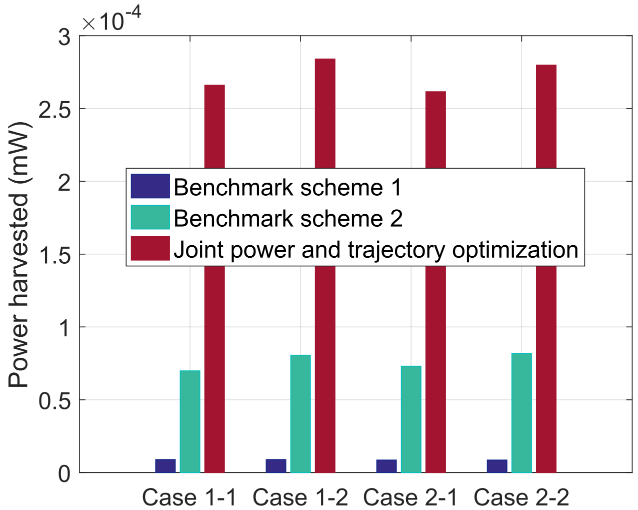


FIGURE 8. Maximization of minimum power harvested comparison in two cases, where Case 1-1 represents Case 1 with $V_{max} = 10$ m/s, Case 1-2 represents Case 1 with $V_{max} = 20$ m/s, Case 2-1 represents Case 2 with $V_{max} = 10$ m/s, and Case 2-2 represents Case 2 with $V_{max} = 20$ m/s.

allocated to the corresponding node. It reflects the fairness of our design, because the system problem considers the maximization of minimum power harvested among all nodes. We can also find the closer the UAV is to a node, the greater the power assigned to the node because of higher channel gain.

To evaluate the performance of the proposed algorithm, some benchmark schemes such as benchmark scheme 1 and benchmark scheme 2 are put forward to be compared as shown in Fig. 8. In benchmark scheme 1, transmit power of the UAV is optimized by standard convex optimization techniques when the UAV passes through each node at a constant speed between two nodes. However, in benchmark scheme 2, the trajectory is optimized by alternate iterative optimization when the power transmitted to each node is equally divided at each time slot. It is observed that the proposed algorithm outperforms those benchmark methods. The main reason is that the proposed algorithm enables UAV to allocate more power to ground nodes when the channel state is better.

As we know, problem (P2) solves the upper bound of average data rate threshold of problem (P1). Although problem (P2) is not convex, we can obtain suboptimal solution by iteratively approximating it into convex set. It has been verified by simulation results shown in Fig. 9 and Fig. 10 that

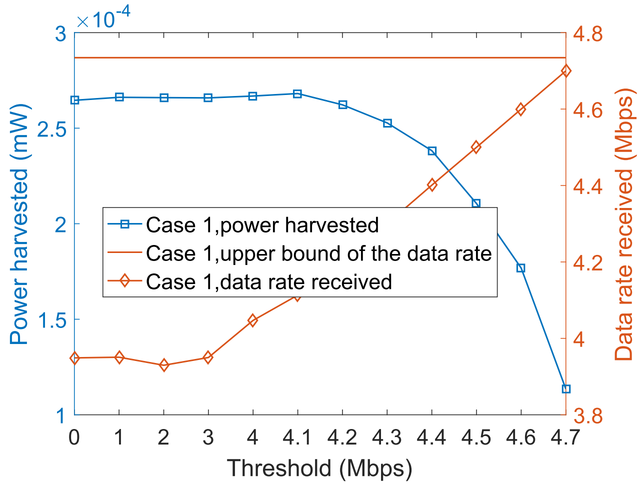


FIGURE 9. Power harvested and average data rate received under different thresholds in case 1.

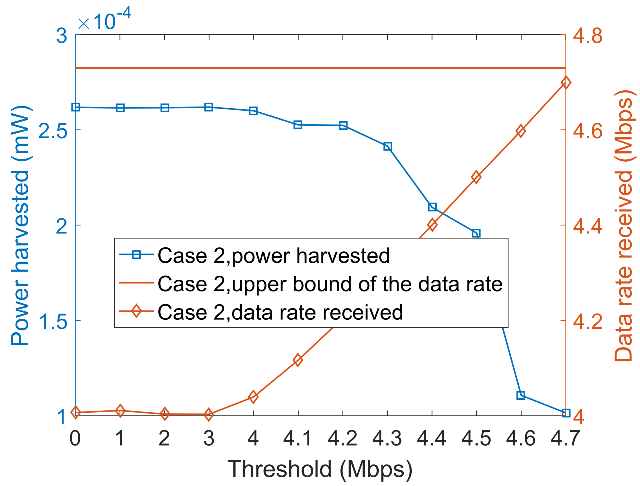


FIGURE 10. Power harvested and average data rate received under different thresholds in case 2.

the average data rate received among each node under different thresholds don't exceed the upper bound of them. It's observed from Fig. 9 and Fig. 10 that when the threshold $\gamma_{th} \leq \gamma_{th}^1 = 4$ Mbps in case 1 and case 2, the constraint (9b) will not affect the optimal value of the objective function and the minimum average data rate received among all nodes in problem (P1). While as the threshold γ_{th} starts increasing from γ_{th}^1 to the upper bound of average data rate threshold γ_{th}^{bound}, the maximum of minimum power harvested descends and the minimum average data rate received in problem (P1) increases infinitely close to the upper bound γ_{th}^{bound}.

As the power splitting ratio ρ is fixed, we conduct some experiments ($\gamma_{th} = 2$ Mbps) to explore the impact of different ratios of power splitting on simulation results by changing the ratio ρ. On account of $0 \leq \rho \leq 1$, we set the value of ρ from 0.1 to 0.9 at the interval of 0.1. It will not change the UAV's flight trajectory and power distribution trend over time. Obviously, we can draw the conclusion from Fig. 11 that the larger the power splitting ratio is, the greater the amount gains. Furthemore, as ρ increases, the more the maximum of

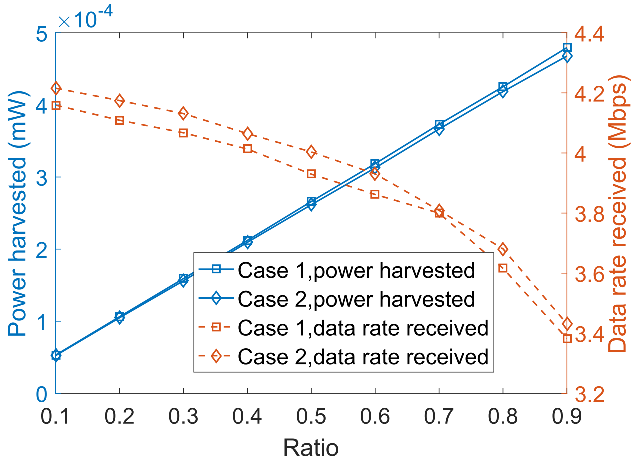


FIGURE 11. **Power harvested and average data rate received in different ratios in case 1 and case 2.**

minimum power among all ground nodes is collected. On the contrary, as ρ increases, the less the maximum of minimum average data rate is received seen from Fig. 11.

VI. CONCLUSIONS

In this paper, we have studied the maximization of minimum power harvested for UAV-assisted SWIPT in IoT with power splitting, which is subject to the minimum average data rate threshold of each ground device. Meanwhile, the UAV's transmit power and speed limit are considered. We have proposed an efficient algorithm to jointly optimize the UAV's transmit power allocation and trajectory via alternately optimizing variables. Moreover, simulation results have validated the superiority of the proposed algorithm over other benchmark methods. Based on the results, on one hand, we observe that not only does the arranged trajectory offer better link quality but it allocates more transmitting power when the channel quality is better. On the other hand, increasing power splitting ratio will improve power collection. What is more, when the UAV hovers over the node, the total transmission power assigned to the node is the maximum. More work about the corresponding scenario where multiple UAVs are deployed is left to be studied in the future.

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