IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received January 8, 2020, accepted January 26, 2020, date of publication February 6, 2020, date of current version February 17, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2971962

Incentive UAV-Enabled Mobile Edge Computing Based on Microwave Power Transmission

YI LIU[1], MING QIU[1], JINLEI HU[2], AND HUIMIN YU[3]
[1]School of Automation, Guangdong University of Technology, Guangzhou 510006, China
[2]Qingyuan Power Supply Bureau, Guangdong Power Grid Corporation, Qingyuan 511515, China
[3]College of Information Science and Engineering, Hunan Normal University, Changsha 410081, China

Corresponding author: Huimin Yu (yhm@hunnu.edu.cn)

This work was supported in part by the programs of National Natural Science Foundation of China (NSFC), under Grant 61773126.

ABSTRACT With the increasing requirements of the flexible and delay-sensitive computing services, UAV has attracted widespread attention for assisting mobile edge computing (MEC) system. However, due to the limited battery capacity, the UAV cannot always fly and serve the users in the air. To address this issue, a UAV-enabled MEC system based on microwave power transmission is proposed in this paper. In this system, the UAV periodically and continually flies over the users' area to provide computing services and will be charged over the microwave station. Considering profit-centric MEC service provider, the UAV will charge fees from users for the computation services. Then, an optimization problem is formulated to maximize the service utility of the UAV by finding the optimal UAV's trajectory, computation offloading decisions and offloading duration. Since the proposed optimization problem is non-convex, the original problem is decomposed into three sub-problems and a three-stage alternative algorithm is presented to solve them iteratively. The numerical results show that the proposed offloading method can achieve better performance than other baseline methods.

INDEX TERMS UAV-enabled mobile edge computing, computation offloading, microwave power transmission.

I. INTRODUCTION

With the rapid development of the Internet of things (IoT), diversified mobile applications such as augmented reality, face recognition, mobile online games, virtual reality, etc., are increasingly appearing in industrial, residential and commercial areas [1]–[4]. With the help of advanced communication, computation and cache technologies, the IoT system achieves highly scalable architecture to adaptively provide services for numerous applications. Although the IoT framework can achieve high magnitudes of connected objects and diverse services, it is difficult to provide low-latency and high-speed computing services for arbitrary applications. The bottleneck of the IoT development is caused by multiple factors: the limited computation and battery capacities of mobile users, the long distance connection between users and servers in remote areas, the dynamic computation demands generated by different users, etc [5], [6].

Mobile edge computing (MEC) has been considered as one of the promising technologies to meet aforementioned challenges in IoT system [7]–[10]. The main feature of the MEC is that the users can be served by the (edge) servers which are deployed at the edge of the network. Since the edge servers are located near the users, they can provide computing services for users with less energy cost and low-latency [11]–[14]. However, the deployment of the edge server at fixed locations may cause inflexibility and difficulty of adjusting the service coverage which is affected by the complicated topography and uncertain demands. Unmanned Aerial Vehicle (UAV)-enabled MEC, which has flexible and rapid deployment capacity, is deemed to be suitable for providing services for particular areas and unexpected computation requirements [15]–[17]. With high speed mobility, the UAV-based edge server can freely approach to the mobile users and provide computation services, which can significantly improve the network performance. In addition, compared with the ground communication, the air-to-ground communication in UAV-enabled MEC network can provide higher link capacity because of the line of sight (LoS) transmission between UAV and users. Hence, the UAV-enabled MEC network is one of the hotspots in current MEC research.

In a UAV-enabled MEC network, the UAV communicates with ground users and computes various tasks while maintaining flight at a certain speed. In this case, it is very

The associate editor coordinating the review of this manuscript and approving it for publication was Alessio Vecchio.

important to design an energy-efficient UAV-enabled MEC system. In [18], the authors come up with an idea to reduce the weight of UAVs to alleviate the energy consumption. In [19], the authors propose an energy-aware path planning for photogrammetric sensing UAVs while satisfying coverage and resolution. In [20], the authors minimize the energy consumption for UAV-enabled communication network by optimizing the UAVs' trajectory. In [21], the authors considered a UAV-enabled wireless powered communication network, in which a UAV can provide electricity charging and communication services for ground users. In [22], the authors present a comprehensive survey for the UAV-enabled MEC networks which highlights the benefits and the challenges in this domain. In [23], the computation efficiency is studied for the UAV-enabled MEC network by jointly optimizing the offloading times, the trajectory of the UAV, etc. In [24], a UAV-enabled wireless powered MEC system is studied for enhancing the quality of experience of mobile users which is greatly limited by their computation capacity and finite battery lifetime. Although many energy-efficient methods are proposed for UAV system, the battery-powered UAVs still restrict the MEC network performance because of the limited battery capacity.

Wireless power transmission (WPT) technology is expected to extend the energy supply of the UAV and prolong the UAVs' operation duration [25]. Particularly, microwave power transmission technology is one of the important WPT technologies which can provide sufficient power for the UAV without landing. In this technology, a large disc-shaped rectifying antenna attached to the fuselage of the UAV is responsible for harvesting the microwave energy from the microwave antenna array on the ground. Then, the UAV turns the harvested energy into direct current to power the electric motor or other equipments attached to the UAVs [26]. Microwave power transmission has been proved to be useful for power supply of small aircraft and helicopters [27]. Moreover, the transfer efficiency of the microwave energy in space exceeds 90% [28], which is higher than that of other scheme, e.g., laser. The UAV-enabled MEC with microwave power transmission, on the one hand, can still keep the advantage of the UAV-enabled MEC to provide quick and convenient computation services for ground users. On the other hand, the microwaves energy transmission can avoid the landing of the UAV for charging or replacing batteries, which increases the practicability of the UAV-enabled MEC network in a remote area with complicated geographical conditions.

In this paper, we propose a UAV-enabled MEC network in which the UAV can be recharged by the microwave power transmission station on the ground. In this network, the users can offload the computing tasks to the UAV through ground-to-air link or compute the tasks by themselves. Meanwhile, the UAV is incentive to provide air-to-ground computation services for users and be periodically flies over the microwave power station for charging. Considering the fixed operation duration, there is a tradeoff between the recharging time and service time of the UAV. The longer recharging time

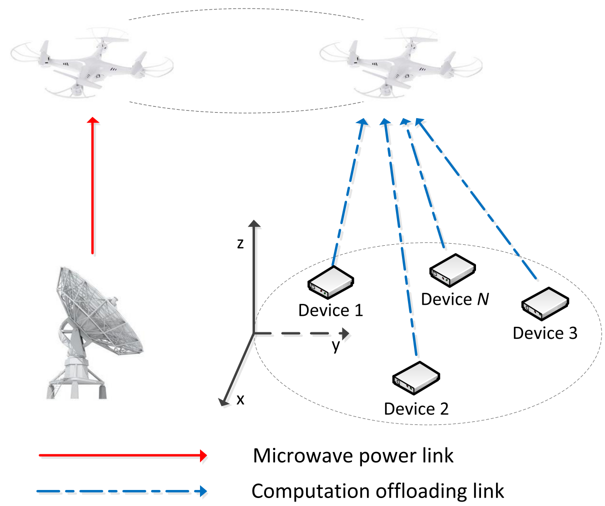


FIGURE 1. System model of microwave powered UAV-enabled MEC network.

will lead to more harvested energy for the UAV's flight and computation, but shorter service time. Hence, the UAV's offloading strategy, recharging/service time as well as the flight trajectory should be carefully decided. Since the computation services of the UAV is profit incentive, our goal is to maximize the service utility of the UAV by jointly optimizing the service (offloading) decisions, service duration, and flight trajectory of the UAV. The proposed problem is a non-convex optimization problem due to the discrete binary variable and practical energy consumption model of the UAV. Hence, we decompose the original problem into three subproblems, which are alternately solved to obtain the optimal operation parameters.

The remainder of this paper is organized as follows. In Section II, the system model of the UAV-enabled MEC network with microwave power transmission is introduced. The problem formulation and the solutions are described in Section III and Section IV, respectively. Section V shows the numerical results of the proposed methods. Finally, the paper is concluded in Section VI.

II. SYSTEM MODEL

A. NETWORK MODEL

We consider a UAV-enabled MEC network as shown in Fig. 1, in which the UAV is powered by the carry-on battery and can be recharged by the microwave power station without landing. The UAV can approach to the users' locations in the air to simultaneously provide communication and computation services. To achieve that, the UAV has an on-board computation processor, wireless communication module and interface as well as the charging units which consists of rectenna array, power management circuit and rechargeable batteries [29]. The ground user has an on-chip micro-processor and a single antenna, which can execute the local task and communicate with the UAV at the same time. We consider the number of the users in the network is K and the set of the users is denoted as $\mathcal{K} = \{1, \ldots, K\}$.

In our model, the UAV keeps a fixed altitude level denoted by $H(H > 0)$ in the air during an operation duration T. The operation duration starts when the UAV leaves the charging point (over the microwave power station) and terminates when the UAV finishes the service operation and returns to the charging point for a new round of recharging. Considering the limited battery capacity of the UAV, we assume that the operation duration T has fixed time length and consists of recharging duration T_c and offloading duration T_s, i.e., $T = T_c + T_s$. The offloading duration T_s is further divided into N time slots. Each time slot t has the same length ϕ_t, then we have $T_s = N\phi_t$. Without loss of generality, the horizontal plane coordinate of the UAV during the service duration can be presented by $q_u(t) = [x_u(t), y_u(t)], t = 1, 2, \cdots, N$. Also, we consider the location of the kth user is denoted by q_k, where $q_k = [x_k, y_k]$, $k \in \mathcal{K}$. The UAV communicates the users through Line of Sight (LOS) channel, which is the block fading channel, i.e., the channel remains static during time duration T.

B. COMPUTATION OFFLOADING MODEL

In the computation offloading model, the users are able to offload the computation tasks to the UAV through wireless communication channels. Let $h_k(t)$ denote the channel power gain between the kth user and the UAV at time slot t, we have

$$h_k(t) = \rho_0 d_k^{-2}(t) = \frac{\rho_0}{H^2 + \parallel q_u(t) - q_k \parallel^2}, \tag{1}$$

where ρ_0 is the channel power gain at a reference distance $d_0 = 1m$, $d_k(t)$ denote the distance between the UAV and the kth user at time slot t. The data rate of the uplink between the kth user and the UAV at time slot t can be described as

$$r_k(t) = B \log_2 \left(1 + \frac{P_k h_k(t)}{N_0}\right), \tag{2}$$

where B is the bandwidth of the communication channel, P_k is the transmit power of the kth user and N_0 is the noise power. Then, the size of the computation task that user k offloads to the UAV at t time slot is given by

$$R_k(t) = \beta_k(t)\phi_t r_k(t), \tag{3}$$

where $\beta_k(t) \in \{0, 1\}$ denotes the offloading factor, $\beta_k(t) = 0$ means the user k computes the task by itself, $\beta_k(t) = 1$ means the user k offloads the computation task to the UAV.

C. UAV ENERGY MODEL

1) ENERGY HARVESTING MODEL

We consider the UAV harvests energy from the microwave power station which adopts a fixed transmit power P_M. In order to achieve the maximum charging efficiency, the UAV hovers above the microwave power station for charging. The gain of the microwave transmitting antenna is denoted as G_M and the gain of the receiving antenna on the UAV is denoted as G_R. Accordingly, the received power at the UAV, denoted by P_R, is expressed as

$$P_R = P_M \frac{G_M G_R \lambda^2}{(4\pi d_s)^2 L}, \tag{4}$$

where λ is the wave length, d_s is the distance between the UAV and the microwave power station when the UAV is charging. L is the path loss factor. Let E_{harv} denote the harvested energy of the UAV during the charging duration T_c, we have

$$E_{harv} = P_R T_c. \tag{5}$$

2) COMPUTATION ENERGY CONSUMPTION MODEL

The harvested energy of the UAV is used for the task computation and flight. To compute the task offloaded from users, the CPU frequency of the UAV at the tth time slot is denoted as $f_u(t)$ (cycles per second), which is given by

$$f_u(t) = c_u r_k(t), \tag{6}$$

where c_u is the number of CPU cycles for calculating one bit data. Then, the energy consumption of the computation can be described as

$$E_{comp}(t) = \gamma_u f_u^3(t)\beta_k(t)\phi_t, \tag{7}$$

where γ_u is the effective switched capacitance.

3) FLIGHT ENERGY CONSUMPTION MODEL

The UAV's energy consumption during the flight can be influence by many factors. To focus on designing the offloading and charging strategy for the microwave powered UAV, a flight energy consumption model which is related to the UAV's velocity v_u and quality M_u is applied in this paper. Hence, the flight energy consumption of the UAV at time slot t is given by

$$E_{fly}(t) = \Gamma \parallel v_u(t) \parallel^2, \tag{8}$$

where $v_u(t) = \frac{\|q_u(t) - q_k\|}{\phi_t}$ and $\Gamma = 0.5\, M_u \phi_t$.

III. PROBLEM FORMULATION

In this paper, we consider a practical scenario where the UAV has profit incentive to provide the computation services for the users. In such case, the UAV will charge users for executing (including computation and communication) the computation task at the unit prices, denoted as η_k per Mbits. Let $U_k(t)$ denote the service utility of the UAV for providing computation and communication services to the kth user at time slot t. Then, we have

$$U_k(t) = \eta_k R_k(t) = \eta_k \beta_k(t)\phi_t r_k(t). \tag{9}$$

The goal of this paper is to maximize the total service utility of the UAV during the operation duration T by deciding the UAV's trajectory, offloading decisions and offloading duration. Then, we have the optimization problem as follows

$$\mathbf{P1} \quad \max_{q_u(t), \beta_k(t), \phi_t} \sum_{k=1}^{K} \sum_{t=1}^{N} U_k(t)$$

$$s.t.\ C1: \sum_{t=1}^{N} E_{comp}(t) + \sum_{t=1}^{N} E_{fly}(t) \leq E_{harv},$$

$$C2: \sum_{k=1}^{K} \beta_k(t) = 1, \quad \beta_k(t) \in \{0, 1\},$$
$$C3: \sum_{t=1}^{N} \beta_k(t)\phi_t r_k(t) \geq R_{TH},$$
$$C4: \parallel q_u(t+1) - q_u(t) \parallel \leq \phi_t V_{\max},$$
$$C5: q_u(1) = q_u(N) = q_0,$$
$$C6: N\phi_t + T_c = T.$$

where $V_{\max}$ is the maximum velocity of the UAV. Constraint C1 ensures that the energy consumption of the UAV for the computation and flight is not exceeding the total harvested energy during an operation duration. Constraint C2 indicates that the UAV can only serve one user during a time slot. Constraint C3 guarantees the amount of the offload data from each user should exceed the threshold (R_{TH}). C4 is the maximum allowable velocity of the UAV and C5 ensures that the UAV can be charged over the location of microwave power station (q_0) at the beginning of each operation duration. The limitation of the UAV's operation duration is given by constraint C6.

Problem **P1** can be solved by finding the optimal trajectory $q_u(t)$, offloading decision $\beta_k(t)$, and offloading duration ϕ_t. Since the objective function and the constraints are non-convex, P1 is a non-convex optimization problem. To solve this problem, we decompose the problem into three subproblems and propose an alternative optimization method to obtain the optimal solutions.

IV. ALTERNATIVE OPTIMIZATION METHOD

In the proposed method, the UAV's trajectory, offloading decisions and offloading duration of users are alternative optimized. We first optimize the users' offloading decisions by given UAV's trajectory and offloading durations, then optimize the UAV's trajectory by given offloading decision and offloading durations. At last, we optimize the users' offloading durations under obtained optimal users' offloading decisions and UAV's trajectory.

A. OFFLOADING DECISION OPTIMIZATION

In this subsection, our goal is to maximizes the UAV's service utility by finding optimal offloading decision $\beta_k(t)$ under given trajectory $q_u(t)$ and offloading duration ϕ_t. Hence, problem **P1** is reduced to the following optimization problem.

$$\textbf{P2} \max_{\beta_k(t)} \sum_{k=1}^{K}\sum_{t=1}^{N} U_k(t)$$
$$s.t.\ C1: \sum_{t=1}^{N} E_{comp}(t) + \sum_{t=1}^{N} E_{fly}(t) \leq E_{harv},$$
$$C2: \sum_{k=1}^{K} \beta_k(t) = 1, \quad \beta_k(t) \in \{0, 1\},$$
$$C3: \sum_{t=1}^{N} \beta_k(t)\phi_t r_k(t) \geq R_{TH}.$$

Since the subproblem **P2** is a 0-1 integer programming problem, we develop a special branch-and-bound method, named implicit enumeration method, to find the near-optimal solutions. The implicit enumeration method consists of the following steps:

Step 1: To use implicit enumeration, the **P2** problem should be firstly transformed to the standard 0-1 integer programming form as follows

$$\textbf{P2.1} \min_{\beta_k(t)} -\sum_{k=1}^{K}\sum_{t=1}^{N} U_k(t) = -\sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \beta_k(t)\phi_t r_k(t)$$
$$s.t.\ C1, C2, C3.$$

Then, let $\beta_k'(t) = 1 - \beta_k(t)$ and substitute $\beta_k'(t)$ into the problem **P2.1**, we have

$$\textbf{P2.2} \min_{\beta_k(t)} \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \beta_k'(t)\phi_t r_k(t) - \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \phi_t r_k(t)$$
$$s.t.\ C2.1: \sum_{k=1}^{K}\sum_{t=1}^{N} \gamma_u f_u^3(t)\phi_t - \sum_{k=1}^{K}\sum_{t=1}^{N} \gamma_u f_u^3(t)\beta_k'(t)\phi_t + \sum_{k=1}^{K}\sum_{t=1}^{N} E_{fly}(t) - E_{hav} \geq 0,$$
$$C2.2: \sum_{k=1}^{K} \beta_k'(t) = K-1, \quad \beta_k'(t) \in \{0, 1\},$$
$$C2.3: \sum_{t=1}^{N} \phi_t r_k(t) - \sum_{t=1}^{N} \beta_k'(t)\phi_t r_k(t) \geq R_{TH}.$$

Step 2: Let $\beta_k'(t) = 0, \forall k, t$, and calculate the value of the objective function $U(\beta_k'(t))$. If the constraints C2.1, C2.2 and C2.3 are satisfied, $\beta_k'(t) = 0, \forall k, t$, is the optimal solution. Otherwise the problem should go to the third step.

Step 3: In this step, we sequentially let one of the variables $\{\beta_k'(t), \forall k, t, \}$ equal to 0 or 1, and other variables equal to 0. Then, the former problem decompose into two subproblems. If the constraints are satisfied, the current $\beta_k'(t)$ is a feasible solution. Otherwise, the branching will be continued. For example, we set $\beta_1(1) = 0$ and $\beta_1(1) = 1$, the two subproblems can be described as follows:

$$\textbf{P2.3} \min_{\beta_k(t)} \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \beta_k'(t)\phi_t r_k(t) - \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \phi_t r_k(t)$$
$$s.t.\ \beta_1'(1) = 1, C2.1, C2.3.$$

$$\textbf{P2.4} \min_{\beta_k(t)} \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \beta_k'(t)\phi_t r_k(t) - \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \phi_t r_k(t)$$
$$s.t.\ \beta_1'(1) = 0, C2.1, C2.3.$$

We can check whether the solutions $\{\beta_1'(1) = 1, \beta_2'(1) = 0, \cdots, \beta_K'(n) = 0\}$ of the subproblems **P2.3** and solutions $\{\beta_1'(1) = 0, \beta_2'(1) = 0, \cdots, \beta_K'(n) = 0\}$ of the subproblems **P2.4** satisfies the constraints. If the constraints of the problems are satisfied, then the solutions are the feasible solutions. The solution with lower objective value will be the optimal solution. Otherwise, the branch will continue until a feasible solution is found. The decision of continuing the branching is according to the "Pruning" principles as shown in [30]. At last, the feasible solution of the reserved branch is the optimal solution.

B. UAV'S TRAJECTORY OPTIMIZATION

In this subsection, we optimize the UAV's trajectory $q_u(t)$ by given offloading decision $\beta_k(t)$ and offloading duration ϕ_t. The UAV's trajectory optimization problem P3 is presented as

$$
\begin{aligned}
\textbf{P3} \quad & \max_{q_u(t)} \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \beta_k(t)\phi_t r_k(t) \\
& s.t.\ C1:\ E_{harv} - \sum_{k=1}^{K}\sum_{t=1}^{N} \gamma_u \beta_k(t)\phi_t (c_u r_k(t))^3 \\
& \qquad - \sum_{k=1}^{K}\sum_{t=1}^{N} E_{fly}(t) \geq 0, \\
& \qquad C4:\ \parallel q_u(t+1) - q_u(t) \parallel \leq \phi_t V_{\max}, \\
& \qquad C5:\ q_u(1) = q_u(N) = q_0.
\end{aligned}
$$

Since C1 is non-convex and the objective function is non-concave with respect to $q_u(t)$, **P3** is a non-convex problem. To solve this problem, we use the successive convex approximation (SCA) method which can guarantee the obtained solutions satisfy the Karush- Kuhn-Tucker (KKT) conditions of **P3** [31].

By using the SCA method, the following inequality can be obtained

$$
r_k(t) = B\log_2\left(1 + \frac{P_k\rho_0}{N_0(H^2 + \parallel q_u(t) - q_k \parallel^2)}\right) \geq r_k^{low}, \tag{10}
$$

where the r_k^{low} is the lower bound of $r_k(t)$ and we have

$$
\begin{aligned}
r_k^{low} & \\
= B\log_2 & \left(1 + \frac{P_k\rho_0}{N_0(H^2 + \parallel q_u^j(t) - q_k \parallel^2)}\right) \\
& - \frac{P_k\rho_0 \log_2 e}{N_0(H^2 + \|q_u^j(t) - q_k\|)(N_0 H^2 + N_0 \|q_u^j(t) - q_k\| + \rho_0 P_k)} \\
& \times (\parallel q_u(t) - q_k \parallel^2 - \parallel q_u^j(t) - q_k \parallel^2)
\end{aligned} \tag{11}
$$

Since the maximum data rate between UAV and users can be obtained when the horizontal distance between them is zero, the upper bound of the $r_k(t)$ is given by

$$
r_k^{up} = B\log_2\left(1 + \frac{P_k\rho_0}{N_0 H^2}\right), \tag{12}
$$

Then, the problem **P3** can be transformed to

$$
\begin{aligned}
\textbf{P3.1} \quad & \max_{q_u(t)} \sum_{k=1}^{K}\sum_{t=1}^{N} \eta_k \beta_k(t)\phi_t r_k^{low} \\
& s.t.\ C3.1:\ E_{harv} - \sum_{k=1}^{K}\sum_{t=1}^{N} \gamma_u \beta_k(t)\phi_t (c_u r_k^{up})^3 \\
& \qquad - \sum_{k=1}^{K}\sum_{t=1}^{N} E_{fly}(t) \geq 0, \\
& \qquad C4, C5.
\end{aligned}
$$

It can be seen that the constraint C3.1 and the objective function of problem **P3.1** is convex with respect to $q_u(t)$. Hence, the problem **P3.1** is a convex problem and can be readily solved by using CVX method [20].

C. OFFLOADING DURATION OPTIMIZATION

The objective of this subsection is to optimize the offloading duration ϕ_t under given UAV's trajectory $q_u(t)$ and offloading decisions $\beta_k(t)$.

$$
\begin{aligned}
\textbf{P4} \quad & \max_{\phi_t} \sum_{k=1}^{K}\sum_{t=1}^{N} U_k(t) \\
& s.t.\ C4.1:\ P_r(T - N\phi_t) - \sum_{k=1}^{K}\sum_{t=1}^{N} \gamma_u \beta_k(t)\phi_t f_u(t)^3 \\
& \qquad - \sum_{k=1}^{K}\sum_{t=1}^{N} 0.5 M_u \frac{\parallel q_u(t+1) - q_u(t) \parallel}{\phi_t} \geq 0 \\
& \qquad C4:\ \parallel q_u(t+1) - q_u(t) \parallel \leq \phi_t V_{\max}.
\end{aligned}
$$

Since $\phi_t \geq 0$, we can rewrite the constraint C4.1 as

$$
\begin{aligned}
-[NP_r + \sum_{k=1}^{K}\sum_{t=1}^{N} \gamma_u \beta_k(t) f_u(t)^3]\phi_t^2 + P_r T\phi_t \\
- \sum_{k=1}^{K}\sum_{t=1}^{N} 0.5 M_u \parallel q_u(t+1) - q_u(t) \parallel \geq 0
\end{aligned}
$$

It can be seen that the objective function and constraints of problem **P4** are convex with respect to ϕ_t. Hence, the problem **P4** is a convex optimization problem which can be solved by the CVX method [20].

D. ALTERNATIVE ALGORITHM FOR SOLVING P1

In this subsection, we propose a three-stage alternative algorithm to solve problem **P1**. As shown in Algorithm 1, the radio environment parameters and the operation parameters are firstly initialized. In the first stage, in order to obtain the optimal offloading decisions $(\beta_k(t), \forall k, t)$, the problem **P2** is solved by using implicit enumeration method given the offloading duration $(\phi_t, \forall t)$ and UAVs' trajectory $(q_u(t), \forall t)$. In the second stage, the optimal offloading duration is obtained by solving the problem **P3** by given UAVs' trajectory and the optimal offloading decisions obtained in **P2**. In the third stage, based on the solutions from the previous

Algorithm 1 Three-Stage Alternative Algorithm

Initialization:

1: Initialize the radio environment parameters B, ρ_0, P_k, H, N_0, the operation parameters G_M, G_R, λ, P_M, d_s, L and the tolerance error ε_1, ε_2

2: Initialize $\beta_k^1(1)$, $q_u^1(1)$, ϕ_t^1 and $U_k^1(1)$

3: **For** each iteration j

4: Solving P2 by using implicit enumeration method for given $q_u^j(t)$ and ϕ_t^j, obtain optimal $\beta_k^{opt}(t)$

5: $\beta_k^{j+1}(t) = \beta_k^{opt}(t)$, $q_u^i(t) = q_u^j(t)$

6: **For** each iteration i

7: Solving P3 by using CVX for given $\beta_k^{j+1}(t)$ and ϕ_t^j and obtain $q_u^{i+1}(t)$

8: **If** $\sum_{t=1}^{N} \parallel q_u^{i+1}(t) - q_u^i(t) \parallel \leq \varepsilon_2$, $q_u^j(t) = q_u^i(t)$, break

9: **End If**

10: Update $i = i + 1$

11: **End For**

12: Solving P4 by using CVX for given $q_u^{j+1}(t)$ and β_t^{j+1}, obtain ϕ_t^{opt} and $\phi_t^{j+1} = \phi_t^{opt}$

13: Compute $S^{j+1} = \sum_{k=1}^{K} \sum_{t=1}^{N} U_k^j(t)$ by using $q_u^{j+1}(t)$, β_t^{j+1} and ϕ_t^{j+1}

14: **If** $\sum_{t=1}^{N} \parallel S^{j+1} - S^j \parallel \leq \varepsilon_1$, break

15: **End If**

16: Update $j = j + 1$

17: **End For**

two problems, the sub-optimal UAVs' trajectory is archived by solving the problem **P4**. In this three-stage alternative algorithm, the tolerance error ε_1 and ε_2 are used to guarantee the convergence.

Note that the proposed Algorithm 1 only solves convex sub-problem at each stage for each iteration. The iteration number of Algorithm 1 is mainly influenced by the stop criterion (the tolerance error ε_1 and ε_2) rather than the problem scale N and K. Hence, the overall computational complexity of Algorithm 1 is polynomial. We also note that with alternating optimization and usage of SCA method in the sub-problems, global optimum cannot be strictly guaranteed. Hence, the maximize service utility achieved by Algorithm 1 might be affected by the initial variables setting, e.g., the UAV's initial trajectory and initial offloading duration.

V. NUMERICAL RESULTS

To illustrate the performance of the proposed methods, we consider a $450 \times 450\ m^2$ area which includes 5 deployed users, each of which is served by one UAV. The flight altitude and the maximum speed of the UAV are set as $H = 50m$ and $V_{max} = 30\ m/s$, respectively. The charging distance $d_s = H$. Other input parameters are listed in table 1. The performance of the proposed offloading method which jointly optimizes the offloading decisions, offloading duration and UAV's trajectory is compared with other three UAV-enabled offloading methods: 1, the offloading method with fixed offloading decisions in which the UAV sequentially provide offloading service for users, 2, the offloading method with fixed offloading duration where the time length of the duration is ϕ_t=2s and 3, the offloading method with fixed trajectory which is a circle around users with radius equal to 100m.

TABLE 1. The input parameters.

G_M	35 dbi	The transmitting antenna gain.
G_R	35 dbi	The receiving antenna gain.
L	3	The path loss factor.
λ	0.122m	The wave length.
B	5 MHz	The channel bandwidth.
ρ_0	-50 dB	The channel power gain at distance d_0.
N_0	10^{-9} W	The receiver noise power.
P_k	0.5 W	The transmitting power of a user.
η_k	1 per Mbits	The unit price of executing computation task.
c_u	1000 cycles/bit	The number of CUP cycles.
γ_u	10^{-28}	The effective switched capacitance.
$\varepsilon_1, \varepsilon_2$	10^{-4}	The error tolerance.

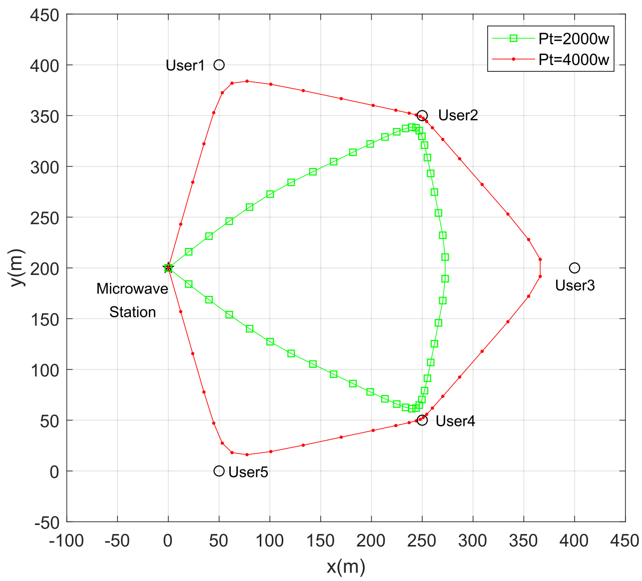


FIGURE 2. The trajectory of the UAV for the circle deployment of users.

A. TRAJECTORY ANALYSIS

Fig.2 shows the UAV trajectory of the proposed offloading method with respect to different transmitting power (P_t) values of the microwave station. In the $P_t = 2000\ W$ case, the trajectory of the UAV is inclined to user 2 and user 4 while other users are served on the way. In the $P_t = 4000\ W$ case, the trajectory of the UAV can approach to all users for providing computation services. The reason is that the higher transmitting power from the microwave station, the more energy can be harvested by the rechargeable UAV, and more users can be served closely. Note that the flying distance during each time slot (the length between two dots of the trajectory line) is distinct in both cases. This is because the incentive offloading method propel the UAV to reach the users' locations as soon as possible to provide computation services.

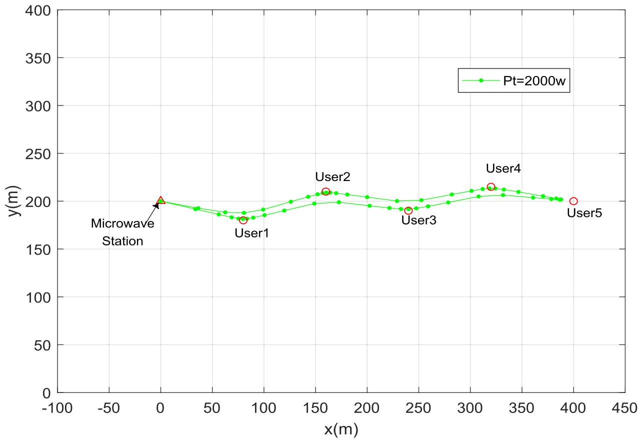


FIGURE 3. The trajectory of the UAV for the straight line deployment of users.

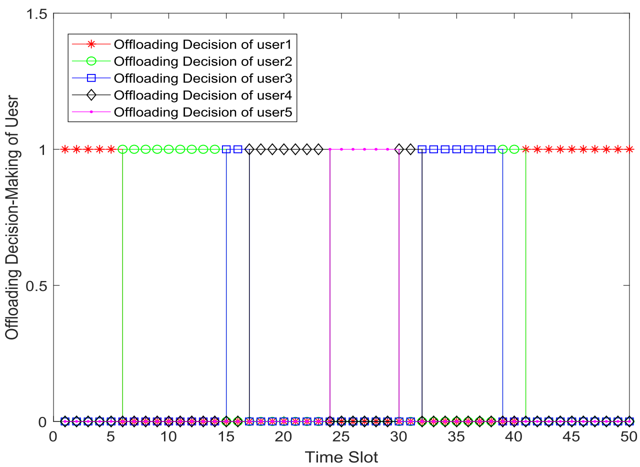


FIGURE 4. The offloading decision for the straight line deployment of users.

In Fig.3, we show that the UAV's trajectory under $P_t = 2000\ W$ case in another user deployment scenario where the users are deployed near a straight line. We can see that the UAV can provide computation services for all users because the energy consumed for flight is largely saved. This indicates that the deployment of the users can largely affect the service performance of the UAV as the flight energy occupies a large part of the energy.

Fig.4 shows the offloading decisions of the UAV when it approaches each user. We can see that the UAV can provide computation services for users during a round trip. It is interesting to see that the UAV can provide the computation services in both of the depart and return routes of the charging point. Meanwhile, the UAV flies to the farthest node (user 5) only provide basic computation services (with shortest offloading time among all users). The reason is that the proposed offloading method can obtain the optimal trajectory and offloading decision of the UAV which is motivated to consume more energy on the computation service near the users and avoid to fly too far to provide services.

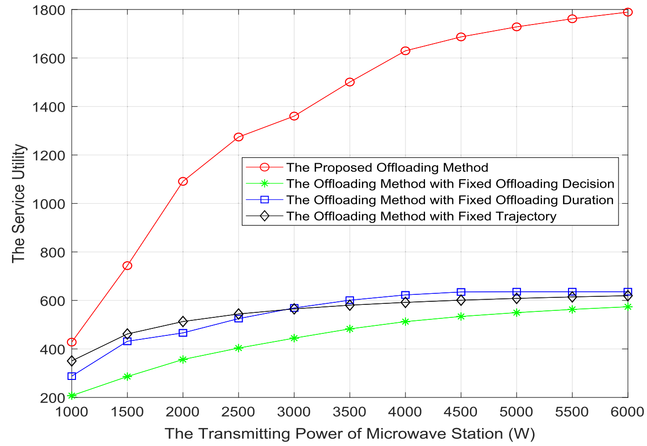


FIGURE 5. Service utility comparison of the UEC network.

B. SERVICE UTILITY COMPARISON

Fig.5 shows the service utility comparison of the proposed offloading method with other three offloading methods with different fixed parameters. It can be seen that the proposed method achieves the highest service utility among all the methods. This is because the proposed offloading method can maximize the service utility of the UAV by jointly optimizing the UAV's trajectory, offloading decisions and offloading duration. By contrast, other three methods only optimize two of the three parameters and cannot obtain the maximum service utility of the UAV. In addition, we can observe that the service utility of the proposed method increases quickly and then slow down with the increase of the transmitting power of microwave station. That is, the higher level of the transmitting power of the microwave station can lead to higher level of the harvested energy of the UAV which achieves higher service utility. However, for given operation duration of the UAV, the charging duration will stop increasing when the optimal offloading duration is achieved, then the increment of the harvested energy of the UAV only depends on the charging power from microwave station which may not achieve remarkable increase.

In Fig.6, we also compare the service utility of the proposed offloading method with other three offloading methods in terms of the transmitting power of users. We can see that the service utility of the proposed offloading method and other three offloading methods increase with the increase of the transmitting power of users. The reason is that the users can offload more computation tasks to the UAVs when the transmitting power is increasing. Then, the UAV is capable of obtaining more computation tasks to compute and achieving higher service utility. Still, we can observe that the proposed offloading method can achieve the highest service utility among all offloading methods. That is, the proposed offloading method is able to make the optimal choices of the UAV's trajectory, offloading decisions and offloading duration according to the system environment and UAV's conditions.

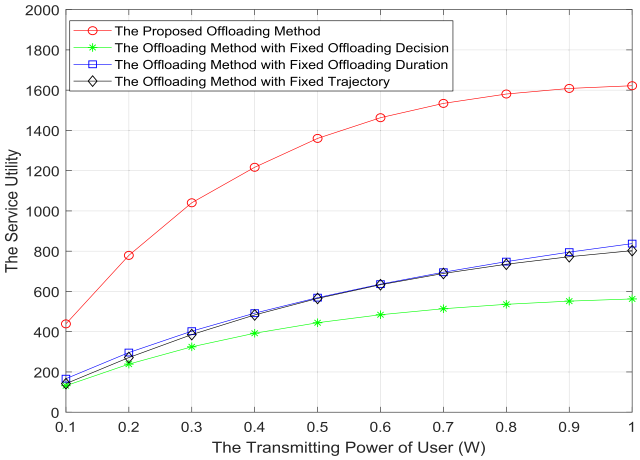


FIGURE 6. Service utility comparison in terms of the transmitting power of users.

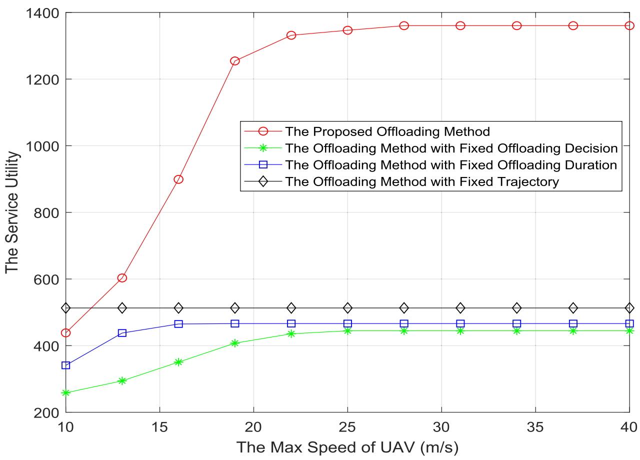


FIGURE 7. Service utility comparison in terms of the maximum speed of UAV.

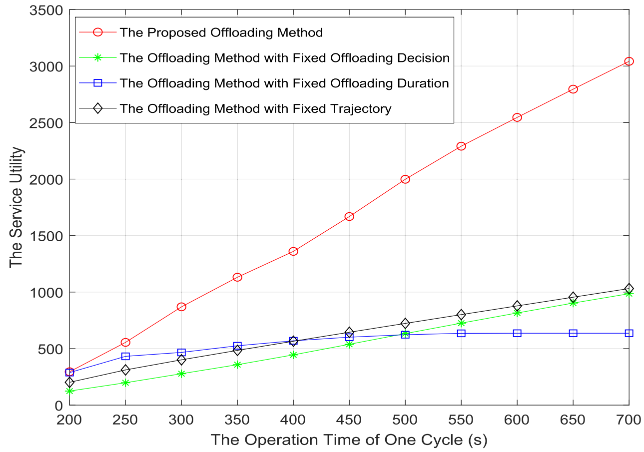


FIGURE 8. Service utility comparison in terms of the operation duration of UAV.

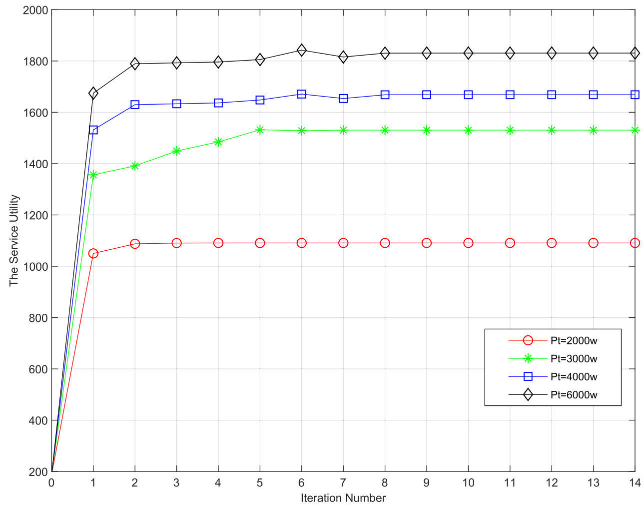


FIGURE 9. Convergence of the proposed Algorithm 1.

Fig. 7 shows the effects of the operation duration of the UAV during one cycle. Similar to the above analysis, the service utility achieved by the proposed offloading method is higher than that in other three offloading methods. In addition, except the offloading method with fixed trajectory, the service utility of the proposed offloading and other two methods firstly increase and then flatten with the increase of the maximum speed of the UAV. This is because the higher speed will make the UAV faster close to the users for computation services. However, the faster speed may cause more energy consumption for flight and reduce the computation energy of the UAV, then the increase of the service utility is slow down whatever the speed constraint is loosing. Note that the service utility of the offloading method with fixed trajectory is a constant. That is, the fixed trajectory means the UAV flies the same distance at each time slot which implies the UAV approach the user with a constant speed. Hence, the maximum speed constraint will not affect the service utility of the UAV in this case.

Fig.8 shows the service utility comparison in terms of the operation duration of the UAV. We can see that the proposed offloading method can achieve much higher service utility than that of other three offloading methods as the operation duration increase. The reason is that the UAV can obtain more energy during the charging duration and provide more computation services during the offloading duration. Then, the UAV is capable of obtaining higher service utility by making the optimal choices of the flight trajectory, offloading decisions and offloading duration. In contrast, other three offloading methods only optimize two of the three parameters, which can obtain lower service utility.

C. ALGORITHM CONVERGENCE

In this subsection, we evaluate the convergence performance of the proposed Algorithm 1 as shown in Fig.9. We can obverse that Algorithm converges within a few rounds of iteration, e.g. 3 iterations in the case with transmitting power of the microwave station $P_t = 2000W$. Moreover, we can see that the case with higher transmitting power of the microwave station converges less efficiently compared to the case with lower transmitting power of the microwave station. This is because the larger value of P_t implies larger solution space of the proposed problem **P1** and may affect the convergence rate of the proposed Algorithm 1.

VI. CONCLUSION

In this paper, we proposed an incentive UAV-enabled MEC network based on the microwave power transfer framework. In this framework, the UAV with rechargeable batteries periodically provide computation services by flying close to the users and recharge itself by hovering over the microwave power station. Given the operation duration of a round trip, there is a tradeoff between the charging time and the offloading time of the UAV to obtain the maximum service utility. Considering the microwave station and UAV's conditions, the joint trajectory and offloading optimization problem was carefully addressed. A three-stage alternative algorithm was proposed for solving the proposed problem. We obtained the results which showed that the proposed offloading method and related solutions can achieve higher service utility than that of other traditional computation offloading methods.

REFERENCES

[1] J. Grubert, T. Langlotz, S. Zollmann, and H. Regenbrecht, "Towards pervasive augmented reality: Context-awareness in augmented reality," *IEEE Trans. Visual. Comput. Graph.*, vol. 23, no. 6, pp. 1706–1724, Jun. 2017.

[2] L.-W. Chen and Y.-F. Ho, "A face-based signage interacting system for mobile users using smartphones," in *Proc. IEEE Conf. Comput. Commun. Workshops (INFOCOM WKSHPS)*, Apr. 2016, pp. 1033–1034.

[3] P. Bertens, A. Guitart, and Á. Periáñez, "Games and big data: A scalable multi-dimensional churn prediction model," in *Proc. IEEE Conf. Comput. Intell. Games (CIG)*, Aug. 2017, pp. 33–36.

[4] Y. Liu, C. Yuen, X. Cao, N. U. Hassan, and J. Chen, "Design of a scalable hybrid MAC protocol for heterogeneous M2M networks," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 99–111, Feb. 2014.

[5] L. Da Xu, W. He, and S. Li, "Internet of Things in industries: A survey," *IEEE Trans. Ind. Informat.*, vol. 10, no. 4, pp. 2233–2243, Nov. 2014.

[6] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Dependable demand response management in the smart grid: A Stackelberg game approach," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 120–132, Mar. 2013.

[7] M. Patel *et al.*, "Mobile-edge computing: Introductory technical white paper," ETSI, Sophia Antipolis, France, White Paper, no. 1, Sep. 2014.

[8] P. Mach and Z. Becvar, "Mobile edge computing: A survey on architecture and computation offloading," *IEEE Commun. Survey Tuts.*, vol. 19, no. 3, pp. 1628–1656, 3rd Quart., 2017.

[9] K. Zhang, S. Leng, Y. He, S. Maharjan, and Y. Zhang, "Mobile edge computing and networking for green and low-latency Internet of Things," *IEEE Commun. Mag.*, vol. 56, no. 5, pp. 39–45, May 2018.

[10] Y. Liu, C. Yang, L. Jiang, S. Xie, and Y. Zhang, "Intelligent edge computing for IoT-based energy management in smart cities," *IEEE Netw.*, vol. 33, no. 2, pp. 111–117, Mar. 2019.

[11] Z. Li, Z. Yang, and S. Xie, "Computing resource trading for edge-cloud-assisted Internet of Things," *IEEE Trans. Ind. Inf.*, vol. 15, no. 6, pp. 3661–3669, Jun. 2019.

[12] X. Huang, P. Li, and R. Yu, "Social welfare maximization in container-based task scheduling for parked vehicle edge computing," *IEEE Commun. Lett.*, vol. 23, no. 8, pp. 1347–1351, Aug. 2019.

[13] Y. Liu, H. Yu, S. Xie, and Y. Zhang, "Deep reinforcement learning for offloading and resource allocation in vehicle edge computing and networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 11, pp. 11158–11168, Nov. 2019.

[14] X. Huang, R. Yu, J. Liu, and L. Shu, "Parked vehicle edge computing: Exploiting opportunistic resources for distributed mobile applications," *IEEE Access*, vol. 6, pp. 66649–66663, 2018.

[15] F. Zhou, Y. Wu, R. Q. Hu, and Y. Qian, "Computation rate maximization in UAV-enabled wireless powered mobile-edge computing systems," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 9, pp. 1927–1941, Oct. 2018.

[16] J. Zhang, L. Zhou, Q. Tang, E. C.-H. Ngai, X. Hu, H. Zhao, and J. Wei, "Stochastic computation offloading and trajectory scheduling for UAV-assisted mobile edge computing," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 3688–3699, Apr. 2019.

[17] S. Zhang, H. Zhang, B. Di, and L. Song, "Cellular cooperative unmanned aerial vehicle networks with sense-and-send protocol," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1754–1767, Apr. 2019.

[18] X. M. Cui, W. J. Wang, and Z. P. Fang, "Present situation and some problems analysis of small-size unmanned air vehicles," *Flight Dyn.*, vol. 23, no. 1, pp. 14–18, Mar. 2005.

[19] C. D. Franco and G. Buttazzo, "Energy-aware coverage path planning of UAVs," in *Proc. IEEE Int. Conf. Auton. Robot Syst. Competitions*, Apr. 2015, pp. 111–117.

[20] Y. Zeng and R. Zhang, "Energy-efficient UAV communication with trajectory optimization," *IEEE Trans. Wireless Commun.*, vol. 16, no. 6, pp. 3747–3760, Jun. 2017.

[21] L. Xie, J. Xu, and R. Zhang, "Throughput maximization for UAV-enabled wireless powered communication networks," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1690–1703, Apr. 2019.

[22] F. Zhou, R. Qingyang Hu, Z. Li, and Y. Wang, "Mobile edge computing in unmanned aerial vehicle networks," *IEEE Wireless Commun.*, to be published.

[23] X. Zhang, Y. Zhong, P. Liu, F. Zhou, and Y. Wang, "Resource allocation for a UAV-enabled mobile-edge computing system: Computation efficiency maximization," *IEEE Access*, vol. 7, pp. 113345–113354, 2019.

[24] F. Zhou, Y. Wu, H. Sun, and Z. Chu, "UAV-enabled mobile edge computing: Offloading optimization and trajectory design," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kansas City, MO. USA, May 2018, pp. 1–6.

[25] B. Strassner and K. Chang, "Microwave power transmission: Historical milestones and system components," *Proc. IEEE*, vol. 101, no. 6, pp. 1379–1396, Jun. 2013.

[26] M. Ishiba, J. Ishida, K. Komurasaki, and Y. Arakawa, "Wireless power transmission using modulated microwave," in *IEEE MTT-S Int. Microw. Symp. Dig.*, May 2011, pp. 51–54.

[27] N. Shinohara, *Wireless Power Transfer Via Radiowaves*. Hoboken, NJ, USA: Wiley, 2014.

[28] W. Brown, "The technology and application of free-space power transmission by microwave beam," *Proc. IEEE*, vol. 62, no. 1, pp. 11–25, Jan. 1974.

[29] S. Dunbar, F. Wenzl, C. Hack, R. Hafeza, H. Esfeer, F. Defay, S. Prothin, D. Bajon, and Z. Popovic, "Wireless far-field charging of a micro-UAV," in *Proc. IEEE Wireless Power Transf. Conf. (WPTC)*, May 2015, pp. 1–6.

[30] J. L. Watters, "Reduction of integer polynomial problems to zero-one linear programming problems," *Oper. Res.*, vol. 15, no. 6, pp. 1171–1174, 1981.

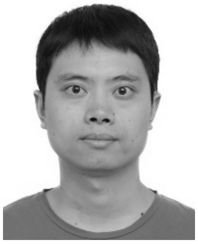
[31] P. H. Randolph,"Nolinear programming," *Technometrics*, vol. 10, no. 3, p. 627, Aug. 1968.

[32] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

YI LIU received the Ph.D. degree from the South China University of Technology (SCUT), Guangzhou, China, in 2011. After that, he joined the Singapore University of Technology and Design (SUTD), as a Postdoctoral Researcher. In 2014, he worked with the Institute of Intelligent Information Processing, Guangdong University of Technology (GDUT), where he is currently a Full Professor. His research interests include wireless communication networks, cooperative communications, smart grid, and intelligent edge computing.

MING QIU received the B.Eng. degree from the Nanchang Institute of Technology, China, in 2017. He is currently pursuing the M.Sc. degree with the School of Information Engineering, Guangdong University of Technology, China. His research interests include unmanned aerial vehicle (UAV) communication, mobile edge computing, and microwave power transfer.

JINLEI HU received the Ph.D. degree from the School of Electric Power Engineering, South China University of Technology (SCUT), Guangzhou, China, in 2008. After that, he joined the Qingyuan Power Supply Bureau, Guangdong Power Grid Corporation, as a Senior Engineer. His research interests include electric power systems, power line inspection technology, smart grid, and the intelligent power IoT systems.



HUIMIN YU received the B.E. degree in electronic engineering from Hunan Normal University, China, in 2003, and the Ph.D. degree in electromagnetic fields and microwave technology from the Institute of Electronics, Chinese Academy of Sciences, Beijing, China, in 2009. He is currently an Associate Professor with the Department of Communication Engineering, Hunan Normal University. His research interests include wireless communication and ultra wideband system design.