Fair Energy-Efficient Resource Optimization for Multi-UAV Enabled Internet of Things

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***Abstract*—Unmanned aerial vehicle (UAV) enabled Internet of Things (IoT) can keep network connectivity when the ground infrastructures are paralyzed. However, its transmission perform will be restricted due to the limited energy of the UAV. In this paper, a multi-UAV enabled IoT is proposed, where the UAVs as base stations send information to the ground IoT nodes via downlink within the flight time. And a fair energy-efficient resource optimization scheme for the IoT is studied to ensure fair energy consumption of multiple UAVs. The optimization problem seeks to maximize the minimum energy efficiency of each UAV by jointly optimizing communication scheduling, power allocations and trajectories of the UAVs. We decompose the non-convex optimization problem into three sub-optimization problems and solve them by Dlinkelbach method and successive convex approximation (SCA). Then a joint optimization algorithm is put forward to obtain the global optimal solutions by iteratively optimizing the three sub-optimization problems. The simulations results show that the multi-UAV enabled IoT can achieve significant performance improvement, and the energy efficiency between UAVs can achieve relative fairness by the fair resource optimization.**

***Index Terms*—IoT, UAV, resource optimization, fairness, energy efficiency**

I. Introduction

Internet of Things (IoT) as a network connecting uniquely identifiable ”things” to the Internet has been increasingly applied to numerous fields such as smart home, agricultural assistance and disaster monitoring [1], [2]. At present, IoT is mostly based on ground infrastructures, which would not work or be isolated when the ground infrastructures are paralyzed [3], [4]. In this case, due to low cost, high mobility and easy deployment of unmanned aerial vehicle (UAV), UAV-enabled IoT has attracted wide attentions in the aspect of maintaining network connectivity without ground infrastructures[5]–[7]. Therefore, the UAV-enabled IoT is more suitable for special emergencies such as remote area communications, disaster relief and logistics support etc[8], [9]. Furthermore, the UAV can connect to the ground user by establishing a line-of-sight (LoS) link, thus improving the quality of service (QoS) for the user [10], [11]. It is difficult for a single UAV to satisfy the desired communication performance of massive IoT nodes, therefore, multiple UAVs can work together to serve the ground IoT [12].

In the UAV-enabled IoT, the UAV can perform as a relay or a base station (BS). Fu *et al.* [13] studied an UAV-aided IoT to increase the signal strength between IoT devices and BS, and its power consumption was minimized by jointly optimizing deployment and transmit power of the UAV. In [14], Song *et al.* proposed a fixed-wing UAV-enabled IoT, where the UAV with sufficient cache was employed as a relay to amplify and forward the signals between the IoT nodes. The energy efficiency (EE) of the IoT was maximized by an optimization algorithm based on successive convex approximation (SCA) and Dinkelbach method. In [15], Ji *et al.* proposed a multi-UAV assisted IoT system enhanced with energy harvesting, whose throughput was improved by optimizing transmit power, scaling factor and UAV relay deployment, while the outage probability and bit error rate of the IoT were reduced. In [16], Lin *et al.* studied an UAV-assisted data-collection IoT, where the UAV relay was used to gather data from ground IoT and relay the data to end user. In this IoT, the tradeoff between throughput and energy efficiency was considered. In [17], Wang *et al.* proposed a space-air-ground IoT consisting of a geosynchronous oribit (GEO), a ground macrocell BS and multi-UAV relays, whose throughput was maximized by optimizing UAV hovering altitude and power control jointly. In [18], a cache-enabled UAV relay was studied to serve the IoT devices, and the throughput of the IoT was maximized by jointly optimizing content caching and UAV location. Compared with the UAV relay, the UAV BS can provide better services for more IoT nodes. In [19], Duan *et al.* considered uplink nonorthogonal multiple access (NOMA) of an UAV-enabled IoT system, where the UAVs were employed as BS for collecting date from the ground nodes. The uplink throughput of the IoT was maximized by SCA. In [20], Hua *et al.* studied an UAV-assisted simultaneous uplink and downlink transmission networks, where one UAV as a transmitter connected multiple nodes and the other UAV as a BS collected data from the IoT nodes. The system throughput was maximized by jointly optimizing 3D trajectory, communication scheduling and transmit power of the UAV. In [21], an UAV-aided IoT

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network was proposed, where the UAV BS served the IoT nodes by time-division duplex (TDD) orthogonal-frequency-division multiple access (OFDMA). The authors maximized the uplink throughput of the IoT by jointly optimizing uplink and downlink time slots and 3D UAV trajectory.

Though the UAV has brought many performance advantages for the IoT, it is still facing many challenges such as energy shortage and power limitation. Small size of UAV not only brings convenience, but also means its energy is limited. Therefore, energy efficiency optimization is significantly important for an UAV-enabled IoT. There have been several studies on the EE of UAV [14], [16], [22]–[24], but these works do not consider the propulsion power of UAV. Some literatures have considered the propulsion power in the EE optimization. In [25], Zeng *et al.* deduced the quantitative formula of the propulsion power consumption of fixed-wing UAV. In [26], an energy-efficiency UAV-to-user communication system was considered, whose throughput and energy efficiency were maximized by optimizing UAV trajectory, propulsion power and UAV speed. In [27], Wang *et al.* considered an UAV-aided security communication system consisting of an UAV, a destination and an eavesdropper, whose secrecy energy efficiency was maximized by jointly optimizing propulsion power and trajectory of the UAV. However, these literatures have ignored the transmit power of the UAV, which is usually large for the UAV BS to serve a large number of IoT nodes. Therefore, both the propulsion power and transmission power should be considered in the energy efficiency optimization of the UAV. In addition, there are fewer literatures on multi-UAV energy efficiency optimization involving complex user scheduling and interference avoidance. In [28], Hua *et al.* presented a multi-UAV enabled energy-efficient secure network, where multiple UAVs sent information to the ground users and multiple jamming UAVs transmitted interference to the eavesdroppers simultaneously. The energy efficiency of each UAV was maximized by jointly optimizing communication scheduling, communication power and UAV trajectory. However, the energy efficiency fairness was not considered in these works, resulting in that an UAV serving more users would consume more energy. Therefore, the energy consumption of each UAV is unfair and inconsistent.

Considering both propulsion power and transmit power of the UAV, a fair energy-efficient resource optimization for multi-UAV enabled IoT is proposed, which is formulated as a max-min optimization problem for jointly optimizing communication scheduling, power allocations and trajectories of the UAVs. The contributions of the paper are summarized as follows

- A multi-UAV enabled IoT is designed, where the UAVs are deployed as BSs to send information to the IoT nodes. The flying speed of each UAV is variable, and the kinematic constraints of the UAVs are given for each time slot. The communication rate and power consumption are derived according to the channel states in each time slot.
- A fair energy-efficient resource optimization scheme for the UAVs is formulated as a joint max-min optimization problem of communication scheduling, communication power and trajectories of the UAVs.
- To solve the proposed non-convex optimization problem, it is divided into three sub-optimization problems including communication scheduling optimization, power allocation optimization and UAV trajectory optimization. These sub-optimization problems are solved by jointly using Dlinkelbach method, Lagrange duality, CVX and SCA. The final solution to the optimization problems can be obtained by iteratively optimizing the three sub-optimization problems, a joint optimization algorithm is put forward to achieve the final solution to the optimization problem.

The remainder of this paper is organized as follows. The multi-UAV enabled IoT system is described in Section I-I, whose fair energy-efficient optimization is formulated as a max-min optimization problem. In Section III, the optimization problem is decomposed into three sub-optimization problems including communication scheduling optimization, power allocation optimization and UAV trajectory optimization, and then a joint optimization algorithm is presented to obtain the final solution by iteratively optimizing the three sub-optimization problems. In Section IV, simulation results are given to verify the solution performance. Finally, the conclusions are obtained in Section V.

II. System Model

Consider a multi-UAV assisted IoT system consisting of M UAVs and K IoT nodes as shown in Fig. 1. Assume that the UAVs fly at a stable and same altitude H, which is generally the minimize altitude for UAV, and there are no obstacles or buildings to make the UAV rise and fall frequently. Cartesian coordinate system with dimensions in meters has been established for the IoT. The IoT nodes are located at $q_k = (x_k, y_k, 0)\,, k = 1, 2, ..., K$. Assume that the prior location information of all the nodes are known to the UAVs and the UAVs have the same flight time T. The flight time can be divided into N time slots with the length of δ_t. Since δ_t is very small, the position of each UAV is approximately unchanged within the time slot. Hence, the trajectory and velocity of each UAV can be described as $q_m(n) = (x_m(n), y_m(n), H)$ and $V_m(n)$ for $m = 1, 2, ..., M, n = 1, 2, ..., N$, respectively. The kinematic and anti-collision constraints of the UAVs are given by

$$q_m(n+1) = q_m(n) + V_m(n)\delta_t + \frac{1}{2}\omega_m(n)\delta_t^2, \forall m, n \quad (1)$$

$$V_m(n+1) = V_m(n) + \omega_m(n)\delta_t, \forall m, n \quad (2)$$

$$d_{min}^2 \leq ||q_m(n) - q_j(n)||^2, m \neq j \quad (3)$$

where $\omega_m(n)$ denotes the acceleration of UAV m and $||.||$ represents the Euclidean distance. In addition, we assume that all the UAVs fly periodically. The starting and ending locations of each UAV are the same, which is shown as follows

$$q_m(1) = q_m(N), \forall m \quad (4)$$

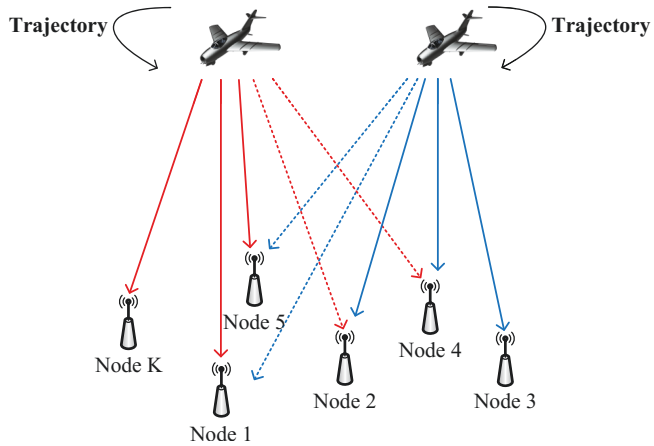

Fig. 1. Multi-UAV enabled IoT model.

Unlike the ground communications, we assume that the channels from the UAVs to the nodes are all line-of-sight (LoS) links. [1] The channel power gain from UAV m to node k at time slot n is given by

$$h_{m,k}(n) = \beta_0 d_{m,k}^{-2}(n) \tag{5}$$

where β_0 is the channel gain at reference distance $d_0 = 1$m, and $d_{m,k}(n) = ||q_m(n) - q_k||$ is the distance from UAV m to node k at time slot n.

A. Achievable Rate

A binary variable $a_{m,k}(n)$ is defined to indicate the UAV's communication scheduling. If $a_{m,k}(n) = 1$, UAV m is serving the node k at the time slot n, otherwise, $a_{m,k}(n) = 0$. In each time slot, one node can be served by at most one UAV, and one UAV can serve at most one node. Hence, we have

$$a_{m,k}(n) = \{0, 1\}, \forall m, n, k \tag{6}$$

$$\sum_{k=1}^{K} a_{m,k}(n) \leq 1, \forall m, n \tag{7}$$

$$\sum_{m=1}^{M} a_{m,k}(n) \leq 1, \forall k, n \tag{8}$$

Assume that the communication power of UAV m received by node k at time slot n is $p_{m,k}(n)$ and the noise power is σ^2. The achievable rate of UAV m serving node k at time slot n is given by

$$\begin{aligned} R_{m,k}(n) &= \log_2\left(1 + \frac{p_{m,k}(n)h_{m,k}(n)}{\sigma^2}\right), \ \forall m, n, k \\ &= \log_2\left(1 + p_{m,k}(n)\gamma_{m,k}(n)\right) \\ &= \log_2\left(1 + \frac{p_{m,k}(n)\gamma_0}{||q_m(n) - q_k||^2}\right) \end{aligned} \tag{9}$$

[1]According to an extensive research for the UAV channel model [29], [30], if the horizontal distance between the UAV and the node is less than 1000m, and the UAV is located above 80m, the probability of LoS link can be approximated to 1.

where $\gamma_{m,k}(n) = \frac{h_{m,k}(n)}{\sigma^2}$ is the channel-to-noise ratio (CNR) from UAV m to node k, and $\gamma_0 = \beta_0/\sigma^2$ is the reference CNR. The total throughput of UAV m in a flight cycle is given by

$$R_m^T = \sum_{k=1}^{K}\sum_{n=1}^{N} a_{m,k}(n)R_{m,k}(n), \forall m \tag{10}$$

B. UAV Power Consumption

The fixed-wing UAV is used in the IoT system, whose total energy consumption includes communication power and propulsion power. The propulsion power of UAV m at time slot n is given by

$$p_m^c(n) = a||V_m(n)||^3 + \frac{b}{||V_m(n)||}\left(1 + \frac{||\omega_m(n)||^2}{g^2}\right) \tag{11}$$

where g is the gravitational acceleration, a and b are constant parameters related to the area of the unmanned wing, the air density and the UAV's weight. The communication power consumption of UAV m can be shown as

$$E_m = \sum_{k=1}^{K}\sum_{n=1}^{N} a_{m,k}(n)p_{m,k}(n), \forall m, n, k \tag{12}$$

The propulsion power consumption of UAV m can be written as

$$E_m^c = \sum_{n=1}^{N} p_m^c(n), \forall m, n \tag{13}$$

Therefore, the total power consumption of UAV m in a flight cycle can be expressed as

$$E_m^T = E_m + E_m^c, \forall m \tag{14}$$

C. Fair Energy-efficient Optimization

We seek to achieve the energy efficiency fairness between the individual UAVs by jointly optimizing communication scheduling, $\mathbf{A} = \{a_{m,k}(n), \forall m, n, k\}$, power allocations, $\mathbf{P} = \{p_{m,k}(n), \forall m, n, k\}$, and UAVs' trajectories, $\mathbf{Q} =$

$\{q_m(n), \forall m, n\}$. The optimization problem is given by

$$\text{(P1)}: \max_{\mathbf{P},\mathbf{Q},\mathbf{A}} \min_{m=1,2,\ldots,M} \frac{R_m^T}{E_m^T}$$

$$\text{s.t.} \quad 0 \leq \frac{1}{N}\sum_{k=1}^{K}\sum_{n=1}^{N} a_{m,k}(n)p_{m,k}(n) \leq P_{max}, \forall m \tag{15}$$

$$p_{m,k}(n) \geq 0, \forall m, n, k \tag{16}$$

$$a_{m,k}(n) = \{0, 1\}, \forall m, n, k \tag{17}$$

$$\sum_{k=1}^{K} a_{m,k}(n) \leq 1, \forall m, n \tag{18}$$

$$\sum_{m=1}^{M} a_{m,k}(n) \leq 1, \forall k, n \tag{19}$$

$$q_m(n+1) = q_m(n) + V_m(n)\delta_t + \frac{1}{2}\omega_m(n)\delta_t^2, \forall m, n \tag{20}$$

$$V_m(n+1) = V_m(n) + \omega_m(n)\delta_t, \forall m, n \tag{21}$$

$$d_{min}^2 \leq ||q_m(n) - q_j(n)||^2, m \neq j \tag{22}$$

$$q_m(1) = q_m(N), \forall m \tag{23}$$

$$V_m(1) = V_m(N), \forall m, n \tag{24}$$

$$V_{min} \leq ||V_m(n)|| \leq V_{max}, \forall m, n \tag{25}$$

$$||\omega_m(n)|| \leq \omega_{max}, \forall m, n \tag{26}$$

where P_{max} is the maximum transmit power of UAV, ω_{max} is the maximum acceleration of UAV, and V_{min} and V_{max} are the minimum speed and the maximum speed of UAV, respectively. (15) represents the communication power constraint, and (24), (25) and (26) denote the velocity and acceleration constraints of UAV, respectively.

The applications of the proposed UAV model are described as follows. The UAVs provide services to the ground users as much as possible over a specific time period, such as emergency communications. The same flight time for all the UAVs is mainly to ensure that the propulsion energy consumption of each UAV will not make a big difference during the flight period. Therefore, the energy efficiency fairness of UAVs can be achieved by optimizing scheduling, transmit power and UAV trajectory, which will guarantee the similar energy consumption of all the UAVs over the same time period and thus avoid the communication interruption caused by the early energy depletion of some UAVs. With the same flight time for all the UAVs, multiple UAVs can be deployed at the same time and evacuate uniformly before running out of their energy. Therefore, all the UAVs may supply services for all the ground users within the specific time period, which obeys the case of emergency communications and guarantees that each ground user has enough serving time.

III. Model Optimization Solution

(P1) is a non-convex optimization problem, which is hard to solve directly. Therefore, we consider to decompose (P1) into three sub-optimization problems, i.e., the communication scheduling optimization, the power allocation optimization and the UAV trajectory optimization. The optimal solution can be achieved by solving the three sub-optimization problems iteratively.

A. Communication Scheduling Optimization

By introducing a variable $\eta_m = \frac{R_m^T}{E_m^T}$, the communication scheduling optimization under any given power allocation $\mathbf{P}$ and UAV trajectory $\mathbf{Q}$ is given by

$$\text{(P1.1)}: \max_{\mathbf{A}} \min_{m=1,2,\ldots,M} \eta_m$$
$$\text{s.t.} \quad (17) \sim (19)$$

It is obvious that $R_m^T > 0$ and $E_m^T > 0$. For simplicity, ψ is denoted to represent the feasible region of (17)$\sim$ (19). Let

$$\begin{aligned}\eta^\star &= \max_{\mathbf{A}\in\psi} \min_m \frac{R_m^T}{E_m^T} \\ &= \min_m \frac{R_m^T}{E_m^T}\bigg|_{\mathbf{A}=\mathbf{A}^\star}\end{aligned} \tag{27}$$

where $\mathbf{A}^\star$ and $\eta^\star$ are the optimal solutions of (P1.1). In order to solve (P1.1), the following proposition is proposed.

Proposition 1: The optimal solution $\mathbf{A}^\star$ is available if and only if

$$\begin{aligned}&\max_{\mathbf{A}\in\psi} \min_m \left[R_m^T - \eta^\star E_m^T\right] \\ &\quad = \min_m \left[R_m^T - \eta^\star E_m^T\big|_{\mathbf{A}=\mathbf{A}^\star}\right] \\ &\quad = 0\end{aligned} \tag{28}$$

Proposition 1 can be proved using a standard result of generalized fractional programming theory [31].

Hence, (P1.1) can be solved equivalently by solving (28). Since $\eta^\star$ is always unknown in advance, we can update $\eta = \min_m \frac{R_m^T}{E_m^T}$ iteratively to replace $\eta^\star$. Therefore, (P1.1) is rewritten as

$$\max_{\mathbf{A}} \min_{m=1,2,\ldots,M} R_m^T - \eta E_m^T$$
$$\text{s.t.} \quad (17) \sim (19)$$

which is non-convex due to that (17) is a non-convex constraint. Relaxing the constraint (17) and introducing variable φ, (P1.1) is redescribed as

$$\text{(P1.2)}: \max_{\varphi,\mathbf{A}} \varphi$$

$$\text{s.t.} \quad 0 \leq a_{m,k}(n) \leq 1, \forall m, n, k \tag{29}$$

$$R_m^T - \eta E_m^T \geq \varphi, \forall m \tag{30}$$

$$constr. \quad (18), (19)$$

which is convex and can be solved by the convex optimization tool CVX. The communication scheduling optimization is shown in Algorithm 1.

B. Power Allocation Optimization

Then we will optimize the UAV power allocation under any given communication scheduling $\mathbf{A}$ and UAV trajectory $\mathbf{Q}$. The optimization problem is given by

$$\text{(P1.3)}: \max_{\mathbf{P}} \min_{m=1,2,\ldots,M} \eta_m$$

$$\text{s.t.} \quad 0 \leq \sum_{k=1}^{K}\sum_{n=1}^{N} a_{m,k}(n)p_{m,k}(n) \leq NP_{max}, \forall m \tag{31}$$

$$p_{m,k}(n) \geq 0, \forall m, n, k \tag{32}$$

Algorithm 1 Communication scheduling optimization.

Initialize: the UAV transmit power $\mathbf{P}$, the initial UAV trajectory $\mathbf{Q}$, the iterative convergence threshold τ, the iteration index $i = 0$ and the energy efficiency $\eta^{[i]} = 0$;

while the non-convergence of objective value **or** the unreached iterative number **do**
  solve (P1.2) with given $\eta^{[i]} = 0$ and obtain the UAV communication scheduling solution $\mathbf{A}^{[i+1]}$;
  if $|\min_m \{R_m^{T,[i+1]} - \eta E_m^{T,[i+1]}\}| \leq \tau$ **then**
    set $\eta^\star = \min_m \frac{R_m^{T,[i+1]}}{E_m^{T,[i+1]}}$;
    break;
  else
    update $\eta^{[i+1]} = \min_m \frac{R_m^{T,[i+1]}}{E_m^{T,[i+1]}}$;
  end if
  set $i = i + 1$;
end while

Output: the UAV communication scheduling $\mathbf{A} = \mathbf{A}^{[i]}$.

Similarly, by applying *Proposition 1*, (P1.3) can be rewritten as follows

$$\begin{aligned} &\max_{\mathbf{P}} \min_{m=1,2,\ldots,M} R_m^T - \eta E_m^T \\ &\text{s.t.} \quad (31), (32) \end{aligned}$$

By introducing a variable φ, (P1.3) can be further expressed as

$$\begin{aligned} \text{(P1.4):} \quad &\max_{\varphi, \mathbf{P}} \varphi \\ \text{s.t.} \quad &R_m^T - \eta E_m^T \geq \varphi, \forall m \\ &constr. \quad (31), (32) \end{aligned} \tag{33}$$

where η can be iteratively obtained as $\eta = \min_m \frac{R_m^T}{E_m^T}$. It can be verified that (P1.4) satisfy the Slater's condition, which can be solved by Lagrange duality method. The Lagrange function for (P1.4) can be given as follows

$$\begin{aligned} L(\mathbf{P}, \varphi, \lambda_m, \mu_m) &= \left(1 - \sum_{m=1}^{M} \lambda_m\right) \varphi \\ &+ \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{n=1}^{N} \lambda_m a_{m,k}(n) \log_2(1 + p_{m,k}(n) \gamma_{m,k}(n)) \\ &- \eta \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{n=1}^{N} \lambda_m a_{m,k}(n) p_{m,k}(n) \\ &- \eta \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_m p_m^c(n) \\ &- \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{n=1}^{N} \mu_m a_{m,k}(n) p_{m,k}(n) + \sum_{m=1}^{M} \mu_m N P_{max} \end{aligned} \tag{34}$$

where $\lambda_m, \forall m$ and $\mu_m, \forall m$ are the non-negative Lagrange multipliers with (31) and (33), respectively. The dual function is shown as follows

$$\begin{aligned} H(\lambda_m, \mu_m) = &\max_{\mathbf{P}, \varphi} L(\mathbf{P}, \varphi, \lambda_m, \mu_m) \\ &\text{s.t.} \quad p_{m,k}(n) \geq 0, \forall m, n, k \end{aligned} \tag{35}$$

Lemma 1: To make $H(\lambda_m, \mu_m)$ finite, $\sum_{m=1}^{M} \lambda_m = 1$ must be hold.

Proof: Lemma 1 can be proved by contradiction. If $\sum_{m=1}^{M} \lambda_m < 1$ or $\sum_{m=1}^{M} \lambda_m > 1$, $H(\lambda_m, \mu_m) \to +\infty$ will be hold by setting $\varphi \to +\infty$ or $\varphi \to -\infty$. ■

Therefore, the dual optimization problem of (P1.4) can be described as follows

$$\min_{\lambda_m, \mu_m} H(\lambda_m, \mu_m) \tag{36}$$

$$\text{s.t.} \quad \sum_{m=1}^{M} \lambda_m = 1 \tag{37}$$

$$\lambda_m \geq 0, \mu_m \geq 0, \forall m \tag{38}$$

Next, we will solve the dual optimization with given λ_m and μ_m. For the sake of analysis, the dual function can be decomposed into two sub-optimization problems. One is to optimize the objective function as follows

$$\max_{\varphi} \left(1 - \sum_{m=1}^{M} \lambda_m\right) \varphi \tag{39}$$

and the other one can be divided into MKN parallel communication power allocation problems as follows

$$\begin{aligned} \max_{\mathbf{P}} \; &\lambda_m a_{m,k}(n) \log_2(1 + p_{m,k}(n) \gamma_{m,k}(n)) \\ &- \eta \lambda_m a_{m,k}(n) p_{m,k}(n) \\ &- \mu_m a_{m,k}(n) p_{m,k}(n), \forall m, n, k \end{aligned} \tag{40}$$

$$\text{s.t.} \quad p_{m,k}(n) \geq 0 \tag{41}$$

In (39), since the objective function satisfies *Lemma 1*, its value is always zero. That is, any value of φ can be chosen as the optimal solution. Thus, we set $\varphi^\star = 0$.[2] By applying the Karush-Kuhn-Tucker (KKT) conditions [32], the optimal solution of (40) is also the solution of (39). Therefore, the optimal power allocation can be obtained as follows

$$p_{m,k}^\star(n) = \left[\frac{\lambda_m}{(\lambda_m \eta + \mu_m) \ln 2} - \frac{1}{\gamma_{m,k}(n)}\right]^+, \forall m, n, k \tag{42}$$

where $[x]^+ = \max\{x, 0\}$. It can be found that (42) conforms to the water-filling structure.

Next, we will start solving the dual optimization problem (36) by the subgradient method. And the subgradient of λ_m and μ_m can be given by

$$\triangle \lambda_m = R_m^T - \eta E_m^T - \varphi, \forall m \tag{43}$$

$$\triangle \mu_m = N P_{max} - \sum_{k=1}^{K} \sum_{n=1}^{N} a_{m,k}(n) p_{m,k}(n), \forall m \tag{44}$$

[2] $\varphi = 0$ can not actually be the optimal solution, and next we will discuss how to obtain the optimal solution.

Then the iterative subgradient optimization can be expressed as

$$\lambda_m = \lambda_m - v_1 \triangle\lambda_m \tag{45}$$

$$\mu_m = \mu_m - v_2 \triangle\mu_m \tag{46}$$

where $v_1 > 0$ and $v_2 > 0$ are the step lengths.

By substituting (45) and (46) into (42) and updating λ_m and μ_m iteratively, the optimal power allocation solution can be obtained until both λ_m and μ_m are convergent. Then we can get the optimal solution of (P1.4) as follows

$$\varphi^\star = \min_{m=1,2,\ldots,M} \left\{ \sum_{n=1}^{N} \left(\sum_{k=1}^{K} a_{m,k}(n) \log_2\big(1 + p^\star_{m,k}(n)\gamma_{m,k}(n)\big) - \eta\big(\sum_{k=1}^{K} a_{m,k}(n) p^\star_{m,k}(n) + p^c_m(n)\big)\right)\right\} \tag{47}$$

The power allocation optimization can be summarized as Algorithm 2.

Algorithm 2 Power allocation optimization.

Initialize: the UAV trajectory $\mathbf{Q}$, the iterative convergence threshold τ, the Lagrange multipliers λ_m and μ_m, the step lengths v_1 and v_2, the maximum number of iterations J, the iteration indexes $i = 0$ and $j = 0$, and the energy efficiency $\eta^{[i]} = 0$;

while the non-convergence of objective value **or** the unreached iterative number **do**
  repeat
    obtain the power allocation from (42) with given $\eta^{[i]}$, $\lambda_m^{[j]}$ and $\mu_m^{[j]}$;
    update $\lambda_m^{[j+1]}$ and $\mu_m^{[j+1]}$ from (43)∼(46);
    set $j = j + 1$;
    if $|\lambda_m^{[j]} - \lambda_m^{[j-1]}| \le \tau$ and $|\mu_m^{[j]} - \mu_m^{[j-1]}| \le \tau$ **then**
      break;
    end if
  until $j \ge J$;
  set $j = 0$;
Output: $p^{[i]}_{m,k}(n)$;
  if $|\min_m\{R_m^{T,[i]} - \eta^{[i]} E_m^{T,[i]}\}| \le \tau$ **then**
    $\eta^\star = \min_m \frac{R_m^{T,[i]}}{E_m^{T,[i]}}$;
    break;
  else
    update $\eta^{[i+1]} = \min_m \frac{R_m^{T,[i]}}{E_m^{T,[i]}}$;
    set $i = i + 1$;
  end if
end while
Output: the UAV power allocation $\mathbf{P} = \{p^{[i]}_{m,k}(n)\}$.

C. UAV Trajectory Optimization

In this section, we will solve the UAV trajectory optimization problem under any given communication scheduling $\mathbf{A}$ and power allocation $\mathbf{P}$. The optimization problem is described as follows

$$\text{(P1.5)}: \max_{\mathbf{Q}, V_m(n)} \min_{m=1,2,\ldots,M} \eta_m$$

$$\text{s.t.} \quad q_m(n+1) = q_m(n) + V_m(n)\delta_t + \frac{1}{2}\omega_m(n)\delta_t^2, \forall m, n \tag{48}$$

$$V_m(n+1) = V_m(n) + \omega_m(n)\delta_t, \forall m, n \tag{49}$$

$$q_m(1) = q_m(N), \forall m \tag{50}$$

$$V_m(1) = V_m(N), \forall m, n \tag{51}$$

$$V_{min} \le ||V_m(n)|| \le V_{max}, \forall n \tag{52}$$

$$||\omega_m(n)|| \le \omega_{max}, \forall m, n \tag{53}$$

$$d^2_{min} \le ||q_m(n) - q_j(n)||^2, m \ne j \tag{54}$$

By applying the Dinkelbach method and introducing variable φ, (P1.5) can be redescribed as follows

$$\text{(P1.6)}: \max_{\varphi, \mathbf{Q}, V_m(n)} \varphi$$

$$\text{s.t.} \quad R_m^T - \eta E_m^T \ge \varphi, \forall m \tag{55}$$

$$const.\ (48) \sim (54)$$

which is non-convex because of the non-convex constraints (54) and (55). From (9), $R_{m,k}(n)$ is convex with $||q_m(n) - q_k||^2$, whose first-order Taylor expansion can be a global under-estimator. Therefore, the SCA can be used to convert (55) to a convex constraint. For any local point $\hat{q}_m(n)$, the following inequality exists as

$$R_{m,k}(n) \ge R^{lb}_{m,k}(n) = \hat{R}_{m,k}(n) - \psi_{m,k}(n)(||q_m(n) - q_k||^2 - ||\hat{q}_m(n) - q_k||^2) \tag{56}$$

where $\hat{R}_{m,k}(n) = \log_2\left(1 + \frac{p_{m,k}(n)\gamma_0}{||\hat{q}_m(n) - q_k||^2}\right)$ and $\psi_{m,k}(n) = \frac{p_{m,k}(n)\gamma_0 \log_2 e}{(||\hat{q}_m(n) - q_k||^2)(||\hat{q}_m(n) - q_k||^2 + p_{m,k}(n)\gamma_0)}$. However, (55) is still non-convex due to that (11) is non-convex with respect to $V_m(n)$. Introducing a slack variable $U_m(n)$, (55) can be convex by adding a new constraint $||V_m(n)||^2 \ge U_m^2(n)$.

Similarly, by applying the SCA, (54) can be converted to the convex constraint as follows

$$||V_m(n)||^2 \ge ||\hat{V}_m(n)||^2 + 2\hat{V}_m^T(n)(V_m(n) - \hat{V}_m(n)) = V^{lb}_m(n) \tag{57}$$

$$d^2_{min}(n) \le Q_{lb}(n) = ||\hat{q}_m(n) - \hat{q}_j(n)||^2 + 2(\hat{q}_m(n) - \hat{q}_j(n))^T(q_m(n) - q_j(n) - (\hat{q}_m(n) - \hat{q}_j(n))) \tag{58}$$

Therefore, the trajectory optimization problem is rewritten by

$$\text{(P1.7)}: \max_{\varphi, \mathbf{Q}, V_m(n), U_m(n)} \varphi$$

$$\text{s.t.} \quad \sum_{n=1}^{N} (R^{lb}_m(n) - \eta E^u_m(n)) \ge \varphi, \forall m \tag{59}$$

$$V^{lb}_m(n) \ge U^2_m(n), \forall m, n \tag{60}$$

$$const.\ (48) \sim (53), (57), (58)$$

where,

$$R^{lb}_m(n) = \sum_{k=1}^{K} a_{m,k}(n) R^{lb}_{m,k}(n) \tag{61}$$

$$E_m^u(n) = \sum_{k=1}^{K} \Bigg(a_{m,k}(n) p_{m,k}(n) \tag{62}$$

$$+ a||V_m(n)||^3 + \frac{b}{||U_m(n)||}\left(1 + \frac{||\omega_m(n)||^2}{g^2}\right)\Bigg) \tag{63}$$

(P1.7) is a convex optimization problem and can be solved by CVX. An iterative trajectory optimization based on the Dinkelbach method is proposed in Algorithm 3. The Dinkelbach method can achieve the global optimal solution to (P1.5) via successively updating the UAV trajectory from (P1.7).

Algorithm 3 UAV trajectory optimization.

Initialize: the initial and final UAV locations, the UAV trajectory $\mathbf{Q}^{[i]}$, the iterative convergence threshold τ, the iteration index $i = 0$ and the energy efficiency $\eta^{[i]} = 0$;

while the non-convergence of objective value **or** the unreached iterative number **do**
  solve (P1.7) with given $\eta^{[i]} = 0$ and obtain the optimal UAV trajectory $\mathbf{Q}^{[i+1]}$;
  if $|\min_m \{R_m^{T,[i]} - \eta^{[i]} E_m^{T,[i]}\}| \leq \tau$ **then**
    $\eta^\star = \min_m \frac{R_m^{T,[i]}}{E_m^{T,[i]}}$;
    break;
  else
    update $\eta^{[i+1]} = \min_m \frac{R_m^{T,[i]}}{E_m^{T,[i]}}$;
    set $i = i + 1$;
  end if
end while

Output: the UAV trajectory $\mathbf{Q} = \mathbf{Q}^{[i]}$.

D. Joint Optimization Algorithm

A joint optimization algorithm are proposed to solve (P1) by iteratively optimizing the previous three sub-optimization problems. Specifically, in the i-th iteration, with the given power allocation $\mathbf{P}^{[i]}$ and UAV trajectory $\mathbf{Q}^{[i]}$, the communication scheduling $\mathbf{A}^{[i+1]}$ can be obtained by solving (P1.1). Next, with the obtained $\mathbf{A}^{[i+1]}$ and the given $\mathbf{Q}^{[i]}$, the optimal $\mathbf{P}^{[i+1]}$ in the $(i+1)$-th iteration is obtained by solving (P1.3). Finally, with the obtained $\mathbf{A}^{[i+1]}$ and $\mathbf{P}^{[i+1]}$, the optimal $\mathbf{Q}^{[i+1]}$ can be obtained by solving (P1.5). The joint optimization is summarized in Algorithm 4.

Algorithm 4 Joint communication scheduling, power allocation and trajectory optimization.

Initialize: the initial and final UAV locations, the iteration index $i = 0$, the communication scheduling $\mathbf{A}^{[i]}$, the transmit power of UAV $\mathbf{P}^{[i]}$, and the UAV trajectory $\mathbf{Q}^{[i]}$;

while the non-convergence of objective value **or** the unreached iterative number **do**
  with given $\mathbf{P}^{[i]}$ and $\mathbf{Q}^{[i]}$, obtain the optimal $\mathbf{A}^{[i+1]}$ by solving (P1.2);
  with given $\mathbf{A}^{[i+1]}$ and $\mathbf{Q}^{[i]}$, obtain the optimal $\mathbf{P}^{[i+1]}$ by solving (P1.4);
  with given $\mathbf{A}^{[i+1]}$ and $\mathbf{P}^{[i+1]}$, obtain the optimal $\mathbf{Q}^{[i+1]}$ by solving (P1.5);
  set $i = i + 1$.
end while

Output: the optimal solutions $\mathbf{A} = \mathbf{A}^{[i]}$, $\mathbf{P} = \mathbf{P}^{[i]}$ and $\mathbf{Q} = \mathbf{Q}^{[i]}$.

IV. Simulation Results

In the simulations, the numbers of IoT nodes and UAVs are $K = 9$ and $M = 3$, respectively. The IoT nodes are randomly distributed in 1000m×1000m region and the UAVs fly at a fixed altitude $H = 100$m. The maximum and minimum speeds of each UAV are 40m/s and 3m/s, respectively. The maximum acceleration of each UAV is $5\mathrm{m/s}^2$. The flight time is $T = 40$s. The minimum collision protection distance is $d_{min} = 10$m. The length of time slot is $\delta_t = 0.5$s. The channel power gain at the reference distance $d_0 = 1$m is $\beta_0 = -60$dB and the noise power is $\sigma^2 = -110$dBm. In terms of energy consumption, the maximum communication power of each UAV in each time slot is $P_{max} = 1$W, and the power propulsion coefficients are $a = 0.001$ and $b = 2250$, respectively.

The initial UAV trajectory has a great influence on the simulations. It can be set as a circle trajectory where the circle center and the radius need to be considered. We first consider the geometric center of all the IoT nodes, which is denoted as $G_c = \frac{\sum_{k=1}^{K} q_k}{K} = (g_x, g_y)$. Then we chose half of the distance between the geometric center and its farthest user as a reference radius, which is denoted as $r_c = \frac{\max_k ||q_k - G_c||}{2}$. Next, we define $O_m = (X_m, Y_m)$ and r_m to be the circle center and radius, respectively. In the case of three UAVs, the centers of their initial trajectories can be represented as $O_1 = (g_x - r_c \sin(\frac{\pi}{3}), g_y + r_c \sin(\frac{\pi}{6}))$, $O_2 = (g_x + r_c \sin(\frac{\pi}{3}), g_y + r_c \sin(\frac{\pi}{6}))$ and $O_3 = (g_x, g_y - r_c)$, respectively. The radius of the initial trajectories can be given by $r_1 = r_2 = r_3 = \frac{r_c}{2}$. We assume that the UAVs make a uniform circular motion. Therefore, the initial trajectory and velocity of UAV m at time slot n is given by

$$q_m^{(0)}(n) = \left(X_m + r_m \cos\frac{2\pi(n-1)}{N-1}, Y_m + r_m \sin\frac{2\pi(n-1)}{N-1} \right) \tag{64}$$

$$V_m^{(0)}(n) = \left(\frac{2\pi r_m}{T} \cos\frac{2\pi(n-1)}{N-1}, \frac{2\pi r_m}{T} \sin\frac{2\pi(n-1)}{N-1} \right) \tag{65}$$

A. Single-UAV enabled IoT

First, the special case of single-UAV enabled IoT is considered, where the fair energy efficiency optimization can be seen as an energy efficiency maximization problem. We discuss some existing optimization schemes, which have no essential difference between the optimizations of multiple UAV system and single UAV system. Therefore, we choose a single UAV system with lower complexity to compare the performance of various optimization schemes. We use a circular initial UAV trajectory, where the circle center coincides with the geometric center and the initial radius is r_m.

Figure 2 shows the optimized UAV trajectories under different optimization goals. We can notice that under the goal of minimizing energy consumption and fair energy efficiency, the optimal UAV trajectory is approximately circular. Under the optimization goal of maximizing throughput, the UAV is more inclined to fly straight between two points to obtain better channel conditions and thus obtain greater throughput. Due to the limited speed and flight time of the UAV, it can be seen that the UAV can only cover the three nodes near the initial trajectory.

Figure 3 shows the UAV speeds in a flight cycle under different optimization goals. We can see that in the case of maximizing throughput, the UAV will gradually accelerate when it is far away from the node, and gradually decelerate when it is close to the node, so that the UAV can stay near the node for a longer time to obtain greater throughput. In the other two cases, the speed value of the UAV will not change much. This is because frequent speed changes make the acceleration value larger, resulting in more energy consumption. The energy efficiency under different optimization goals are shown in Fig. 4. It can be seen that the fair optimization can achieve the maximal energy efficiency due to that it degenerates into energy efficiency maximization problem in a single UAV case.

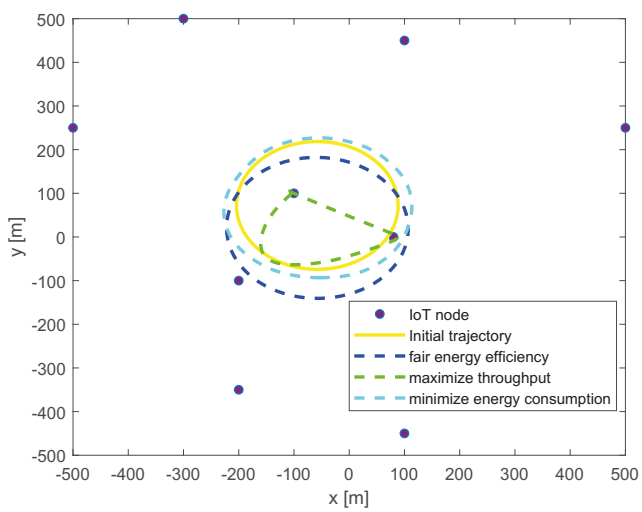

Fig. 2. Optimized UAV trajectories under different optimization goals.

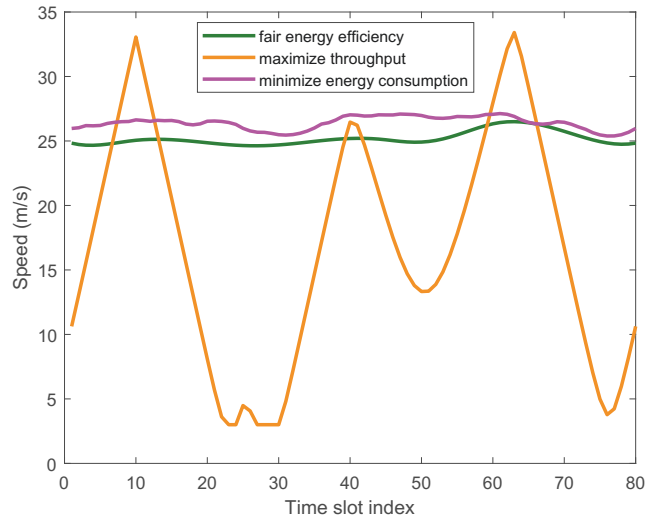

Fig. 3. Optimized UAV speeds versus flight time under different optimization goals.

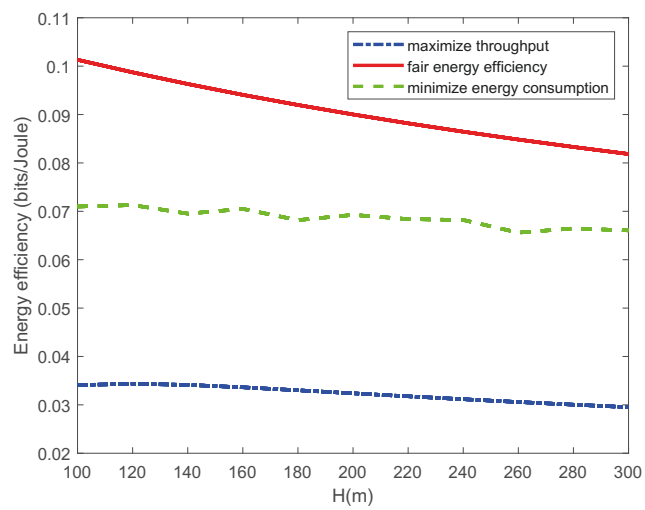

Fig. 4. Energy efficiency versus flight altitude under different optimization goals.

B. Multi-UAV enabled IoT

For the simulations of multi-UAV system, we mainly show the optimization results of UAVs.

Figure 5 shows the initial trajectories of multiple UAVs and their optimized trajectories obtained by Algorithm 4. In this figure, the numbers 1∼9 denote the node indexes. It can be seen that the optimized trajectory is still approximately circular, which is as close as possible to the IoT nodes.

Figure 6 shows the UAV speeds during a flight cycle. We can see that the UAV speed will decrease when it approaches to the IoT nodes to obtain greater throughput. Under the goal of fair energy-efficient optimization, the speed difference of UAVs is small to ensure that the small difference of propulsion power.

Figure 7 shows the communication scheduling of each UAV. When the UAV provides communication services for the IoT node, the corresponding node index is set as the ordinate value in the served time slots. It can be observed that since the locations of nodes $3, 5$ and 8 are close to the initial trajectories of the two UAVs, they are served by the two UAVs at different time slots.

The power allocation for each IoT node is illustrated in Figure 8. It can be seen that the total power allocated to the nodes far away from the UAV trajectories is relatively small. That is because the longer the distance, the greater the communication power required to guarantee the throughput of the nodes. Therefore, under the goal of optimizing energy efficiency, each UAV will serve more nodes close to it, in order

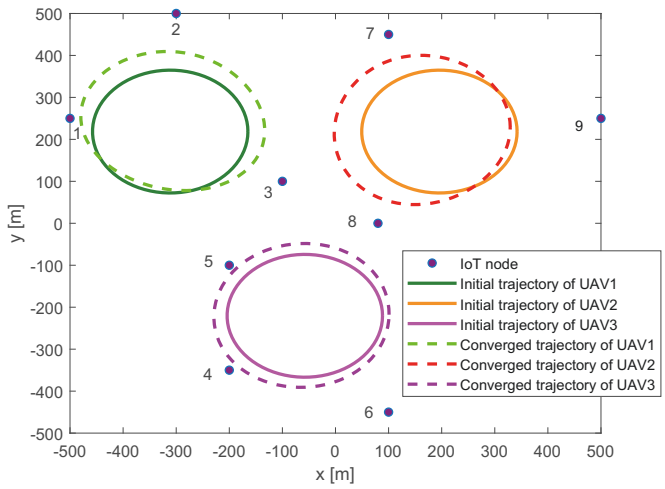

Fig. 5. Multi-UAV initial trajectories and optimized trajectories.

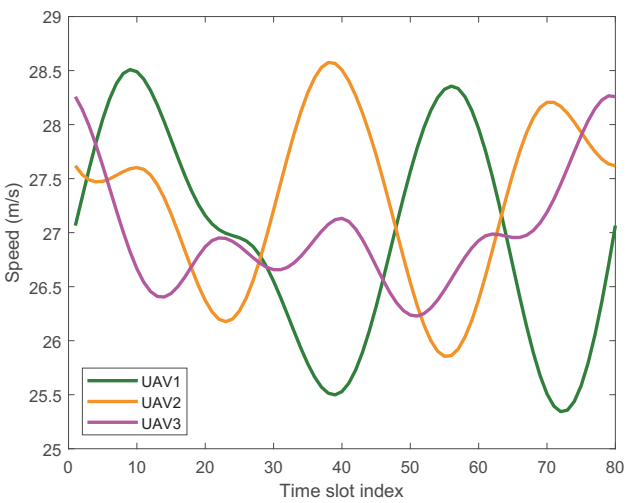

Fig. 6. Multi-UAV speeds versus flight time.

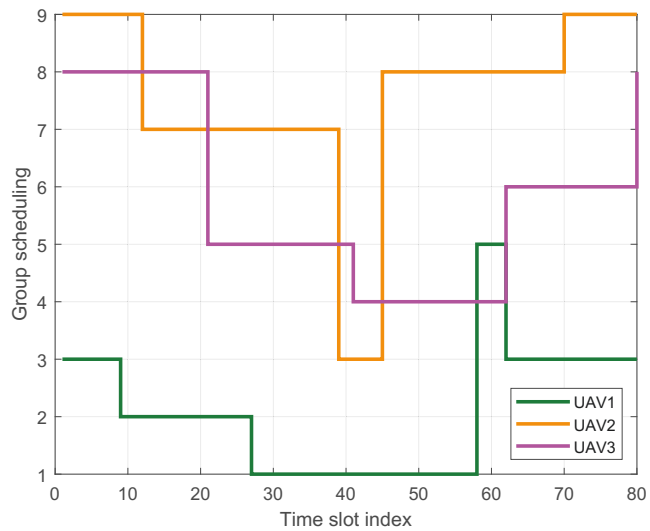

Fig. 7. Communication scheduling of each UAV.

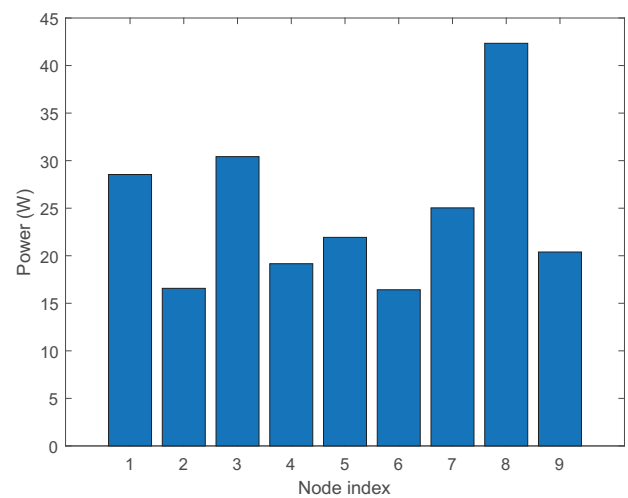

Fig. 8. Power allocation of different IoT nodes.

to obtain better energy efficiency. In addition, it can be found that nodes 3 and 8 get more power allocation because they are served by two UAVs. Although node 5 is also served by two UAVs, the service time and the total allocated power for the node is relatively less due to that it is far away from UAV 1.

The energy efficiency of each UAV versus the flight altitude H is shown in Figure 9. It can be found that with the increase of H, the energy efficiency of UAVs gradually decrease. That is because with the increase of UAV altitude, the channel power gain between the UAV and each IoT node gradually decreases. Therefore, due to the limitation of the maximum communication power, the throughput of each IoT node gradually decreases, which ultimately leads to a reduction in energy efficiency. In addition, as the altitude increases, the energy efficiency difference of the UAVs becomes smaller. That is because the difference of the horizontal distances between the UAVs and the nodes has less influence on the channel power gain.

Figure 10 shows the energy efficiency of UAVs versus flight time. It can be seen that the energy efficiency increases with the flight time T. That is because the UAVs have more time to fly closer to the surrounding nodes for increasing the throughput, but the flying distance is not the main influence factor of energy consumption.

The initial and the optimized energy efficiency obtained by Algorithm 4 are shown in Figure 11, where we set relatively fair initial variables. After the optimization, we can see that the energy efficiency of UAVs has been significantly improved, and the energy efficiency difference between UAVs has also become smaller.

V. Conclusion

This paper studies a multi-UAV enabled IoT, where the UAVs as BSs send information to the ground IoT nodes via downlink. We aim to maximize the minimum energy

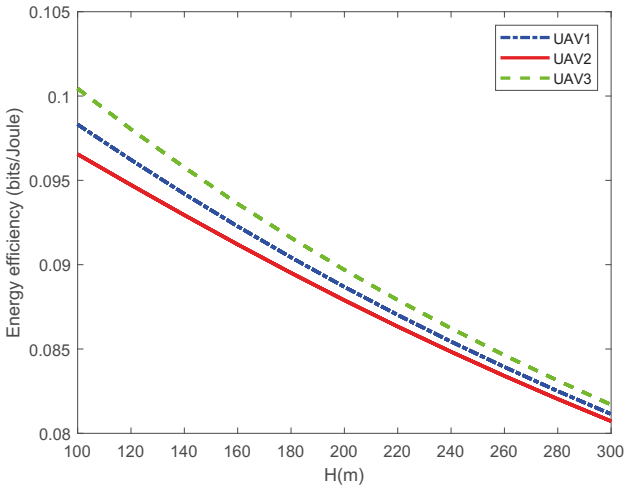

Fig. 9. Energy efficiency of each UAV versus flight altitude.

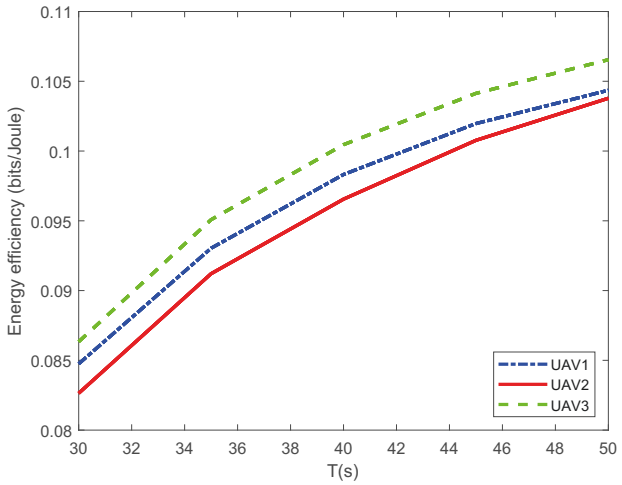

Fig. 10. Energy efficiency of each UAV versus flight time.

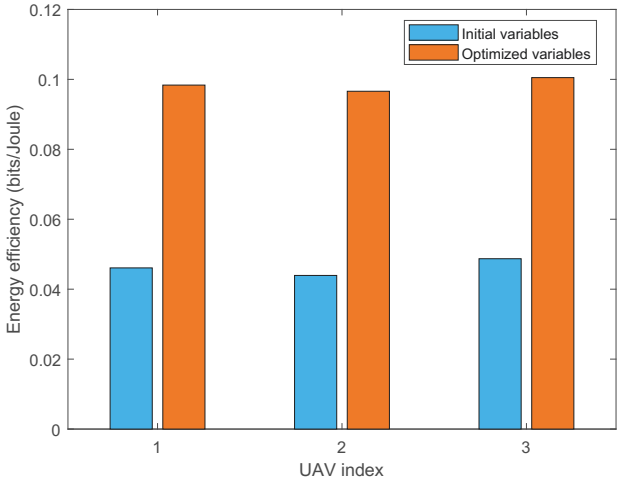

Fig. 11. Energy efficiency comparison after optimization

efficiency of each UAV by jointly optimizing communication scheduling, power allocations and trajectories of the UAVs. The non-convex optimization problem can be decomposed into three sub-optimization problems including communication scheduling optimization, power allocation optimization and UAV trajectory optimization. Based on solving the sub-optimization problems, a joint iterative optimization algorithm is proposed to obtain the globe optimal solutions. The simulation results show that through the proposed fair energy-efficient resource optimization, the energy efficiency between UAVs can be relatively fair, which is conducive to the fair energy consumption of the UAVs in a multi-UAV system.

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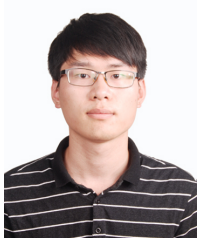

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