Joint Wireless Charging and Data Collection for UAV-enabled Internet of Things Network

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***Abstract*—IoT devices usually lack perpetual power supply since they are generally deployed at remote areas with limited battery capacities. Moreover, the computing power of the IoT devices is usually limited and the generated data needs to be offloaded to a more powerful computing server for further processing. In this paper, we study a novel unmanned aerial vehicle (UAV)-enabled Internet of Things (IoT) network, where the UAV delivers energy to the ground IoT devices by employing wireless power transfer (WPT) in the downlink and collects data in the uplink. In our work, we try to minimize the total energy consumption of the UAV by determining the trajectory and charging power of the UAV, the resource allocation and the transmission scheme subject to task collection and resource budget requirements. To make the formulated problem more tractable, we decompose the primal problem into three subproblems (i.e., the transmission association problem, the trajectory design problem and the resource allocation problem) and utilize the block coordinate descent (BCD) method to solve them alternately. Since the trajectory design problem is still highly non-convex, we further transform it into a convex one by leveraging the successive convex approximation (SCA) technique. In the simulation, we provide extensive numerical results to corroborate the effectiveness of our proposed algorithm.**

***Index Terms*—unmanned aerial vehicle (UAV), wireless power transfer (WPT), resource allocation, trajectory optimization.**

I. INTRODUCTION

RECENTLY, Internet of Things (IoT) has been increasingly popular as it can greatly improve the quality of human life in application scenarios such as smart cities, smart healthcare, and environmental surveillance. It is estimated that the number of IoT devices will reach 25 billion by 2025 [1], and such multitudes of wirelessly connected devices will increase the burden on the existing communication infrastructure as the radio resource is limited. In addition, it is challenging to collect the data generated by the IoT devices for further processing as the devices are generally sparsely and determinately distributed. With the development of UAV technology and miniaturization of the communication equipment, UAV-enabled IoT can dramatically enhance the performance of the existing infrastructure since the UAV can establish the favorable line of sight (LoS) links with the IoT devices and therefore reduce the path loss [2]–[5].

Since the IoT devices are generally deployed in areas which are hard to reach or lack stable power supply, the energy issue poses a great challenge on designing a robust and reliable UAV-enabled IoT network. To overcome the above challenge, radio frequency (RF) wireless power transfer (WPT) has been proposed to provide reliable energy supply to low-power IoT devices [6], [7]. By utilizing electromagnetic waves, WPT delivers energy from the transmitter to the receiver in the form of radiation. Thanks to the broadcast nature of electromagnetic waves, WPT can charge multiple target devices over the air and thus shows more flexibility as compared with conventional charging methods with cord. However, the efficiency of WPT can be significantly influenced by the channel condition between the energy transmitter and receiver. To guarantee the performance of WPT, we need to establish LoS links and/or reduce the distance between the energy transmitter and receiver (i.e., the IoT device).

To address the above challenges altogether, we propose to employ the UAV to improve the performance of IoT network and raise the transmit efficiency of WPT with mounted communication equipment and energy transmitter. Specifically, we charge the IoT devices in the downlink utilizing the RF signal and collect the data generated by the IoT devices in the uplink. UAV has attracted intensive research interests in application scenarios such as environment monitoring and surveillance and communication platforms [8]–[10]. Particularly, UAV-assisted communications can enhance the performance of existing cellular infrastructure by working as a relay between the macro base station (MBS) and the ground users, or provide coverage recovery for areas where the MBS is malfunctioned or destroyed by disasters [11], [12]. The UAV can also be dispatched in an on-demand fashion and be retreated once the event is ended. Therefore, deploying a UAV is more flexible and economical as compared with building a small base station (SBS). UAVs can be classified into two main categories: rotary wing and fixed wing. A rotary wing UAV can theoretically hover at a fixed location while a fixed-wing UAV has to maintain a minimum speed to stay aloft in the air. However, a rotary wing UAV generally consumes more energy and has less on-board energy as compared with a fixed-wing UAV. Since we try to deliver energy to the IoT devices wirelessly from the UAV, the fixed-wing UAV which has more on-board energy possesses an apparent advantage over the rotary wing UAV. To increase the amount of time that the UAV can stay in the air, it is critical to optimize the trajectory to minimize the propulsion energy consumption and maximize the charging efficiency.

Although the UAV-enabled IoT network has been studied, considering wireless charging and data collection together in the trajectory design still requires further investigation.

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1) What are the optimal trajectory of the UAV and the charging power?
The trajectory design (i.e., the location of the UAV at each time slot) not only determines the propulsion energy consumption of the UAV [13], but also influences the transmit efficiency between the energy transmitter (mounted on the UAV) and IoT devices. Decreasing the charging power for users which consume less and increasing the charging power when the distances between the energy receivers and transmitter are small can decrease the energy consumption of the UAV. Moreover, decreasing the charging power when the channel conditions are good (i.e., when the distance between the UAV and the IoT devices are closer) can also reduce the energy consumption of the UAV. Therefore, the trajectory design and charging power are coupled together and should be jointly considered to reduce the energy consumption of the UAV.
2) How to allocate the limited resources in the uplink data offloading?
Since the UAV provides the power supply of the IoT devices, the uplink transmit power design directly affects the energy consumption of the UAV. Moreover, an optimized bandwidth allocation scheme can also reduce the energy consumption by allocating more bandwidth to those which have better channel conditions. Otherwise, the transmit power should be raised to meet the quality of service (QoS) requirements, i.e., more energy is needed (larger energy consumption of the UAV) to fully charge the IoT devices.
3) What is the optimal association policy of the IoT devices?
In the uplink communication, the data generated by all IoT devices should be offloaded to the UAV. At certain time slot, each IoT device can decide whether to offload the data to the UAV or not. However, choosing to offload data when the UAV is farther means more transmit power is needed to transmit the generated data, which will increase the energy consumption for charging the UAV. Therefore, the association policy needs to be carefully designed to save the energy of the UAV.

Note that the trajectory design of the UAV, the resource allocation scheme and association policy of the IoT devices are mutually dependent. Hence, we should jointly consider these three subproblems to minimize the energy consumption of the UAV. To address the above challenges, we propose a block coordinate descent (BCD) based cyclic iterative algorithm which decomposes the joint optimization problem into three subproblems, i.e., the resource allocation problem, the trajectory design problem and the association problem. In particular, this paper makes the following main contributions:
1) We propose a fixed-wing UAV-enabled IoT network where the UAV wirelessly charges the IoT devices using RF WPT in the downlink and collects data generated by the IoT devices in the uplink. Different from prior works, we assume that each IoT device can be associated with the UAV in multiple time slots and multiple IoT devices can be associated with the UAV at certain time slot; this is more practical and can potentially save energy. Note that only one IoT device is allowed to offload data at certain time slot is a special case of our scheme. However, the generalization of the association scheme yields new challenges: 1) which time slots should be associated with each IoT device? 2) how to allocate the limited bandwidth to avoid interference between multiple IoT devices? Furthermore, as compared to constant charging power assumption in previous works [18], [19], we allow flexible charging power adjustment such that it can be reduced to save energy when necessary.
2) We formulate the joint resource allocation, trajectory design and time slot association as an optimization problem aiming to minimize the energy consumption of the UAV. To make the formulated problem more tractable, we decompose it into three subproblems by utilizing the BCD method. Specifically, we sequentially optimize each subproblem by exploiting the solutions of the other two subproblems as the input. However, the trajectory design problem is still non-convex and difficult to solve. We transform it into a convex optimization problem by leveraging the SCA technique. The iterative algorithm is stopped when no further performance improvement can be achieved or the maximum allowed number of iterations is reached.

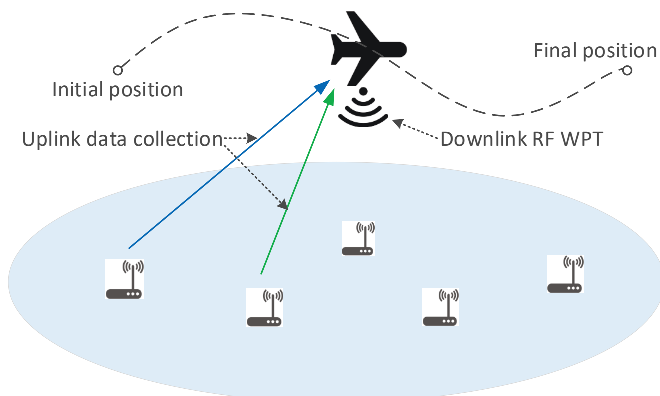

Fig. 1. The systen model.

The remainder of this paper is organized as follows. We review the related works in Section II. Section III presents the system model and the UAV energy minimization problem. In Section IV, we propose a cyclic iterative algorithm to solve the formulated problem by utilizing the BCD and SCA technique. In Section V, simulations are conducted to demonstrate the performance of the proposed algorithm. Finally, Section VI concludes this paper.

II. Related Works

UAV has been widely studied to improve the throughput and/or extend the service range of current wireless cellular networks. Zeng *et al.* [14] proposed to deploy a UAV to work as a mobile relay between the transmitter and receiver. The transmit power and the trajectory of the UAV are optimized to achieve the highest data rate between the source node and the target node. However, the UAV is only working as a data collector for the single ground terminal without providing energy supply. Al-Hourani *et al.* [15] approximated the probability function of LoS links by using a simple Sigmoid function. Based on the simplified model, they further analyzed the optimal altitude of the UAV that maximizes the coverage area given the maximum allowed pathloss. Mozaffari *et al.* [16] studied a UAV-assisted heterogeneous network with underlaid device-to-device (D2D) communications. Two application scenarios, i.e., a mobile UAV and a static UAV, are considered to improve capacity and coverage of the existing network. The coverage probability and system throughput of deploying a static UAV are analyzed. By transforming the primal problem into a disk covering problem, the minimum number of stop points to provide fully coverage to all users is derived in the mobile UAV-assisted network. Sohail *et al.* [17] investigated the case of non-orthogonal multiple access (NOMA) for an aerial base station. They analyzed the energy efficiency of the system under two different cases, i.e., the optimized altitude and fixed altitude of the UAV, respectively. However, the rotary wing UAV is assumed to be quasi-stationary and only two users, which work as the data transmitter and receiver, respectively, are considered.

Another application scenario for studying UAV-enabled communications is deploying UAVs in the IoT networks. Xie *et al.* [18] proposed to dispatch a UAV to periodically charge and serve the ground users by utilizing WPT. They aimed to maximize the minimum data rate in the uplink with the constraints of the UAV's maximum speed and the users' power budget. However, they assumed the transmit power in the downlink WPT to be constant, which may increase the energy consumption of the UAV and therefore reduce the time remaining in the air. Yan *et al.* [20] investigated the use of UAV to work as an energy transmitter and a data collector. The UAV is charged at a base station before sending out to collect data of the sensors. Upon arrival, the total time slots are split into two parts, i.e., the charging period and data transmission period, to charge the ground sensors in the downlink and collect data in the uplink, respectively. The UAV then flies back to the base station to offload the collected data. However, the proposed paradigm may suffer from data incompletion that hinders the further processing of the data since they aim to maximize the amount of data collected without guaranteeing the data collection completion. Moreover, the UAV's location when collecting data is fixed. This may result in data collection unfairness since some sensors have good channel conditions while others are suffering from bad ones. Lu *et al.* [21] tried to maximize the timeliness of data collection in a UAV-aided IoT network in the presence of a warden Willie which tries to eavesdrop the data sent from the IoT device to the UAV. The UAV simultaneously works as a power supplier and a data collector. Particularly, the IoT device first harvests the wireless energy transmitted from the UAV and then offloads its generated data to the UAV as covertly and timely as possible. However, the authors only considered only one IoT device and the rotary-wing is deployed at a fixed location. This proposed system can thus only apply to scenarios where the number of IoT devices is limited or they are distributed in a very small area. Zhan *et al.* [22] studied the minimization of energy consumption and completion time of the UAV-enabled mobile edge computing (MEC) system for IoT computation offloading. However, they assumed that only one user is allowed to be associated with the UAV in each time slot when offloading the computation task. Oubbati *et al.* [23], [24] considered deploying two sets of UAVs in a target area to collect data of the ground devices. Specifically, one set of UAVs is working as dedicated flying energy sources while the other set working as the data collector. Multi-agent deep Q network methods are utilized to deal with the non-convexity of the formulated problems and the dynamic environment. However, the authors assumed only several discrete trajectories of the UAV are available in the action space, which will reduce the optimality of the obtained solution. Table I summarizes the difference of related works.

TABLE I. Comparison of references

Ref.	Deployment	Optimize	Charging	Association	Wing
[18]	Mobile	SCA	Constant	TDMA	Rotary
[19]	Mobile	Traditional	Constant	None	Rotary
[20]	Stationary	Convex	Constant	TDMA	Rotary
[21]	Stationary	Traditional	Constant	TDMA	Rotary
[22]	Mobile	SCA	None	TDMA	Fixed
[23]	Stationary	Learning	Constant	TDMA	Rotary
[24]	Mobile	Learning	Constant	FDMA	Rotary

Different from the above works, we propose to jointly deliver wireless energy in the downlink and collect data generated by the IoT devices in the uplink with flexible time slot association. We try to minimize the total energy consumption of the UAV while taking into account of the QoS requirements, the limited available resource and maximum allowed speed of the UAV.

III. System Model

The application scenario of the fixed-wing UAV-enabled IoT network is shown in Fig. 1, where the UAV delivers wireless power to the IoT devices in the downlink. Meanwhile, the UAV collects data generated by the IoT devices for further processing in the uplink. Denote i as the index of the IoT devices, $\mathcal{I}$ as the set of IoT devices and $(x_i, y_i, 0)$ as the location of IoT device i in a 3D Euclidean coordinate. We assume the locations of the IoT devices are fixed and known *a priori* to the UAV. We allow multiple IoT devices to be associated with the UAV at certain time slot and adopt orthogonal frequency division multiplex access (OFDMA) scheme when allocating the bandwidth resources in the uplink communication. The cruising duration of the UAV is divided into N time slots to simplify the analysis. The time duration of each time slot can be calculated by $\delta = T/N$, where T is the cruising duration of the UAV. We further assume that the location of the UAV is fixed during each time slot by setting δ small enough. Denote $q[n] = (x[n], y[n], H), \forall n \in \mathcal{N}$ as the location of the UAV at time slot n, where $\mathcal{N} = \{n | 1 \leq n \leq N\}$ is the set of time slots.

The channel pathloss model and the power consumption model of the fixed-wing UAV are presented in this section. Then, an optimization problem that aims to minimize the total energy consumption of the UAV, subject to the resource budget constraints, the user QoS requirements and the UAV's maximum allowed speed, is formulated.

A. Pathloss model between the IoT devices and the UAV

The data rate of the uplink communication depends on the pathloss model between the UAV and the IoT devices. In this paper, we assume the IoT devices are located outdoors, i.e., the uplink channels are LoS-dominated. Therefore, the pathloss between IoT device i and the UAV at time slot n can be calculated by [9]

$$\begin{aligned}\xi_i[n] &= \beta_0 (d_i[n])^2 \\ &= \beta_0 \left[(x[n]-x_i)^2 + (y[n]-y_i)^2 + H^2\right], \end{aligned} \quad (1)$$

where $d_i[n]$ is the distance between IoT device i and the UAV at time slot n, and β_0 is the pathloss at the reference distance $d = 1$ m. Then, the link capacity of the uplink data transmission can be calculated by the Shannon formula as

$$R_i[n] = b_i[n] \log_2 (1 + \frac{p_i[n]}{\xi_i[n]\sigma^2}), \quad (2)$$

where $p_i[n]$ and $b_i[n]$ represent the transmit power and the allocated bandwidth of IoT device i at time slot n, respectively. σ^2 denotes the noise power at the receiver. To ensure that all the data generated by IoT device i are successfully offloaded to the UAV within the cruising duration, the following constraint should be satisfied, i.e.,

$$\delta \sum_{n=1}^{N} R_i[n] u_i[n] \geq D_i, \quad (3)$$

where $u_i[n] = 1$ if IoT device i offloads data to the UAV at time slot n and $u_i[n] = 0$, otherwise. D_i denotes the size of the data generated by IoT device i measured in bits.

B. Propulsion energy consumption model

Note that we propose to deliver wireless energy to the IoT devices by employing WPT. Therefore, not only the energy for flying but also the energy used for wireless charging in the WPT mode needs to be considered to obtain the total energy consumption of the UAV. Assume the duration of each time slot is small enough such that the UAV can be seen as flying at a constant speed. As derived in [13], the propulsion power of the UAV during time slot n can be approximated as

$$p^f[n] = \left(c_1 ||v[n]||^3 + \frac{c_2}{||v[n]||}\right), \forall n \in \mathcal{N}, \quad (4)$$

where c_1 and c_2 are parameters whose values are determined by the UAV's wind area, weight, air density, etc. $v[n]$ is the velocity of the UAV during time slot n:

$$v[n] = \frac{q[n] - q[n-1]}{\delta}, \ \forall n \in \mathcal{N}. \quad (5)$$

The IoT devices should possess enough energy to finish the data offloading, i.e., the energy harvested by each IoT device should be greater or equal to the energy used for uplink transmission within the cruising duration, i.e.,

$$\eta \sum_{n=1}^{N} p^c[n] h_i[n] \geq \sum_{n=1}^{N} p_i[n] u_i[n], \forall i \in \mathcal{I}, \quad (6)$$

where $0 \leq \eta \leq 1$ denotes the conversion efficiency from radio frequency to direct current energy at the IoT devices. $p^c[n]$ and $h_i[n] = 1/\xi_i[n]$ are the charging power and channel gain between IoT device i and the UAV at time slot n, respectively.

C. Problem formulation

In this section, we formulate the problem aiming to minimize the total energy consumption of the UAV by determining the UAV's trajectory and charging power, the time slot association scheme and the uplink resource allocation scheme of the IoT devices subject to the QoS requirement and resource budget of each IoT device and the UAV's maximum allowed speed. Specifically,

$$\textbf{P0:} \min_{q[n], b_i[n], p_i[n], p^c[n], u_i[n]} \quad \delta \sum_{n=1}^{N} (p^c[n] + p^f[n]) \quad (7)$$

$$\begin{aligned}
\textit{s.t.} \quad & (3),\ (6) \\
& ||q[n] - q[n-1]|| \leq \delta V^m, \forall n \in \mathcal{N}, && (8) \\
& q[0] = Q, && (9) \\
& \sum_{i=1}^{|\mathcal{I}|} b_i[n] \leq B, \forall n \in \mathcal{N}, && (10) \\
& 0 \leq b_i[n], \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, && (11) \\
& 0 \leq p_i[n] \leq P_i^{max}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, && (12) \\
& u_i[n] = \{0, 1\}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, && (13)
\end{aligned}$$

where V^m is the maximum velocity of the UAV, Q is the initial point of the UAV. B denotes the total available bandwidth; P_i^{max} denotes IoT device i's maximum transmit power. The resource budgets of the IoT devices are guaranteed by Constraints (11) and (12). Constraint (13) imposes u_i to be a binary variable.

Since $p^f[n]$ and $R_i[n]$ are non-linear and non-convex w.r.t. $q[n]$ and $u_i[n]$ is an integer variable, it is challenging to solve problem **P0**. To make it more tractable, we partition the entire decision variables into three blocks (i.e., the UAV trajectory design, the resource allocation and the time slots association) by utilizing the BCD method where each block is alternatively optimized given the solutions of the other two blocks. The iteration is stopped until the algorithm converges or the maximum allowed steps are reached.

IV. BCD-based Algorithm for P0

Owing to the integer variables and non-convexity, it is challenging to solve problem **P0**. In our proposed BCD-based algorithm, we solve each subproblem by using the solutions of the other two as input. We next discuss these three subproblems in detail.

A. Trajectory design

In this subproblem, given the time slot association and resource allocation, we design the trajectory of the UAV to minimize its total energy consumption. Substituting Eq. (2) into Eq. (3) and obtaining Constraint (15), and Eq. (1) into Eq. (6) and obtaining Constraint (16), we have

$$\textbf{P1:} \min_{q[n]} \quad \delta \sum_{n=1}^{N} (p^c[n] + p^f[n]) \quad (14)$$

$$\begin{aligned}
\textit{s.t.} \quad & (9), \\
& \sum_{n=1}^{N} b_i[n] \log_2 (1 + \frac{p_i[n]}{\xi_i[n]\sigma^2}) u_i[n] \geq \frac{D_i}{\delta}, \forall i \in \mathcal{I}, && (15)
\end{aligned}$$

$$\eta \sum_{n=1}^{N} \frac{p^c[n]}{\beta_0[(x[n]-x_i)^2+(y[n]-y_i)^2+H^2]} \geq \sum_{n=1}^{N} p_i[n]u_i[n], \forall i \in \mathcal{I}, \tag{16}$$

$$(x[n]-x[n-1])^2+(y[n]-y[n-1])^2 \leq (\delta V^m)^2, \forall n \in \mathcal{N}, \tag{17}$$

Note that the functions in Constraints (9) and (17) are convex w.r.t. $(x[n], y[n])$. However, **P1** is still challenging to solve because $p^f[n]$ and $R_i[n]$ are neither linear nor convex w.r.t. $(x[n], y[n])$. In addition, the set of trajectories of the UAV that satisfies Constraint (16) is not convex because $h_i[n] = 1/\xi_i[n]$ is a convex function rather than a concave function w.r.t. $(x[n], y[n])$. Next, we try to replace $p^f[n]$, $R_i[n]$ and $h_i[n]$ with the convex approximations and solve the transformed problem based on the SCA technique.

Lemma 1. *As $p^f[n]$ is convex w.r.t. $||v[n]||^2$ and given a local point $||v_r[n]||^2$, we have*

$$p^f[n](||v[n]||^2) \geq p^f[n]\Big|_{||v_r[n]||^2} + p^f[n]'\Big|_{||v_r[n]||^2} \left(||v[n]||^2 - ||v_r[n]||^2\right) \tag{18}$$

where $p^f[n]'$ is the first derivative of $p^f[n]$.

Proof: $p^f[n]$ can be rewritten as a function of $\|v[n]\|^2$ as

$$p^f[n] = c_1 \left(||v[n]||^2\right)^{3/2} + \frac{c_2}{(||v[n]||^2)^{1/2}}. \tag{19}$$

To simplify the analysis, we make use of $f(z) = c_1 z^{3/2} + c_2/z^{1/2}$ instead of $p^f[n]$ since $f(z)$ and Eq. (19) share the same convexity. Then, we can obtain the first derivative of $f(z)$ as

$$f'(z) = \frac{3c_1 z^2 - c_2}{2z^{\frac{3}{2}}}. \tag{20}$$

Furthermore, we can obtain the second derivative of $f(z)$ as

$$f''(z) = \frac{3(c_1 z^2 + c_2)}{4z^{5/2}}. \tag{21}$$

Since c_1 and c_2 are positive values determined by the UAV's wing area and weight, we have $f''(z) > 0$ if $z > 0$, i.e., $f(z)$ is a convex function. Equivalently, $p^f[n]$ is convex w.r.t. $||v[n]||^2$ (note that $\|v[n]\|^2 > 0$). Recall that the first order Taylor expansion of a convex function at any given local point incurs a lower bound [25], and thus

$$\begin{aligned} p^f[n] &\geq p^f[n]\Big|_{||v_r[n]||^2} + p^f[n]'\Big|_{\|v_r[n]\|^2} \left(\|v[n]\|^2 - \|v_r[n]\|^2\right) \quad (22) \\ &\overset{a}{=} p^f[n]\Big|_{||v_r[n]||^2} + p^f[n]'\Big|_{||v_r[n]||^2} \Big(\frac{(x[n]-x[n-1])^2+(y[n]-y[n-1])^2}{\delta^2} - ||v_r[n]||^2\Big) \\ &\triangleq p^f_{lb}[n]. \quad (23) \end{aligned}$$

where step (a) holds by substituting Eq. (5) into Eq. (22). ■

For Constraint (15), although $R_i[n]$ is not convex w.r.t. the UAV's location $q[n] = (x[n], y[n])$, $R_i[n]$ can be proven to be convex w.r.t. the pathloss $\xi_i[n]$ as follows. Note that the second derivative of $R_i[n]$ w.r.t. $\xi_i[n]$ can be expressed as

$$R_i''[n] = \frac{d^2 R_i[n]}{d(\xi_i[n])^2} = \frac{b_i[n]p_i[n]/\sigma^2(2\xi_i[n] + p_i[n]/\sigma^2)}{\xi_i[n]^2(\xi_i[n] + p_i[n]/\sigma^2)^2 \ln 2}. \tag{24}$$

We can observe that $R_i''[n] > 0$ (i.e., $R_i[n]$ is convex) since both $b_i[n]$ and $p_i[n]$ are positive values. As $R_i[n]$ is proven to be convex w.r.t. $\xi_i[n]$, given a local point $\xi_i^r[n]$, we have

$$\begin{aligned} R_i[n] &\geq R_i[n]\big|_{\xi_i^r[n]} + R_i'[n]\big|_{\xi_i^r[n]} (\xi_i[n] - \xi_i^r[n]) \\ &= R_i[n]\big|_{\xi_i^r[n]} + R_i'[n]\big|_{\xi_i^r[n]} \Big(\beta_0 \big[(x[n]-x_i)^2 + (y[n]-y_i)^2 + H^2\big] - \xi_i^r[n]\Big) \\ &\triangleq R_i^{lb}[n], \end{aligned} \tag{25}$$

where $R_i[n]\big|_{\xi_i^r[n]} = b_i[n] \log_2(1 + \frac{p_i[n]}{\xi_i^r[n]\sigma^2})$ and $R_i'[n]\big|_{\xi_i^r[n]} = -\left(b_i[n]p_i[n]/\sigma^2\right) / \left(\xi_i^r[n](\xi_i^r[n] + p_i[n]/\sigma^2) \ln 2\right)$.

For Constraint (16), $h_i[n]$ can also be easily proven to be convex w.r.t. $\xi_i[n]$. By following a similar process as deriving Eq. (25), we can also derive the lower bound of $h_i[n]$ as

$$\begin{aligned} h_i[n] &= \frac{1}{\xi_i[n]} \geq \frac{1}{\xi_i^r[n]} + \frac{-1}{(\xi_i^r[n])^2} (\xi_i[n] - \xi_i^r[n]) \\ &= \frac{1}{\xi_i^r[n]} + \frac{-1}{(\xi_i^r[n])^2} \Big(\beta_0 \big[(x[n]-x_i)^2 + (y[n]-y_i)^2 + H^2\big] - \xi_i^r[n]\Big) \\ &\triangleq h_i^{lb}[n]. \end{aligned} \tag{26}$$

Finally, by replacing $p^f[n]$, $R_i[n]$ and $h_i[n]$ with their convex lower bounds, we transform **P1** into the following problem,

$$\textbf{P1-a:} \quad \min_{q[n]} \quad \delta \sum_{n=1}^{N} (p^c[n] + p^f_{lb}[n]) \tag{27}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} R_i^{lb}[n] \geq \frac{D_i}{\delta}, \forall i \in \mathcal{I}, \tag{28}$$

$$\eta \sum_{n=1}^{N} p^c[n] h_i^{lb}[n] \geq \sum_{n=1}^{N} p_i[n]u_i[n], \forall i \in \mathcal{I}, \tag{29}$$

$$(9), (17),$$

Note that $R_i^{lb}[n]$ and $h_i^{lb}[n]$ are concave w.r.t. $q[n] = (x[n], y[n])$ as given in Eq. (25) and Eq. (26), respectively. As a result, the sets of trajectories that satisfy Constraints (28) and (29), respectively, constitute two convex sets. Since **P1-a** is a convex problem now, we can utilize CVX to obtain its solution.

B. Resource allocation

If the UAV trajectory and time slot association are given, we can obtain the resource allocation problem as

$$\textbf{P2:} \quad \min_{b_i[n], p_i[n], p^c[n]} \quad \delta \sum_{n=1}^{N} (p^c[n] + p^f[n]) \tag{30}$$

$$\text{s.t.} \quad \delta \sum_{n=1}^{N} b_i[n] \log_2 \left(1 + \frac{p_i[n]}{\xi_i[n]\sigma^2}\right) u_i[n] \ge D_i, \forall i \in \mathcal{I}, \tag{31}$$

$$\eta \sum_{n=1}^{N} p^c[n] h_i[n] \ge \sum_{n=1}^{N} p_i[n] u_i[n], \forall i \in \mathcal{I}, \tag{32}$$

$$0 \le p_i[n] \le P_i^{max}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{33}$$

$$\sum_{i=1}^{|\mathcal{I}|} b_i[n] \le B, \forall n \in \mathcal{N}, \tag{34}$$

$$b_i[n] \ge 0, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{35}$$

In **P2**, Eq. (30) and all of the constraints are linear functions w.r.t. $(b_i[n], p_i[n], p^c[n])$ except for Constraint (31). Next, we derive the Hessian matrix of Constraint (31) and prove it to be concave w.r.t. $(b_i[n], p_i[n])$.

Lemma 2. *$b_i[n] \log_2 \left(1 + \frac{p_i[n]}{\xi_i[n]\sigma^2}\right)$ is concave w.r.t. $(b_i[n], p_i[n])$.*

Proof: The Hessian matrix of $b_i[n] \log_2 \left(1 + \frac{p_i[n]}{\xi_i[n]\sigma^2}\right)$ w.r.t. $(b_i[n], p_i[n])$ can be expressed as

$$R_i''[n] = \begin{bmatrix} 0, & \frac{1}{(p_i[n] + \xi_i[n]\sigma^2)\ln 2} \\ \frac{1}{(p_i[n] + \xi_i[n]\sigma^2)\ln 2}, & -\frac{b_i[n]}{(p_i[n] + \xi_i[n]\sigma^2)^2 \ln 2} \end{bmatrix}.$$

Since $b_i[n], p_i[n] \ge 0$, we can conclude that $R_i''[n]$ is negative semidefinite. Thus, $R_i[n] = b_i[n] \log_2 \left(1 + \frac{p_i[n]}{\xi_i[n]\sigma^2}\right)$ is concave w.r.t. $(b_i, p_i[n])$. ■

Note that $u_i[n]$ and δ are given non-negative values in **P2** and the sum operation preserves convexity, therefore, Constraint (31) incurs a convex set. Hence, we can also utilize CVX to obtain the solution of **P2** as it is a convex problem.

C. Time slot association

Assuming the UAV trajectory and resource allocation are fixed, the time slot association (i.e., the time slot association policy for each IoT device) problem can be simplified as

$$\textbf{P3:} \quad \min_{u_i[n]} \quad \delta \sum_{n=1}^{N} (p^c[n] + p^f[n]) \tag{36}$$

$$\text{s.t.} \quad \delta \sum_{n=1}^{N} R_i[n] u_i[n] \ge D_i, \forall i \in \mathcal{I}, \tag{37}$$

$$\eta \sum_{n=1}^{N} p^c[n] h_i[n] \ge \sum_{n=1}^{N} p_i[n] u_i[n], \forall i \in \mathcal{I}, \tag{38}$$

$$u_i[n] = \{0, 1\}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}. \tag{39}$$

Note that the objective function is independent of $u_i[n]$ since $p^c[n]$ and $p^{fly}[n]$ are given in **P3**. Therefore, there may exist more than one feasible solution which satisfies Constraints (37)-(39). Among all feasible solutions, we select the one that maximizes the sum rate of IoT device i, i.e.,

$$\textbf{P3-a:} \quad \max_{u_i[n]} \quad \sum_{n=1}^{N} R_i[n] u_i[n] \tag{40}$$

$$\text{s.t.} \quad \eta \sum_{n=1}^{N} p^c[n] h_i[n] \ge \sum_{n=1}^{N} p_i[n] u_i[n], \forall i \in \mathcal{I}, \tag{41}$$

$$u_i[n] = \{0, 1\}, \forall n \in \mathcal{N}, \forall i \in \mathcal{I}, \tag{42}$$

Note that **P3-a** is a *0-1 Multiple Knapsack Problem*, where time slot n and IoT device i can be seen as item n and knapsack i, respectively. Then, $R_i[n]$ is the profit incurred when placing item n in knapsack i, $p_i[n]$ is the corresponding weight and $\sum_{n=1}^{N} p^c[n] h_i[n]$ is the capacity of knapsack i. **P3-a** can be efficiently solved by utilizing the dynamic programming algorithm.

The BCD-based algorithm to jointly determine the UAV trajectory, time slot association and resource allocation is embodied in Algorithm 1. Line 1 initializes all parameters. The complexities of line 3 and line 4 are both $O(\sqrt{|\mathcal{I}| + |N|})$ since they are both solving a convex optimization problem; that of line 5 is $O(|\mathcal{I}| * |N|)$ in the worst case. Hence, the complexity of Algorithm 1 is $O(|\mathcal{I}| * |N|)$.

Denote $E(\mathbf{Q}^r, \mathbf{A}^r, \mathbf{U}^r)$ as the objective value of **P0** with given trajectory $\mathbf{Q}^r$, resource allocation $\mathbf{A}^r$ and time slot association $\mathbf{U}^r$ at the r-th iteration. It then follows that:

$$\begin{aligned} & E(\mathbf{Q}^r, \mathbf{A}^r, \mathbf{U}^r) \overset{(a)}{\le} E(\mathbf{Q}^{r+1}, \mathbf{A}^r, \mathbf{U}^r) \\ & \overset{(b)}{\le} E(\mathbf{Q}^{r+1}, \mathbf{A}^{r+1}, \mathbf{U}^r) \overset{(c)}{\le} E(\mathbf{Q}^{r+1}, \mathbf{A}^{r+1}, \mathbf{U}^{r+1}) \end{aligned} \tag{43}$$

where (a), (b) and (c) hold due to the monotonicity of SCA-based algorithms [13] at lines 3-5, respectively. Note that the optimal value of **P0** is upper bounded by a finite value. Hence, Algorithm 1 is guaranteed to converge.

Algorithm 1 BCD-based Algorithm for **P0**

1: Initialize $\mathbf{A}^0$ and $\mathbf{U}^0$. Set $r = 0$;
2: **repeat**
3: Obtain $\mathbf{Q}^{r+1}$ by solving **P1-a** with given $\mathbf{A}^r$ and $\mathbf{U}^r$;
4: Obtain $\mathbf{A}^{r+1}$ by solving **P2** with given $\mathbf{Q}^{r+1}$ and $\mathbf{U}^r$;
5: Obtain $\mathbf{U}^{r+1}$ by solving **P3-a** with given $\mathbf{Q}^{r+1}$ and $\mathbf{A}^{r+1}$;
6: Update $r = r + 1$;
7: **until** There is no update of the objective function or the maximum number of iterations is reached,

where $\mathbf{A} = \{b_i, p_i[n], p^c[n], \forall i \in \mathcal{I}, \forall n \in \mathcal{N}\}$, $\mathbf{Q} = \{q[n], \forall n \in \mathcal{N}\}$, $\mathbf{U} = \{u_i[n], \forall i \in \mathcal{I}, \forall n \in \mathcal{N}\}$ and the superscript r denotes the r-th iteration.

V. Numerical Results

We consider a 300 m $\times$ 300 m area with 6 IoT devices in the simulations. The flying height of the UAV H is set as 10 m. The start location of the UAV is set as $Q = (0, 0)$. The data size of IoT devices follows the Poisson distribution with the average value of 1 Mb. The noise power at the receiver $\sigma^2 = -80$ dBm. Assume $c_1 = 9.26 \times 10^{-4}$ and $c_2 = 2250$

[13]. The efficiency for converting the harvested RF energy to the direct current energy is $\eta = 50\%$. $\beta_0 = -30$ dB. Unless otherwise stated, the system parameters are set as follows: $T = 20$ s, $V^m = 30$ m/s, $\delta = 1$ s, $P^{max} = 0.5$ W and $B = 10$ MHz.

Fig. 2 and Fig. 3 illustrate the UAV trajectories and total energy consumption under different total available bandwidth. It can be observed that the trajectory of the UAV reduces to a smaller circle with the increase of the total available bandwidth. Because the increase of the available bandwidth allows IoT devices to consume less transmit energy to offload the same amount of data. Therefore, the energy consumption for charging is reduced as the IoT devices consume less energy. Meanwhile, the UAV does not need to hover close to each IoT device to improve the harvesting efficiency, thus reducing the flight energy consumption.

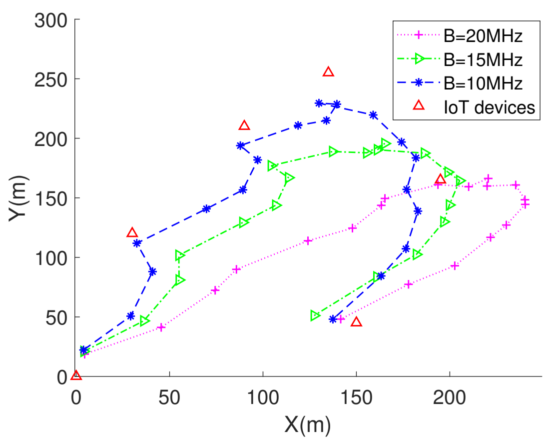

Fig. 2. Trajectories with different total available bandwidth.

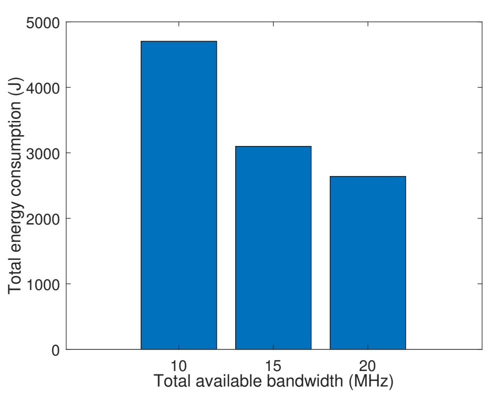

Fig. 3. Total energy consumption vs total available bandwidth.

Fig. 4 illustrates the energy consumption for charging and flying under different cruising durations. We can observe that the energy consumption for charging increases slightly while the energy consumption for flying increases drastically with the increase of the cruising duration of the UAV. The reason is that all data are collected and IoT devices are fully charged within 20 seconds. After all IoT devices are fully charged, the charging power will be set as 0 and no more energy

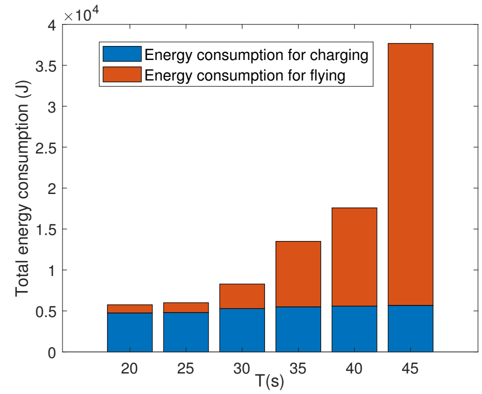

Fig. 4. Total energy consumption vs cruising duration.

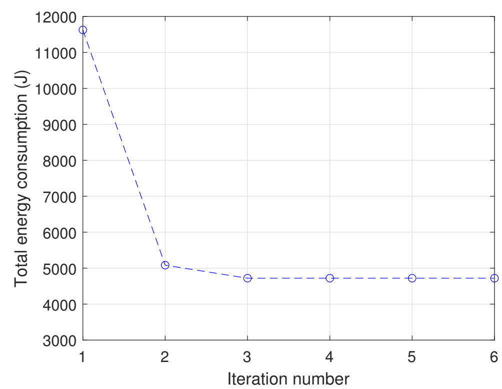

Fig. 5. Convergence behavior of Algorithm 1.

is consumed for charging. However, more energy will be consumed to keep the UAV stay in the air. Fig. 5 shows the convergence performance of Algorithm 1. We can observe that the total energy consumption decreases monotonically after each iteration and the algorithm converges fast (the objective function value does not change after 3 iterations).

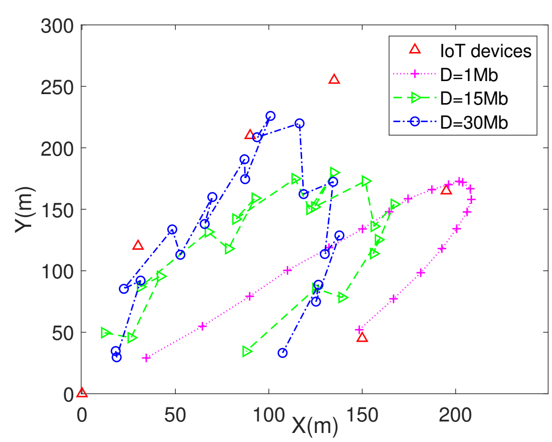

Fig. 6. Trajectories for different data sizes.

Fig. 6 and Fig. 7 show the trajectories and energy consumption for charging and flying for different data sizes.

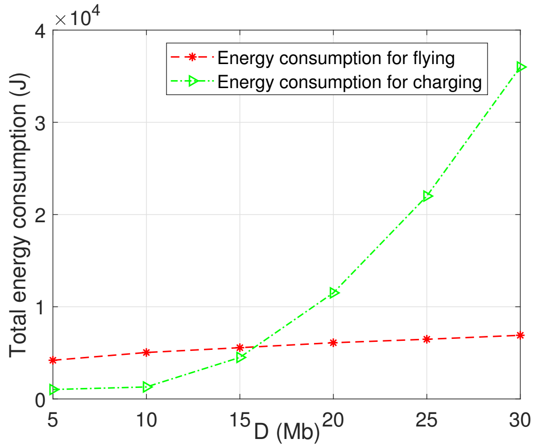

Fig. 7. Charging and flying energy consumption for different data sizes.

The trajectories in Fig. 6 are similar to those shown in Fig. 2 because the increase of the data size incurs more transmit energy consumption of the IoT devices. The UAV needs to fly closer to the location of each IoT device to reduce the communication pathloss and increase the energy harvesting efficiency. Note that the energy consumption for charging in Fig. 7 increases significantly while the propulsion energy consumption remains roughly the same as the data size increases. This is because the trajectory of the UAV has already been optimized (hovering right above each IoT device) and the IoT devices have to increase the transmit power to complete the data offloading.

VI. Conclusion

The fixed-wing UAV-enabled IoT network can not only collect the data offloaded by the IoT devices but also provide perpetual power by utilizing RF WPT. Considering the limited on-board energy, we have formulated the problem to minimize the UAV's energy consumption by jointly designing the resource allocation, the UAV trajectory and the time slot association scheme. We have developed a cyclic iterative algorithm based on the BCD method to efficiently solve the formulated problem. We have proven the resource allocation and the time slot association to be a convex problem and a *0-1 Multiple Knapsack* problem, and solved them by utilizing CVX and dynamic programming, respectively. To make the trajectory design problem more tractable, we replace the non-convex functions in the objective function and constraints with the convex approximations by leveraging first order Taylor expansion. We have proven the transformed problem to be a convex optimization problem and solved it by utilizing CVX. We have conducted extensive numerical experiments to corroborate the effectiveness of the proposed algorithm.

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