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Multiple-UAV-Assisted SWIPT in Internet of Things: User Association and Power Allocation

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ABSTRACT Simultaneous wireless information and power transfer (SWIPT) has sparked a wave of interest in research, while unmanned aerial vehicles (UAVs) can offer a high level of service for Internet of Things (IoT) due to its deployment flexibly. In this paper, we employ multiple UAVs as transmitters to realize information-transmitting and energy-transferring for ground IoT devices simultaneously to expand the capacity and coverage of the network, where each UAV is associated with multiple ground devices. This paper investigates joint optimization of three-dimensional (3D) locations, user association and power allocation of the UAVs with the aim of maximizing the minimum data rate among multiple dispersed users on the ground while guaranteeing the energy requirement of each user. Meanwhile, the proposed optimization problem contains the transmit power budget of each UAV and constraints on user association. The feasibility analysis ensures that the problem can be solvable. To address the combinatorial optimization problem, non-convex problems are decomposed into two subproblems. Then they are transformed into a series of convex problems alternately via successive convex optimization technique. Subsequently, we develop a multi-variable iterative algorithm to settle the overall problem. Next, the convergence performance of the proposed algorithm is confirmed. In conclusion, simulation results operated under various parameter configurations substantiate the proposed algorithm can achieve a higher data rate compared with other benchmark schemes.

INDEX TERMS Simultaneous wireless information and power transfer, unmanned aerial vehicles, 3D locations, user association, power allocation.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

The goal of Internet of Things (IoT) is to make things to be linked anywhere, anytime ideally providing any service and utilizing any network. In general, the IoT system is made up of small, energy-constrained devices such as sensors, so these devices normally cannot transmit/receive over a long distance and a period of long time. Moreover, the system performance is limited by the energy availability of the devices for many practical applications [1]. Nevertheless, simultaneous wireless information and power transfer (SWIPT) plays a key role in devices with limited energy, since it takes full advantages of radio signals to achieve both information-transmitting and energy-transferring simultaneously. Therefore, SWIPT becomes more and more appealing recently by essentially providing ubiquitous and sustainable energy source as well as information service for wireless networks [2]–[6]. The utilization of unmanned aerial vehicles (UAVs) acting as aerial wireless communication platforms has attracted an ever-increasing level of attention in recent years due to their adjustable altitude and high flexibility [7], [8]. Therefore, UAV-enabled SWIPT has great development prospects in IoT systems.

In UAV-enabled IoT systems, UAVs can flexibly fly towards IoT devices, then transmit information and transfer energy to them simultaneously [9]. However, in term of the multi-UAV enabled SWIPT in IoT communications, several challenges must be dealt with [10]. For example, to make the best of the spatial flexibility of the UAVs, their locations

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issue is no longer a 2D placement deployment problem compared with conventional terrestrial wireless communications networks. Instead, it is indeed a 3D placement deployment problem. Different from the circumstances where there is a single UAV, multiple UAVs inevitably raise up the issue on user association to be handled. Because the IoT devices have both information and energy requirements, the rate-energy tradeoff is an important existing problem placed in front of us. Furthermore, in addition to the power allocation of the UAVs, the design of power splitting ratio of each node cannot be ignored. As a result, the joint optimization of UAVs' transmit power and nodes' power splitting ratios is also a problem to be solved urgently.

B. RELATED WORK

There are some existing work on UAV-assisted information transmitting or energy transferring in the last few years. For example, in [11], [12], the authors investigate that a UAV only charges users on the ground. The authors in [13]–[18] do research on a UAV transmitting information to users on the ground. In [19], the authors investigate that a UAV first transfers the downlink energy signals to the ground users, then the ground users transmits information signals to the UAV in the uplink. The authors in [20] conduct a study on ground users transmitting information to the UAV. The scene is presented in [21] that the UAV acting as a relay to facilitate communication between the source node and the destination node. In [22], the authors investigate that a UAV charges multiple mobile users and offers computation services in the UAV-enabled systems. In [23], authors study that a mobile UAV assists separated nodes without direct link to communicate with each other. The study in [24] investigates the UAV communicates with each other. Notably, these studies have not been extended to the research on SWIPT in UAV-enable systems.

Though the research on SWIPT has been widely carried out in wireless communication networks recently, most of the studies haven't been directly combined with UAV-assisted systems yet [1], [2], [25]–[28]. Some related work on UAV-assisted SWIPT are presented in [29], [30]. However, those authors investigate the UAV-assisted SWIPT systems, where each node on the ground does not really receive information and harvest energy simultaneously.

However, the authors in [31]–[34] investigate that 3D deployment of the UAV when the UAV transmits information to users on the ground. Furthermore, the authors in [35] do research on joint optimization of 3D UAV location and the UAV's transmit power to assist multiple mobile users in relaying networks. In [36], [37], the authors investigate the user association for a multi-UAV-assisted wireless network. However, this work was restricted to downlink wireless communications and did not involve 3D locations deployment of the UAVs. The work in [38] studies joint UAV-user association and 3D placement problem for flying wireless relays in a cellular network. But it did not refer to the UAV-enabled SWIPT system. Specifically, in our previous work in [39], we investigate the power allocation and trajectory optimization problem for UAV-assisted SWIPT with power splitting in IoT, where there is a single UAV and the UAV flies at a fixed height. Therefore, there are no optimization of 3D location deployment and user association. Furthermore, the power splitting ratio is fixed, which is not jointly optimized with transmit power of the UAV. Differently, in this paper, we extend from a single UAV to multiple UAV, which leads to the discussion about the 3D location deployment and user association. Moreover, the power splitting ratios of nodes are also jointly optimized with the 3D location deployment, user association and transmit power of UAVs. Differently, in this paper, we extend from a single UAV to multiple UAV, which leads to the discussion about the 3D location deployment and user association. Most notably, the power splitting ratios of nodes are also jointly optimized with the 3D location deployment, user association and transmit power of UAVs.

C. CONTRIBUTIONS

In this paper, we consider a multi-UAV-assisted SWIPT in IoT, in which the efficient 3D locations of UAVs are analyzed to exploit high flexibility of the UAVs. The situation where there are multiple UAVs and multiple ground nodes has led to our studies on the user association. Moreover, each ground node installed with a power splitter divides the received signal into two streams of different power for decoding information and harvesting energy, respectively. In addition, the ground nodes receive information and harvest energy simultaneously, so the transmit power of the UAVs and power splitting ratio of each node are needed to be co-optimized. For possible real-world applications, the multi-UAV-assisted SWIPT can be applied in IoT with specific energy requirements where wire charging is unavailable. Specifically, the main contributions of this paper are listed as follows:

- We present a formulated problem framework of joint optimization of 3D location, user association and power allocation for multi-UAV-assisted SWIPT with power splitting. The aim is to maximize the minimum average data rate received among all ground nodes, while satisfying a minimum energy requirement threshold of each node. Moreover, the transmit power of each UAV is limited by a maximum budget. The 3D locations of the UAVs and user association design are two tightly coupled problems. Similarly, UAVs' transmit power and nodes' power splitting ratios are also highly coupled variables. Based on the formulation, this problem is a highly non-convex optimization problem with mutual coupled variables and complicated constraints.
- We implement the feasibility analysis of the formulated problem with different energy requirements. Firstly, we present the tradeoff between the minimum data rate received and the minimum energy harvested among all ground nodes. We analyzed in which case, we can obtain the maximum value of the objective function. Based on the feasibility analysis, we can more reasonably set the

energy requirement threshold according to the actual situation.

- We develop an efficient algorithm to solve the minimum data rate maximization problem and prove that the convergence of the proposed algorithm. Specifically, we deal with the formulated problem by decomposing it into two subproblems. For the subproblem of UAVs' 3D locations and user association, we handle the intricate problem including mixed integer variables by principle of selecting the best qualified channel. Nevertheless, for the subproblem of co-optimization of UAVs' transmit power and nodes' power splitting ratios, we iteratively optimize this problem by replacing the objective function with the auxiliary variable and relaxing the strict energy requirement constraint. Finally, we present an overall optimization algorithm by applying multi-variable fixed iterative optimization and successive convex optimization methods.
- We provide extensive simulations under various parameter configurations. Theoretical analysis and numerical results reveal the convergence performance of the proposed algorithm. Moreover, simulation results substantiate the superiority of the proposed algorithm, which significantly increases the minimum data rate received among all of the ground nodes in contrast with other benchmark methods. It also provides a perspective for studying the influence under different parameter configurations on system performance and helps achieve a good tradeoff between data rate received and energy harvested among ground nodes.

The rest of this paper is organized as follows. In Section II, we introduce the system model and formulate the optimization problem for a multi-UAV-assisted SWIPT wireless network. Feasibility analysis of the problem is provided in Section III. We design optimization algorithms in Section IV. Simulation results are illustrated in Section V. In the end, we present the conclusions of this paper in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

We consider a UAV-enabled network where multiple separated nodes are evenly distributed on the ground expecting to receive information and harvest energy simultaneously. Multiple UAVs are deployed to perform SWIPT services for those ground nodes with power splitting, as shown in Fig. 1.

We deploy M UAVs to transmit information and transfer energy simultaneously to K nodes on the ground, in which $\mathcal{M} \triangleq \{1, \ldots, M\}$ denotes the set of the UAVs and $\mathcal{K} \triangleq \{1, \ldots, K\}$ indicates the set of the ground nodes. To save energy on flight, each UAV is stationary in the air. Therefore, in this paper, we adopt the rotary-wing UAVs, which can hover in the air compared with fixed-wing UAVs. Each UAV $m \in \mathcal{M}$ has own fixed 3D location, denoted by $\left(x_{U,m}, y_{U,m}, h_m\right)$. Each node $k \in \mathcal{K}$ locates at $w_k = (x_k, y_k)$

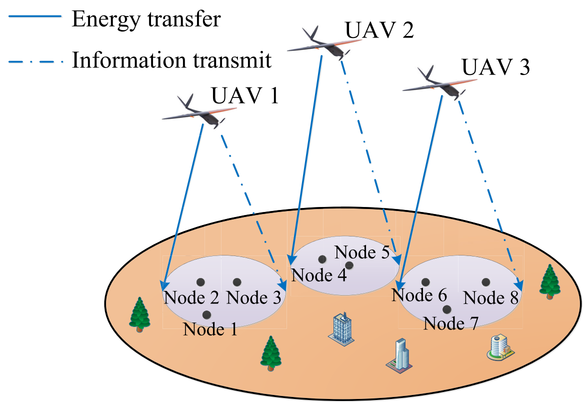


FIGURE 1. Scenario illustration of multi-UAV-enabled SWIPT.

on the horizontal plane. The UAV ought to accomplish the given SWIPT task within a time duration of T, denoted by $\mathcal{T} \triangleq (0, T]$. We consider the allocation of spectrum has been completed in this work. The total system bandwidth is denoted by B, which is evenly divided into K subcarriers allocated to K ground nodes, separately. Thus, the bandwidth occupied by each node is B/K. Denote $b_{m,k}$ as a binary variable of user association that demonstrates whether the k-th node is served by the m-th UAV. If the m-th UAV serves the k-th node, $b_{m,k} = 1$, otherwise $b_{m,k} = 0$. Furthermore, a single UAV can serve multiple nodes, but a single node can be only served by a UAV. Therefore, those yield the following constraints:

$$\sum_{m=1}^{M} b_{m,k} = 1, \forall k \in \mathcal{K}, \tag{1}$$

$$b_{m,k} \in \{0, 1\}, \quad k \in \mathcal{K}, \ \forall m \in \mathcal{M}. \tag{2}$$

As is discussed in [40]–[42], the authors put forward two kinds of UAV-ground link, such as LOS and NLOS, which have their own probability of occurrence, respectively. On account of the LOS or NLOS links, the channel power gain from the m-th UAV to the k-th node is respectively given by

$$g_{m,k} = \begin{cases} d_{m,k}^{-\alpha}, & \textit{LOS} \text{ link}, \\ \zeta d_{m,k}^{-\alpha}, & \textit{NLOS} \text{ link}, \end{cases} \tag{3}$$

where

$$d_{m,k} = \sqrt{\left(x_{U,m} - x_k\right)^2 + \left(y_{U,m} - y_k\right)^2 + h_m^2}. \tag{4}$$

ζ is an additional attenuation factor caused by the NLOS link. α denotes the path-loss exponent for UAV-ground connection. Since the probability of the LOS and NLOS groups of is markedly higher than that of the multipath fading, the multiple multipath effect can be neglected [43]. The probability of LOS link depends on the relevant locations between the UAV and the nodes, the elevation angle θ between them and the environment. We can approximate the

LOS probability with the following equation [43]:

$$\mathrm{Pr}_{LOS} = \frac{1}{1+\xi \exp\left(-\chi\left[\theta-\xi\right]\right)}, \tag{5}$$

where the constants ξ and χ are associated with the surroundings, such as height and density of buildings, population density, street layouts, etc. Next, the elevation angle θ (the sight of ground node towards the UAV, measured by "degree") is expressed by

$$\theta = \frac{180}{\pi}\sin^{-1}\left(\frac{h_m}{\sqrt{\left(x_{U,m}-x_k\right)^2+\left(y_{U,m}-y_k\right)^2+{h_m}^2}}\right). \tag{6}$$

As we know, the probability of having NLOS link is $\mathrm{Pr}_{NLOS} = 1 - \mathrm{Pr}_{LOS}$. Therefore, the channel power gain between the m-th UAV and the k-th node can be given by in the following [44]:

$$g_{m,k} = \mathrm{Pr}_{LOS} \times \left(\sqrt{\left(x_{U,m}-x_k\right)^2+\left(y_{U,m}-y_k\right)^2+h_m^2}\right)^{-\alpha} + \mathrm{Pr}_{NLOS} \times \zeta \left(\sqrt{\left(x_{U,m}-x_k\right)^2+\left(y_{U,m}-y_k\right)^2+h_m^2}\right)^{-\alpha}. \tag{7}$$

We consider the circumstance of information-transmitting and energy-transferring with a power splitter installed in each node. Regarding the k-th node, the received signal is split into two signal streams with a fixed power ratio ρ_k to the information receiver and the rest ratio $1-\rho_k$ to the energy receiver, as shown in Fig. 2. Moreover, we have

$$0 \le \rho_k \le 1, \quad \forall k \in \mathcal{K}. \tag{8}$$

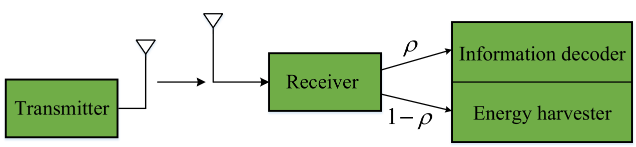


FIGURE 2. The system design of power splitting.

We denote that the power transmitted by the m-th UAV allocated to the k-th node as $p_{m,k}$. Consider instantaneous maximum budget of power transmitted by a UAV is set as P. Thus, it's expressed as

$$\sum_{k=1}^{K} b_{m,k}p_{m,k} \le P, \quad \forall m \in \mathcal{M}. \tag{9}$$

The energy harvested by the k-th node during the whole duration T is thus given by [11], [12]

$$E_k = T\sum_{m=1}^{M} b_{m,k}\eta\left(1-\rho_k\right)p_{m,k}g_{m,k}, \quad \forall k \in \mathcal{K}, \tag{10}$$

where $0 \le \eta \le 1$ represents the energy conversion efficiency of rectifier installed in each node.

Hence, the achievable data rate at the k-th node during the whole operating time is given by

$$R_k = \frac{B}{K}\sum_{m=1}^{M} b_{m,k}\log_2\left(1+\frac{\rho_k p_{m,k}g_{m,k}}{B/K\sigma^2}\right), \quad \forall k \in \mathcal{K}, \tag{11}$$

where σ^2 is the noise power spectrum density.

B. PROBLEM FORMULATION

In order that each ground node owns the relatively fair opportunity to receive information, maximizing the minimum data rate received among all the nodes is considered via joint optimization of 3D UAV location, user association and power allocation. Besides, all the ground nodes have their own demands to harveste energy. Therefore, the energy threshold of each node is set to satisfy the energy requirement, denoted by ψ. Thus, the utility maximization problem is summarized as follows

$$\begin{aligned}
(\mathrm{P1}): \quad & \max_{\{x_{U,m},y_{U,m},h_m,b_{m,k},\rho_k,p_{m,k}\}} \min_k R_k && (12a)\\
& s.t.\ E_k \ge \psi, \quad \forall k \in \mathcal{K}, && (12b)\\
& \sum_{k=1}^{K} b_{m,k}p_{m,k} \le P, \quad \forall m \in \mathcal{M}, && (12c)\\
& 0 \le \rho_k \le 1, \forall k \in \mathcal{K}, && (12d)\\
& \sum_{m=1}^{M} b_{m,k} = 1, \quad \forall k \in \mathcal{K}, && (12e)\\
& b_{m,k} \in \{0,1\}, \quad \forall k \in \mathcal{K}, \forall m \in \mathcal{M}, && (12f)
\end{aligned}$$

where constraint (12b) ensures that each node can satisfy the energy requirement and constraint (12c) represents the feasibility of each UAV's transmit power. Then constraint (12d) restricts the validity of each node's power splitting ratio. Additionally, constraints (12e) and (12f) specify the rule of user association. The optimization problem (P1) containing multiple highly coupled variables is non-convex and thus the existing convex optimization methods cannot be utilized to efficiently solve this problem. Next, we analyze the investigated problem by decomposing the original problem into two subproblems. Afterwards, an efficient iterative algorithm is designed by sufficiently exploiting the structure of the challenging problem.

III. FEASIBILITY ANALYSIS

Since we investigate SWIPT in this paper, both information-transmitting and energy-transferring must be taken into consideration at the same time. It can be seen that the constraint (12b) is equal to the condition that the minimum energy harvested among all ground nodes is no less than the threshold value ψ. Therefore, the constraint (12b) is equivalent to

$$\min E_k \ge \psi, \quad \forall k \in \mathcal{K}. \tag{13}$$

As a result, we need to analyze the tradeoff between the minimum average data rate received and the minimum power harvested among all ground nodes. Next, the minimum average data rate received and the minimum energy harvested among all nodes are expressed as follows

$$\min R_k = \frac{B}{K}\sum_{m=1}^{M} b_{m,k}\log_2\left(1+\frac{\rho_k p_{m,k} g_{m,k}}{B/K\sigma^2}\right), \quad \forall k\in\mathcal{K}, \quad (14)$$

$$\min E_k = T\sum_{m=1}^{M} b_{m,k}\eta\left(1-\rho_k\right) p_{m,k} g_{m,k}, \quad \forall k\in\mathcal{K}, \quad (15)$$

respectively.

Theorem 1: The circumstance classifications about the optimal value of objective function in problem (P1) and the solution set of the objective function value, in which ψ^{bound} is the upper bound of the threshold ψ, are summarized in the following:

- *Case 1: When the threshold $0 \leq \psi \leq \psi^{bound}$, the minimum average data rate received among all nodes decreases and the minimum energy harvested among all nodes increases as the threshold ψ grows.*
- *Case 2: When the threshold $\psi \geq \psi^{bound}$, there is no solution of problem (P1). This aboved-mentioned value ψ^{bound} is what we need later, which is the upper bound of the threshold ψ in problem (P1).*

Proof: Let denote $x_{m,k} = p_{m,k}g_{m,k}$, so formula (14) and (15) are turned to

$$\min R_k = \frac{B}{K}\sum_{m=1}^{M} b_{m,k}\log_2\left(1+\frac{\rho_k x_{m,k}}{B/K\sigma^2}\right), \quad \forall k\in\mathcal{K}, \quad (16)$$

$$\min E_k = T\sum_{m=1}^{M} b_{m,k}\eta\left(1-\rho_k\right) x_{m,k}, \quad \forall k\in\mathcal{K}, \quad (17)$$

respectively.

The value of formula (16) depends on the value of $\rho_k x_{m,k}$ and the value of formula (17) rests with the value of $(1-\rho_k)\,x_{m,k}$. The formula (16) is monotonically increasing regarding $\rho_k x_{m,k}$ and the formula (17) is also monotonically increasing regarding $(1-\rho_k)\,x_{m,k}$. However, the growth trend of $\rho_k x_{m,k}$ and $(1-\rho_k)\,x_{m,k}$ is opposite, so the formula (14) and (15) are on the opposite sides of the scale. If the formula (15) increases, the formula (14) necessarily decreases, vice versa. Therefore, when the energy threshold $\psi = 0$, the objective function reaches its maximum value of problem (P1). Moreover, we can draw a conclusion that the upper bound of the threshold ψ is the maximum of minimum energy harvested among all ground node provided only constraints (12c-12f) are met.

Therefore, the upper bound of the threshold ψ can be obtained by solving the formulated problem as follows

$$\text{(P2)}: \max_{\{x_{U,m},y_{U,m},h_m,b_{m,k},\rho_k,p_{m,k}\}} \min_k E_k \quad (18a)$$

$$s.t. \sum_{k=1}^{K} b_{m,k}p_{m,k} \leq P, \quad \forall m\in\mathcal{M}, \quad (18b)$$

$$0 \leq \rho_k \leq 1, \quad \forall k\in\mathcal{K}, \quad (18c)$$

$$\sum_{m=1}^{M} b_{m,k} = 1, \quad \forall k\in\mathcal{K}, \quad (18d)$$

$$b_{m,k} \in \{0,1\}, \quad \forall k\in\mathcal{K}, \forall m\in\mathcal{M}. \quad (18e)$$

Hence, as long as the threshold ψ is less than its upper bound, there is always a solution in problem (P1). ■

IV. ALGORITHM DESIGN

By introducing an auxiliary variable $s = \min_{\forall k\in\mathcal{K}} \{R_k\}$, which corresponds to the lower bound of the objective function in problem (P1), the formulated problem (P1) above can be transformed into the mathematical expression as follows

$$\text{(P3)}: \max_{\{x_{U,m},y_{U,m},h_m,b_{m,k},\rho_k,p_{m,k}\},s} s \quad (19a)$$

$$s.t.\ R_k \geq s, \quad \forall k\in\mathcal{K}, \quad (19b)$$

$$E_k \geq \psi, \quad \forall k\in\mathcal{K}, \quad (19c)$$

$$\sum_{k=1}^{K} b_{m,k}p_{m,k} \leq P, \quad \forall m\in\mathcal{M}, \quad (19d)$$

$$0 \leq \rho_k \leq 1, \quad \forall k\in\mathcal{K}, \quad (19e)$$

$$\sum_{m=1}^{M} b_{m,k} = 1, \quad \forall k\in\mathcal{K}, \quad (19f)$$

$$b_{m,k} \in \{0,1\}, \quad \forall k\in\mathcal{K}, \forall m\in\mathcal{M}. \quad (19g)$$

The above optimization problem is still complicated and non-convex, so it needs to search I) over many coupled optimization variables, such as 3D UAV location, user association, UAVs' transmit power and nodes' power splitting ratios, as well as II) over the non-convex elements in the constraints. Generally, there is no standard method for directly solving such non-convex problems efficiently.

In this paper, we develop an efficient iterative algorithm for problem (P3) by applying the exhaustive search (ES) and successive convex optimization methods. Particularly, we update the variables alternatively. Given an initialization of them, we update the 3D locations of UAVs and user association with UAVs' transmit power and nodes' power splitting ratios fixed. Then, we update the transmit power of the UAVs and power splitting ratios of the nodes with UAVs' 3D locations and user association fixed. The above process repeats until a stopping criterion is met.

A. USER ASSOCIATION AND 3D UAV LOCATION OPTIMIZATION

Giving the transmit power of the UAVs and power splitting ratios of the nodes, this subproblem is to maximize the minimum data rate received among all ground nodes by optimizing 3D UAV location and user association. The UAV-user association mechanism depends on the UAVs' locations while the optimal location of each UAV itself depends on which users are to be served by the UAV. As such, problem (P3) can be rewritten as

$$\text{(P4)}: \max_{\{x_{U,m},y_{U,m},h_m,b_{m,k}\},s} s \tag{20a}$$

$$\text{s.t.} \frac{B}{K}\sum_{m=1}^{M} b_{m,k}\log_2(1+\phi g_{m,k}) \geq s, \quad \forall k \in \mathcal{K}, \tag{20b}$$

$$T\sum_{m=1}^{M} b_{m,k}\varpi g_{m,k} \geq \psi, \quad \forall k \in \mathcal{K}, \tag{20c}$$

$$\sum_{m=1}^{M} b_{m,k} = 1, \quad \forall k \in \mathcal{K}, \tag{20d}$$

$$b_{m,k} \in \{0,1\}, \quad \forall k \in \mathcal{K}, \forall m \in \mathcal{M}, \tag{20e}$$

where $\phi = \frac{\rho_k p_{k,m}}{B/K\sigma^2}$ and $\varpi = \eta(1-\rho_k)p_{m,k}$.

Notice that problem (P4) contains a mixed integer programming problem. In this paper, we can solve such a problem by exhaustive search (ES) and the principle of seeking best channel condition. This subproblem is divided into two steps as follows:

1) USER ASSOCIATION WITH GIVEN 3D UAV LOCATION

Giving UAVs' 3D locations, it's observed from problem (P4) that the better the channel quality, the more data rate the node receives and the more energy the node harvests. Therefore, the nodes choose the best channel quality link with the UAV, then establish connection with the UAV. If the k-th node is served by the m-th UAV, then $m = m^*$. Thus, it's given by

$$b_{m,k} = \begin{cases} 1, & m = m^* \\ 0, & m \neq m^* \end{cases}, \quad \forall k \in \mathcal{K}. \tag{21}$$

2) 3D UAV LOCATION OPTIMIZATION WITH GIVEN USER ASSOCIATION

Since user association is fixed, we find the optimal 3D UAV location through exhaustive search (ES) and all the possible locations of the UAVs are searched thoroughly at intervals of per unit length τ. If the m-th UAV's location $(x_{U,m}, y_{U,m}, h_m) = (x_{U,m}, y_{U,m}, h_m)^*$, the channel quality between the UAV and ground nodes is the best. Then we choose the location $(x_{U,m}, y_{U,m}, h_m)^*$ as the m-th UAV's optimal location in the air.

As a result, we design an algorithm to indicate the operation of the above two steps presented in Algorithm 1. To get the optimal 3D UAV location and user association, we initialize the 3D locations of the UAVs then operate the step 2 and step 3 of Algorithm 1 in turn mentioned above.

Algorithm 1 User Association and 3D UAV Location Optimization for (P4)

1: Initialize the UAVs' 3D locations $(x_{U,m}, y_{U,m}, h_m)^0$
2: Find the optimal user association $b^*_{m,k}$ to problem (P4) by the principle of seeking best channel condition
3: Find the UAVs' 3D locations $(x_{U,m}, y_{U,m}, h_m)^*$ to problem (P4) by exhaustive search (ES)
4: Return the optimal UAVs' 3D locations $(x_{U,m}, y_{U,m}, h_m)^*$ and user association $b^*_{m,k}$

B. JOINT TRANSMIT POWER AND POWER SPLITTING RATIO OPTIMIZATION

Giving 3D UAV location and user association, namely the channel power gain is fixed, this subproblem is to maximize the minimum data rate received among all ground nodes by jointly optimizing transmit power of UAVs and power splitting ratios of the nodes. Therefore, problem (P3) can be transformed into the following problem,

$$\text{(P5)}: \max_{\{\rho_k,p_{m,k}\},s} s \tag{22a}$$

$$\text{s.t.} \frac{B}{K}\sum_{m=1}^{M} b_{m,k}\log_2\left(1+\frac{\rho_k p_{m,k} g_{m,k}}{B/K\sigma^2}\right) \geq s, \quad \forall k \in \mathcal{K}, \tag{22b}$$

$$T\sum_{m=1}^{M} b_{m,k}\eta(1-\rho_k)p_{m,k}g_{m,k} \geq \psi, \quad \forall k \in \mathcal{K}, \tag{22c}$$

$$\sum_{k=1}^{K} b_{m,k}p_{m,k} \leq P, \quad \forall m \in \mathcal{M}, \tag{22d}$$

$$0 \leq \rho_k \leq 1, \quad \forall k \in \mathcal{K}. \tag{22e}$$

In constraints (22b) and (22c), it is observed that R_k and E_k are not convex regarding joint variables ρ_k and $p_{m,k}$. Firstly, to address the non-convex constraint (22b), we gradually approximate it into the convex set iteratively.

Since $xy = \frac{1}{2}(x+y)^2 - \frac{1}{2}(x^2+y^2)$, there is

$$xy \geq -\frac{1}{2}\left(x^2+y^2\right) + \frac{1}{2}(x_0+y_0)^2 + (x_0+y_0)(x+y-x_0-y_0). \tag{23}$$

Then $\log_2(1+x)$ is a monotonously increasing function about x, so

$$\log_2(1+xy) \geq \log_2\left(1-\frac{1}{2}\left(x^2+y^2\right)+\frac{1}{2}(x_0+y_0)^2 + (x_0+y_0)(x+y-x_0-y_0)\right). \tag{24}$$

Through analyzing, $\log_2(1-\frac{1}{2}(x^2+y^2)+\frac{1}{2}(x_0+y_0)^2 + (x_0+y_0)(x+y-x_0-y_0))$ is a concave function of x and y.

The lower bound $R^{i+1}_{k,lb}$ for R^{i+1}_k is obtained through the first-order Taylor expansion when ρ^i_k and $p^i_{m,k}$ at the i-th iteration is given. Thus,

$$R^{i+1}_k \geq R^{i+1}_{k,lb}. \tag{25}$$

Denote $x = \rho^{i+1}_k$ and $y = p^{i+1}_{m,k}$, we can obtain

$$R^{i+1}_{k,lb} = \frac{B}{K} \times \sum_{m=1}^{M} b_{m,k}\log_2\left(1+\frac{g_{m,k}}{B/K\sigma^2}\left(-\frac{1}{2}\left(\left(\rho^{i+1}_k\right)^2 + \left(p^{i+1}_{m,k}\right)^2\right)+\frac{1}{2}\left(\rho^i_k+p^i_{m,k}\right)^2 + \left(\rho^i_k+p^i_{m,k}\right) \times \left(\rho^{i+1}_k+p^{i+1}_{m,k}-\rho^i_k-p^i_{m,k}\right)\right)\right). \tag{26}$$

In the sequel, since $(1-x)\,y{=}y-\frac{1}{2}(x+y)^2+\frac{1}{2}\left(x^2+y^2\right)$, there is

$$(1-x)\,y \geq y-\frac{1}{2}(x+y)^2 + \frac{1}{2}\left({x_0}^2+{y_0}^2+2x_0\,(x-x_0)+2y_0\,(y-y_0)\right). \quad (27)$$

Through analyzing, $y-\frac{1}{2}(x+y)^2+\frac{1}{2}\left({x_0}^2+{y_0}^2\right)+x_0\,(x-x_0)+y_0\,(y-y_0)$ is a concave function of x and y. Likewise, the lower bound $E_{k,lb}^{i+1}$ for E_k^{i+1} is obtained with given ρ_k^i and $p_{m,k}^i$ at the i-th iteration. Therefore,

$$E_k^{i+1} \geq E_{k,lb}^{i+1}. \quad (28)$$

Then, we denote that "$x=\rho_k^{i+1}$" and "$y=p_{m,k}^{i+1}$". Therefore, we can obtain that

$$\begin{aligned} E_{k,lb}^{i+1} = T\sum_{m=1}^{M} b_{m,k}\eta g_{m,k}\Bigg(& p_{m,k}^{i+1}-\frac{1}{2}\left(\rho_k^{i+1}+p_{m,k}^{i+1}\right)^2 \\ &+\frac{1}{2}\left(\left(\rho_k^i\right)^2+\left(p_{m,k}^i\right)^2\right)+\rho_k^i\left(\rho_k^{i+1}-\rho_k^i\right) \\ &+p_{m,k}^i\left(p_{m,k}^{i+1}-p_{m,k}^i\right)\Bigg). \end{aligned} \quad (29)$$

Given the transmit power of UAVs and power splitting ratios of the nodes at i-th iteration, the transmit power of UAVs and power splitting ratios of the nodes at $i+1$-th iteration can be acquired via solving the optimization problem in the following, expressed by

$$\text{(P6)}: \max_{\{\rho_k,p_{m,k}\},s} \; s \quad (30a)$$
$$s.t.\; R_{k,lb}^{i+1} \geq s, \quad \forall k \in \mathcal{K}, \quad (30b)$$
$$E_{k,lb}^{i+1} \geq \psi, \quad \forall k \in \mathcal{K}, \quad (30c)$$
$$\sum_{k=1}^{K} b_{m,k}p_{m,k} \leq P, \quad \forall m \in \mathcal{M}, \quad (30d)$$
$$0 \leq \rho_k \leq 1, \quad \forall k \in \mathcal{K}. \quad (30e)$$

Thus, the above problem has been successfully transformed into a convex problem. Then we iteratively solve problem (P6) until an acceptable accuracy is met [45]. However, the limitation of the proposed approach is that we can only obtain the suboptimal solution by the proposed algorithm since finding its optimal solution is nontrivial.

C. OVERALL OPTIMIZATION

The joint 3D locations, user association and power allocation optimization problem investigated is non-convex, which leads to finding the global optimal solution is extremely difficult. Nevertheless, the suboptimal solution needs to be obtained with an acceptable complexity and at a proper accuracy. Finally, we propose an efficient algorithm in basis of the two subproblems above-mentioned, which is summarized in Algorithm 2.

Algorithm 2 Multi-Variable Fixed Iterative Algorithm

1: Initialize the UAVs' transmit power $p_{m,k}^i$ and nodes' power splitting ratios ρ_k^i. Set the iteration number from $i=0$ and the tolerance accuracy ε
2: **Repeat**
3: Fix UAVs' transmit power $p_{m,k}^i$ and nodes' power splitting ratios ρ_k^i, find the optimal solution $\left(x_{U,m}, y_{U,m}, h_m\right)^*$ and $b_{m,k}^*$ to problem (P4)
4: Update the UAVs' 3D locations $\left(x_{U,m}, y_{U,m}, h_m\right)^{i+1}$, user association $b_{m,k}^{i+1}$ and minimum data rate s^{i+1}
5: **Repeat**
6: Solve problem (P6) with given UAVs' 3D location $\left(x_{U,m}, y_{U,m}, h_m\right)^{i+1}$, user association $b_{m,k}^{i+1}$, and get the optimal solution $p_{m,k}^*$ and ρ_k^*
7: Update the UAVs' transmit power $p_{m,k}^{k+1}$, nodes' power splitting ratios ρ_k^{k+1}, and minimum data rate s^{k+1}
8: **Until** $\frac{s^{k+1}-s^k}{s^k} \leq \varepsilon$
9: Update the 3D location $\left(x_{U,m}, y_{U,m}, h_m\right)^{i+1} = \left(x_{U,m}, y_{U,m}, h_m\right)^{k}$, user association $b_{m,k}^{i+1}=b_{m,k}^k$
10: **Until** $s^{i+1}=s^i$
11: Return the UAVs' 3D locations $\left(x_{U,m}, y_{U,m}, h_m\right)^*$, user association $b_{m,k}^*$, the UAVs' transmit power $p_{m,k}^*$, and nodes' power splitting ratios ρ_k^* to problem (P1)

1) CONVERGENCE ANALYSIS OF ALGORITHM 2

Since constraint (19d) in problem (P3), namely the transmit power budget of the UAV prevents the value s to grow unrestrictedly, the objective value s is bounded. Furthermore, we can verify that the lower bound s is non-decreasing through each iteration. Firstly, in step 3-4 of Algorithm 2, giving the optimized UAVs' transmit power $p_{m,k}^i$ and nodes' power splitting ratios ρ_k^i, we can first obtain that $s((x_{U,m}, y_{U,m}, h_m)^i, b_{m,k}^i, \rho_k^i, p_{m,k}^i) \leq s((x_{U,m}, y_{U,m}, h_m)^{i+1}, b_{m,k}^{i+1}, \rho_k^i, p_{m,k}^i)$. Afterwards, in step 6-7 of Algorithm 2, we can observe that $s((x_{U,m}, y_{U,m}, h_m)^i, b_{m,k}^i, \rho_k^k, p_{m,k}^k) \leq s((x_{U,m}, y_{U,m}, h_m)^i, b_{m,k}^i, \rho_k^{k+1}, p_{m,k}^{k+1})$. So, we can come to the conclusion that $s((x_{U,m}, y_{U,m}, h_m)^i, b_{m,k}^i, \rho_k^i, p_{m,k}^i) \leq s((x_{U,m}, y_{U,m}, h_m)^{i+1}, b_{m,k}^{i+1}, \rho_k^{i+1}, p_{m,k}^{i+1})$. After the analysis above, since the objective value s is non-decreasing along with the iterations and value s is upper bounded [46], the lower bound s exists. As a result, we can reach a conclusion that the convergence of the proposed overall algorithm can be guaranteed.

2) COMPUTATION COMPLEXITY ANALYSIS OF ALGORITHM 2

The main computational cost of the proposed algorithm depends on exhaustive search (ES) in step 3-4 and successive convex optimization methods in step 6-7, seen from Algorithm 2. Since we consider a 3D area of size $x \times y \times z$ in the simulation, the computational cost of step 3-4 is $x \times y \times (h_{\max}-h_{\min})$. We can obtain that the worst-case computational complexity of interior point method is

$O(n)^{3.5}\log(1/\varepsilon)$, where n is the number of optimization variables and ε is a given solution accuracy [47]. Since step 6-7 uses the interior point method, the computational cost of step 6-7 is about $O\left(\left(MK^2\right)^{3.5}\right)\log(1/\varepsilon)$, in which M and N are the numbers of UAVs and nodes, respectively. Finally, we can come to the conclusion that the whole computation complexity is $x \times y \times (h_{\max} - h_{\min}) + O\left(\left(MK^2\right)^{3.5}\right)\log(1/\varepsilon)$ in Algorithm 2.

V. SIMULATIONS AND DISCUSSION

In this section, we carry out simulations to evaluate the effectiveness and superiority of our proposed algorithm. In the simulations, we consider a 100×100 m^2 area horizontally. The system parameters are displayed in Table I, in addition to special instructions. To guarantee the effectiveness of our algorithm design, we have studied two different scenarios in the following:

- Case I: There are $K = 8$ nodes randomly distributed on the ground and $M = 3$ UAVs deployed in the air.
- Case II: There are $K = 6$ nodes randomly distributed on the ground and $M = 2$ UAVs deployed in the air.

TABLE 1. **Major parameters used in simulations.**

Parameter	Value	Definition
B	1 MHz	The total system bandwidth
P	1 W	The transmit power budget of each UAV
T	100 s	The operating duration
σ^2	-169 dBm/Hz	The white power spectral density
α	2	The path-loss exponent
ζ	20 dB	The additional attenuation factor
η	0.5	The energy harvesting efficiency
β_0	-30 dB	The channel power gain at the reference distance
ξ, χ	11.95, 0.136	The channel parameters for urban environment

Furthermore, the flight height of the UAV is also limited in both cases. Based on security consideration, the minimum height of each UAV is limited by $h_{\min} = 5$ m. Besides, in order to ensure the effectiveness of SWIPT and save energy consumption, the maximum altitude of each UAV is limited to $h_{\max} = 20$ m. We set $\varepsilon = 10\hat{\ } - 4$ and $\tau = 1$.

A. SYSTEM PERFORMANCE

In order to verify the superiority of the proposed algorithm in system performance, we put forward benchmark scheme 1 and benchmark scheme 2 as the baseline schemes to make comparison with our design. The two benchmark schemes are presented as follows:

I) Benchmark scheme 1: the user association, UAVs' transmit power and nodes' power splitting ratios are jointly optimized by alternating iterations when the 3D locations of the UAVs are fixed.

II) Benchmark scheme 2: the 3D locations of the UAVs, the user association and UAVs' transmit power are jointly optimized by alternate iterative optimization when the nodes' power splitting ratios are pre-set.

Notably, the proposed algorithm has better performance than other two benchmark schemes above as shown from Fig. 3. Since our algorithm design enables the UAVs to hover in the relatively optimal location, where the better the channel state between the UAV and nodes is, the more the power is transmitted to ground nodes associated with the UAV. Moreover, the power splitting ratio of each node is designed flexibly according to different energy requirements for maximizing the objective function value in a more energy-efficient way.

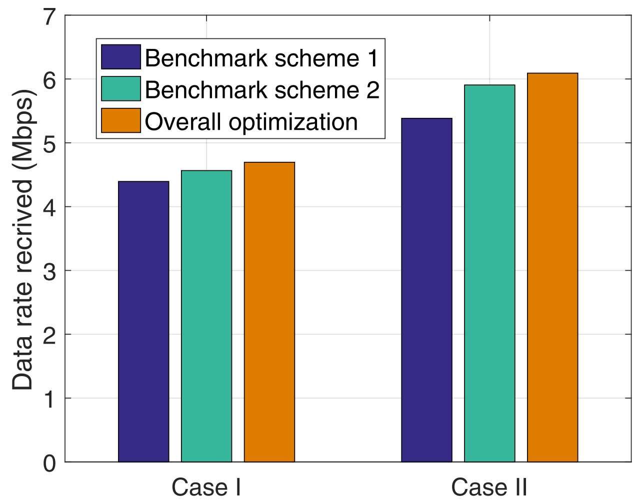
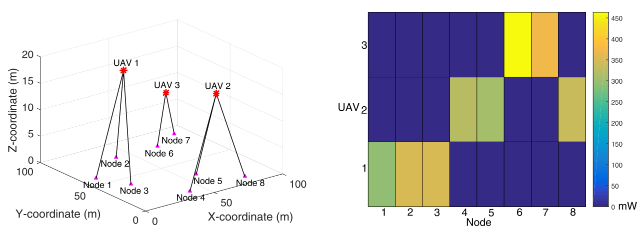


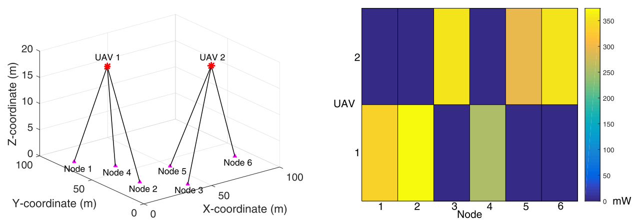
FIGURE 3. **Maximization of minimum data rate received comparison in two cases.**

Fig. 4(a) and Fig. 5(a) show the user association states between UAVs and ground nodes in two cases, where the energy threshold $\psi = 1$ mJ. Furthermore, when the process of the user association is completed, the UAVs only transmit information and transfer energy to the nodes associated with them observed from Fig. 4(b) and Fig. 5(b). The transmit



(a) User association in case I. (b) UAVs' transmit power in case I.

FIGURE 4. **User association and UAVs' transmit power in case I.**



(a) User association in case II. (b) UAVs' transmit power in case II.

FIGURE 5. User association and UAVs' transmit power in case II.

power of UAV is almost equally allocated to their matching nodes, in which the closer the node is to the UAV, the less power the UAV will transmit to it. Thus the fairness of nodes' receiving information can be guaranteed.

In the feasibility analysis, the upper bound of the energy threshold in problem (P1) can be obtained by solving problem (P2). It has been verified that the energy harvested among each node under different thresholds all don't go beyond the upper bound of the threshold shown in Fig. 6 and Fig. 7. Furthermore, as the energy threshold increases, the maximization of minimum data rate received among all nodes decreases and the minimum energy harvested among all nodes increases. So there's a tradeoff between the data rate received and the energy harvested by ground nodes. When the energy threshold $\psi = 0$, the objective function value, namely maximization of minimum data rate received reaches the upper bound in problem (P1). Thereby, the conclusion of the feasibility analysis is verified.

Since the power splitting ratio is an optimized variable cannot be ignored, we conduct some experiments to explore the influence of different energy requirements on simulation results by changing the threshold value ψ. Four sets of thresholds are selected to be compared in case I and case II, respectively. Fig. 8 and Fig. 9 show that the more the threshold is, the less the power splitting ratio is. It means when more

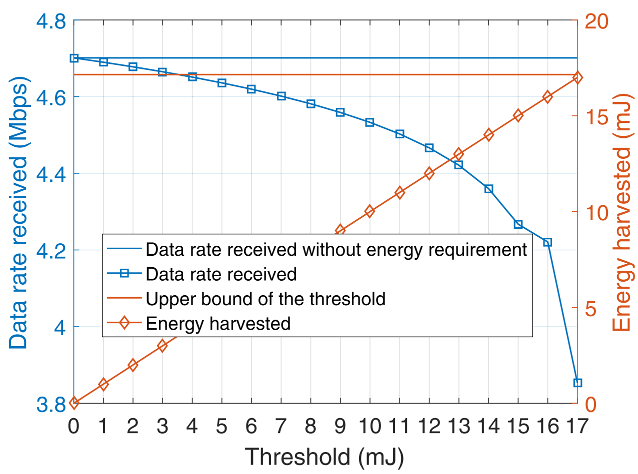


FIGURE 6. Data rate received and energy harvested under different thresholds in case I.

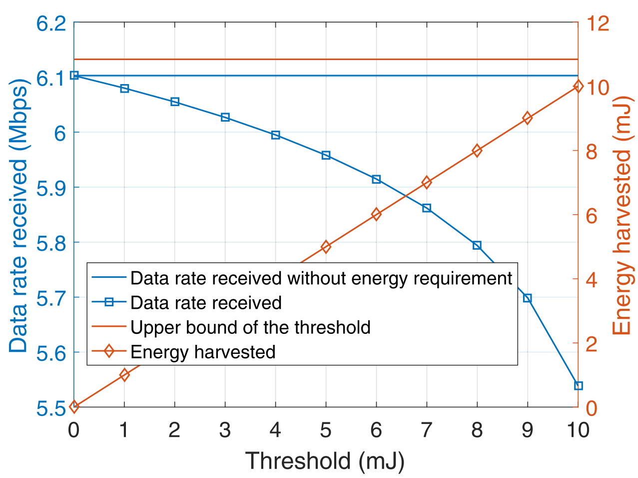


FIGURE 7. Data rate received and energy harvested under different thresholds in case II.

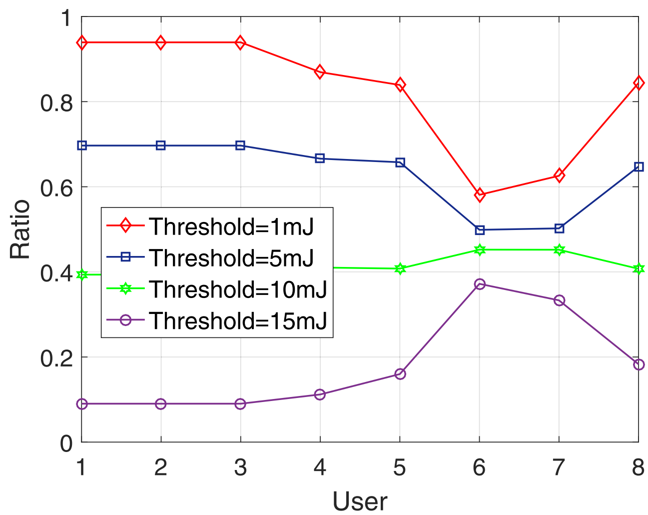


FIGURE 8. Comparison of power splitting ratios among different thresholds in case I.

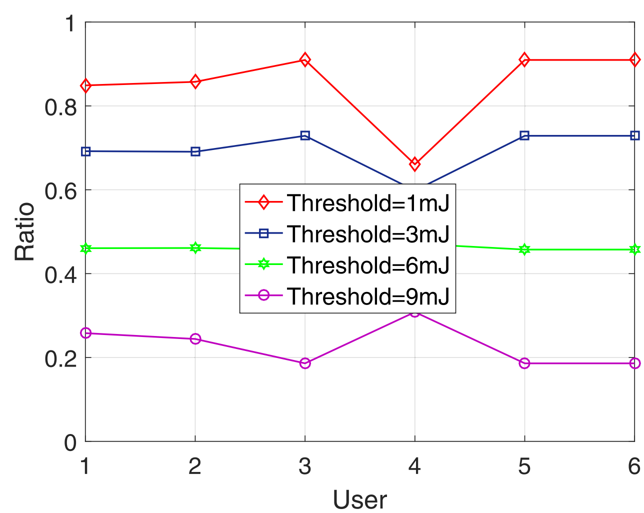
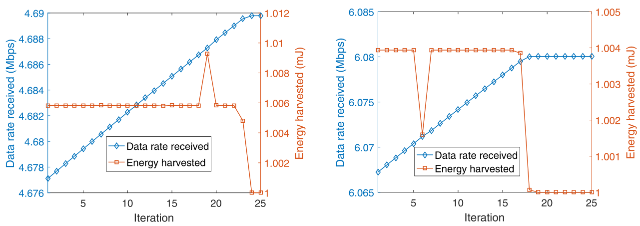


FIGURE 9. Comparison of power splitting ratios among different thresholds in case II.

energy needs to be harvested, more transmit power of UAV is split to the energy receiver.

Fig. 10 demonstrates that the maximization of minimum data rate received is monotonically increasing as the iterative process until convergence, which is in accordance with the theoretical analysis in Section IV-C1. Since the outermost iteration is for optimizing UAVs' 3D locations and user association, we find the optimal 3D locations of UAVs and user association through every iteration. The reason why the objective function of each iteration does not improve much is that the relatively suitable locations of UAVs are found after the first iteration, then we jointly optimize UAVs' transmit power and the nodes' power splitting ratios when the UAVs hover relatively good locations in each subsequent iteration. Moreover, even if there are fluctuations of the minimum energy harvested during the iterations, the minimum energy harvested among all ground nodes also eventually converges to the threshold value. Therefore, if only the energy requirement is satisfied, the minimum data rate received among all nodes is achieved as more as possible. In this way, the system performance can be up to the optimal state.



(a) Case I. (b) Case II.

FIGURE 10. Maximization of minimum data rate received and energy harvested versus iteration.

VI. CONCLUSION

In this paper, we have investigated the 3D UAV location deployment, user association and power allocation in a multi-UAV system with power splitting. Specifically, we maximized the minimum data rate received among all nodes on the ground while meeting the minimum energy threshold of each node. Meanwhile, each UAV's transmit power budget is considered due to practical limitations. We have developed a multi-variable fixed iterative algorithm for jointly optimizing the 3D UAV location, user association, UAVs' transmit power and nodes' power splitting ratios via alternately optimizing those variables. Furthermore, simulation results have confirmed the proposed algorithm outperforms over other baseline schemes. According to the results, UAVs will search the optimal 3D locations to ensure better channel states between them and the nodes. Moreover, the transmit power of the UAV assigned to the node depends on its position associated with the UAV. The closer the node is to the UAV, the less the power of the UAV will transmit to it. Furthermore, the power splitting ratios of the nodes rest with the energy threshold. With the increase of the threshold, the power splitting ratio decreases. At last, our next work is to investigate the trajectory optimization of multiple UAVs with tasks to accomplish.

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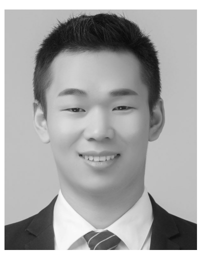

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