Energy-Efficient Resource Allocation in UAV Based MEC System for IoT Devices

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***Abstract*—This paper considers an unmanned aerial vehicle based mobile edge computing (UAV based MEC) system, where we assume there is one UAV, acts as an edge cloud, providing data processing services to the Internet of things devices (IoTDs). We consider the UAV hovers at difference places for different time to receive and process data for IoTDs. We aim to minimize the energy consumption of the UAV, including its hovering energy and computation energy, by optimizing the hovering time, scheduling and resource allocation of the tasks received from IoTDs, subject to the quality of service (QoS) requirement of all the IoTDs and the computing resource available at UAV. This is formulated as a mixed-integer non-convex optimization problem, which is difficult to solve in general. We propose an efficient iterative algorithm to get a high-quality suboptimal solution. Simulation results show that our proposed method has a very good performance compared with the other benchmarks.**

***Index Terms*—Internet of Things, Mobile edge computing, Unmanned aerial vehicle, Resource allocation.**

I. Introduction

With the increasing popularity of Internet of things devices (IoTDs), such as smart home, wearable, traffic and other monitoring devices, more and more interesting applications (e.g., pattern recognition, augmented-reality (AR), agriculture monitoring) spring up in our daily life [1]. However, some kinds of IoTDs (e.g., security cameras, meter collection devices, temperature sensors) normally have very limited or even no computation capability due to their limited physical sizes. Therefore, it is difficult for these devices to process its collected data and respond to environmental or other changes intelligently. Fortunately, mobile edge computing (MEC) brings the computation resource [2] closer to the users and has the potential to provide the IoTDs with 'intelligence' [3]. Nevertheless, in some areas, e.g., farming, their IoTDs for monitoring may be too far from the wireless access point or edge cloud infrastructure. In these cases, it is very difficult for IoTDs to enjoy the benefit provided by the MEC. On the other hand, it may not be cost-effective to install the whole infrastructure to those remote devices as well.

Unmanned aerial vehicle (UAV), due to its high flexibility, low cost and ease of deployment, has been widely applied in civilian environment, such as natural disaster rescuing, delivery of goods, and monitoring [4], [5].

By deploying the cloud computing-enabled UAV to the remote IoTDs, we can not only save the cost of installing the physical infrastructure, but also provide the computing resource on demand [6]. Different from the previous systems [7][8], the proposed system uses UAV as a flexible and flying computing platform. Also, compared with traditional wireless communication networks, UAVs may provide the line-of-sight (LoS) air-to-ground communication links [9], which can save the data transmission energy for low-battery IoTDs as well.

To illustrate how our proposed MEC-enabled UAV works, we take the intelligent farming monitoring system as an example. Assume the farm is far from the city and it installs a lot of IoTD devices for monitoring purposes. The IoTD collects the data from the environment in a certain frequency and may store the data locally. The MEC-enabled UAV flies up to the IoTDs to collect data and process them using its computing capacity. The UAV may apply the trained machine learning model to process data and then return the instructions to the IoTDs. According to the computations in UAV, the instructions to IoTDs may include adjustment of their data collection frequencies or the working patterns. Then, the IoTDs will conduct the operations following the instructions from the UAV and wait for the next time when UAV hovers up to the IoTDs again.

In this paper, we assume the UAV flies up to IoTDs and hovering at certain locations. We aim to minimize the energy consumption of the UAV, including its hovering energy and computation energy, by optimizing the hovering time, resource allocation and scheduling of the tasks received from IoTDs, subject to the quality of service (QoS) requirement of all the IoTDs and the computing resource available at UAV. We formulate this problem as a mixed-integer non-convex optimization, which is difficult to solve in general. An efficient iterative algorithm is proposed to obtain a high-quality suboptimal solution. Simulation results show that our proposed method outperforms other traditional solutions.

The rest of this paper is organized as follows. Section II introduces the system model and the optimization problem. In Section III, an efficient iterative algorithm is proposed to solve the proposed problem. Section IV provides the simulation results. Finally, we conclude the paper in Section V.

II. System Model and Problem Formulation

A. System Model

An UAV-based MEC system for IoT devices is shown in Fig.1, where we consider there are N IoTDs. The UAV flies over all the IoTDs at a fixed altitude H meters in order to process the data for IoTDs.

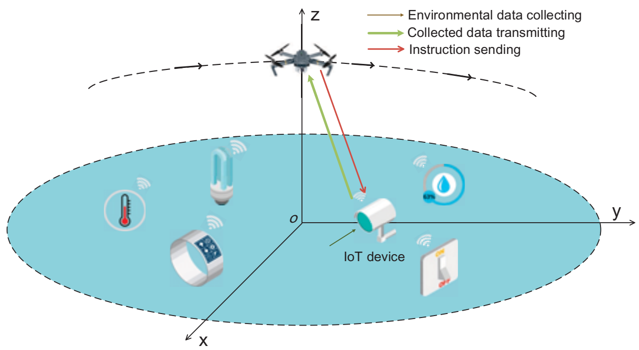

Fig. 1. A new UAV based MEC system for IoT devices.

Without loss of generality, a three-dimensional (3D) Euclidean coordinate is adopted. We define O as the geometric center of all IoTDs. The location of each i-th IoTD is given as $(x_i, y_i, 0)$, $i \in \mathcal{N} = \{1, 2, ..., N\}$. We assume that the UAV flies through the target area and hovers at M given locations, and the location of the UAV is denoted by $(X[t], Y[t], H)$, $t \in \mathcal{M} = \{1, 2, ..., M\}$. Each t-th hovering duration lasts the time of $T[t]$ seconds, where each IoTD selects one time interval to transmit their data and waits for the executions and instructions from the UAV.

Assume D_i as the amount of transmitted data from each i-th IoTD to the UAV and F_i is the total number of CPU cycles that the UAV costs to process the data. Thus, one can express the task from each i-th IoTD as

$$I_i = (D_i, F_i), \ i = 1, 2, ..., N \tag{1}$$

D_i and F_i can be obtained by using the approaches provided in [10].

We consider the returned instructions only cost a small amount of data and therefore can be ignored from our model. Assume each IoTD only chooses one UAV's hovering stop to offload its data but in UAV's one stop, it can serve more than one IoTD. Thus, one can have

$$a_i[t] = \{0,1\}, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{2}$$

where $a_i[t] = 1$ means the i-th IoTD chooses the t-th time interval to transmit data, and otherwise, $a_i[t] = 0$. Also, one has

$$\sum_{t=1}^{M} a_i[t] = 1, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{3}$$

In UAV's t-th hovering duration, we define $T_i[t]$ as the time allocated to each i-th IoTD. Then one can have

$$T[t] = \sum_{i=1}^{N} T_i[t], \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{4}$$

where, we assume the tasks from IoTDs will be received and executed sequentially. Then, the time used to send the data from each i-th IoTD to the UAV in each t-th time slot is

$$T_i^{Tr}[t] = \frac{D_i}{r_i[t]}, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{5}$$

We define B as the channel bandwidth and P_i as the transmission power of each i-th IoTD, σ^2 as the noise power at the receiver of each IoTD. The channel power gain of each i-th IoTD in each t-th time slot is $h_i[t] = \frac{h_0}{(X[t]-x_i)^2+(Y[t]-y_i)^2+H^2}$ [6]. The h_0 represents the received power at the reference distance d_0 = 1 m. In each t-th hovering place, the achievable uplink data rate for each i-th IoTD to the UAV is given by

$$r_i[t] = B \log_2 \left(1 + \frac{P_i h_i[t]}{\sigma^2}\right), \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{6}$$

In each t-th hovering place, the required time for data processing at the UAV is

$$T_i^C[t] = \frac{F_i}{f_i[t]}, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{7}$$

We assume the maximal computation resource of the UAV assigning to each IoTD as f_{max} and then one can have

$$0 \le f_i[t] \le f_{max}, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{8}$$

where $f_i[t]$ is the actual computation resource allocated by the UAV. Assume all the transmitting and computing process for each IoTD has to be completed in $T_i[t]$, then one has

$$a_i[t](T_i^{Tr}[t] + T_i^C[t]) \le T_i[t], \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{9}$$

Also, the UAV is required to provide sufficient computing resource for each IoTD

$$\sum_{t=1}^{M} a_i[t] f_i[t] T_i^C[t] \ge F_i, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{10}$$

We define the computing energy consumption of the UAV for each task as $\kappa_i (f_i[t])^{v_i} T_i^C[t]$, where $\kappa_i \ge 0$ is the effective switched capacitance and v_i is the positive constant. To match the realistic measurements, we set $\kappa_i = 10^{-27}$ and v_i = 3 [11] here.

Define P^h as the power consumption when the UAV is hovering, ϕ as the weight between the computing energy consumption (denoted by E^C) and the hovering energy consumption (denoted by E^H) of the UAV. Also, define the hovering energy of the UAV in each t-th stop as $E^h[t]$. Using eq. (7), the total energy consumption (denoted by E) of the UAV can be given as

$$E = E^C + E^H \tag{11a}$$

$$= \sum_{i=1}^{N} \sum_{t=1}^{M} a_i[t] \kappa_i (f_i[t])^{v_i} T_i^C[t] + \phi \sum_{t=1}^{M} E^h[t] \tag{11b}$$

$$= \sum_{i=1}^{N} \sum_{t=1}^{M} \kappa_i F_i a_i[t] (f_i[t])^2 + \phi P^h \sum_{i=1}^{N} \sum_{t=1}^{M} T_i[t] \tag{11c}$$

B. Problem Formulation

Let $\boldsymbol{A} = \{a_i[t], \forall i \in \mathcal{N}, \forall t \in \mathcal{M}\}$, $\boldsymbol{F} = \{f_i[t], \forall i \in \mathcal{N}, \forall t \in \mathcal{M}\}$, $\boldsymbol{T} = \{T_i[t], \forall i \in \mathcal{N}, \forall t \in \mathcal{M}\}$. Also, assume the locations of IoTDs are fixed and known. In the optimization problem below, we aim to jointly optimize the scheduling (i.e., $\boldsymbol{A}$), resource allocation (i.e., $\boldsymbol{F}$), and UAV's hovering durations (i.e., $\boldsymbol{T}$) at each location.

$$\mathcal{P}: \underset{\boldsymbol{A},\boldsymbol{F},\boldsymbol{T}}{\text{minimize}} \sum_{i=1}^{N}\sum_{t=1}^{M} \kappa_i F_i a_i[t](f_i[t])^2 + \phi P^h \sum_{i=1}^{N}\sum_{t=1}^{M} T_i[t] \tag{12a}$$

$$\text{s.t.} \sum_{t=1}^{M} a_i[t] f_i[t] T_i^C[t] \geq F_i, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{12b}$$

$$a_i[t](T_i^{Tr}[t] + T_i^C[t]) \leq T_i[t], \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{12c}$$

$$a_i[t] = \{0,1\}, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{12d}$$

$$0 \leq f_i[t] \leq f_{max}, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{12e}$$

$$\sum_{t=1}^{M} a_i[t] = 1, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{12f}$$

One can see that $\mathcal{P}$ is a mixed-integer non-convex problem, which is difficult to solve in general. Next, we will propose an efficient iterative algorithm to obtain a high-quality suboptimal solution.

III. Proposed Algorithm

To solve $\mathcal{P}$, firstly, we relax the binary variables in the constraint (12d) into continuous variables as

$$0 \leq a_i[t] \leq 1, \forall i \in \mathcal{N}, \forall t \in \mathcal{M} \tag{13}$$

However, due to the non-convex objective function (12a) and non-convex constraints (12b-d), $\mathcal{P}$ still cannot be solved directly using standard optimization methods. Thus we propose an efficient iterative algorithm for the relaxed problem by using the block coordinate descent [12] optimization technique.

A. Computing Resource Allocation Optimization

Given any IoTDs selection scheme $\boldsymbol{A}$ and the UAV hovering durations $\boldsymbol{T}$, we can obtain the following computing resource allocation optimization problem as

$$\underset{\boldsymbol{F}}{\text{minimize}} \sum_{i=1}^{N}\sum_{t=1}^{M} \kappa_i F_i a_i[t](f_i[t])^2 \tag{14a}$$

$$\text{s.t.} \frac{a_i[t] r_i[t] F_i}{T_i[t] r_i[t] - a_i[t] D_i} \leq f_i[t] \leq f_{max} \tag{14b}$$

$$\text{(12b)}, \forall i \in \mathcal{N}, \forall t \in \mathcal{M}$$

The constraint (14b) is obtained by simplifying the constraint (12c) and combining the constraint (12e) with (12c). The objective function (14a) is the sum of $N \times M$ convex functions and the constraint function of (12b) and (14b) is also convex. Therefore, problem (14) is a convex problem and can be solved by applying convex optimization technique such as the interior-point method [13]. To gain more insight, we next use the Lagrange dual method to obtain a well-structured solution for gaining essential engineering insights.

The Lagrange multipliers associated with the constraints in (12b) is given as $\boldsymbol{\mu} \triangleq \{\mu_i \geq 0, \forall i \in \mathcal{N}\}$. The partial Lagrangian function of problem (14) is

$$\begin{aligned} \mathcal{L}(\boldsymbol{F}, \boldsymbol{\mu}) = &\sum_{i=1}^{N}\sum_{t=1}^{M} \kappa_i F_i a_i[t](f_i[t])^2 + \\ &\sum_{i=1}^{N} \mu_i (F_i - \sum_{t=1}^{M} a_i[t] f_i[t] T_i^C[t]) \end{aligned} \tag{15}$$

Then the dual function of problem (14) can be given as

$$\begin{aligned} g(\boldsymbol{\mu}) = &\min_{\boldsymbol{F}} \mathcal{L}(\boldsymbol{F}, \boldsymbol{\mu}) \\ &\text{s.t. (14b)} \end{aligned} \tag{16}$$

Thus, the dual problem of problem (14) is

$$\max_{\boldsymbol{\mu}} g(\boldsymbol{\mu}) \tag{17a}$$

$$\text{s.t. } \mu_i \geq 0, \ \forall i \in \mathcal{N} \tag{17b}$$

Since problem (14) is convex and it also satisfies the Slater's condition, strong duality holds between problems (14) and (17). As a result, one can solve problem (14) by equivalently solving its dual problem (17).

1) Derivation of Dual Function $g(\boldsymbol{\mu})$: Given any $\boldsymbol{\mu}$, we obtain $g(\boldsymbol{\mu})$ by solving problem (16). Note that problem (16) can be decomposed into the following $N \times M$ subproblems.

$$\begin{aligned} &\min_{\boldsymbol{F}} \ \kappa_i F_i a_i[t](f_i[t])^2 - \mu_i a_i[t] f_i[t] T_i^C[t] \\ &\text{s.t. (14b)} \end{aligned} \tag{18}$$

According to the monotonicity of objective function, we present the optimal solution of problem (18) as

$$\begin{cases} f_{i,a}^*[t] = \dfrac{a_i[t] r_i[t] F_i}{T_i[t] r_i[t] - a_i[t] D_i}, \ if \ 0 \leq \mu_{i,a} < b_i[t] & \text{(19a)} \\ f_{i,b}^*[t] = \dfrac{\mu_i T_i[t]}{2\kappa_i F_i}, \ if \ b_i[t] \leq \mu_{i,b} \leq \dfrac{2\kappa_i F_i f_{\max}}{T_i^C[t]} & \text{(19b)} \\ f_{i,c}^*[t] = f_{\max}, \ if \ \mu_{i,c} > \dfrac{2\kappa_i F_i f_{\max}}{T_i^C[t]} & \text{(19c)} \end{cases}$$

In eq. (19a-c), we divide the optimal solution to $\boldsymbol{F}$ as $f_{i,a}^*[t]$, $f_{i,b}^*[t]$ and $f_{i,c}^*[t]$, respectively, in accordance with three parts of $\boldsymbol{\mu}$'s defined domain in (19a-c). Let $\mu_{i,a}$, $\mu_{i,b}$ and $\mu_{i,c}$ represent three different kinds of μ_i in (19a-c) intervals. Also, we define $b_i[t] = \frac{2\kappa_i a_i[t] r_i[t] F_i^2}{T_i^C[t](T_i[t] r_i[t] - a_i[t] D_i)}$ for simplification.

2) Obtaining $\boldsymbol{\mu}^*$ to Maximize $g(\boldsymbol{\mu})$: Solving dual problem (17) means obtaining $\boldsymbol{\mu}^*$ in their defined domain to maximize $g(\boldsymbol{\mu})$. In accordance with eq. (19a-c), we first put eq. (19b) into problem (17), thus we obtain

$$\max_{\boldsymbol{\mu}} g(\boldsymbol{\mu}) = \sum_{i=1}^{N} [-(\sum_{t=1}^{M} \frac{a_i[t] T_i^C[t]^2}{4\kappa_i F_i}) \mu_i^2 + F_i \mu_i] \tag{20a}$$

$$\text{s.t. } b_i[t] \leq \mu_i \leq \frac{2\kappa_i F_i f_{\max}}{T_i^C[t]} \tag{20b}$$

Note that problem (20) can be decomposed into the following N sub problems.

$$\max_{\boldsymbol{\mu}} \; -(\sum_{t=1}^{M} \frac{a_i[t]T_i^C[t]^2}{4\kappa_i F_i})\mu_i^2 + F_i\mu_i \quad \text{s.t. (20b)} \tag{21}$$

According to the monotonicity of objective quadratic function, one can have $\boldsymbol{\mu}^*$ under the constraint (20b). Similarly, we can obtain $\boldsymbol{\mu}^*$ under the constraint (19a) and (19c), thus the optimal solution to $\boldsymbol{\mu}^*$ is

$$\mu_{i,a}^* = \begin{cases} b_i[t] & \sum_{t=1}^{M} \frac{a_i[t]^2 r_i[t] T^C[t]}{T_i[t]r_i[t] - a_i[t]D_i} < 1 \\ 0 & otherwise \end{cases} \tag{22}$$

For brevity, we define $\beta_i = \sum_{t=1}^{M} \frac{a_i[t]T^C[t]^2}{4\kappa_i F_i}$, thus we obtain

$$\mu_{i,b}^* = \begin{cases} \frac{2\kappa_i F_i f_{\max}}{T_i^C[t]} & \beta_i < \frac{T_i^C[t]}{4\kappa_i f_{\max}} \\ b_i[t] & \frac{F_i}{2\beta_i} < b_i[t] \\ \frac{F_i}{2\beta_i} & otherwise \end{cases} \tag{23}$$

$$\mu_{i,c}^* = \begin{cases} \frac{2\kappa_i F_i f_{\max}}{T_i^C[t]} & F_i \le \sum_{t=1}^{M} a_i[t]T_i^C[t]f_{\max} \\ +\infty & otherwise \end{cases} \tag{24}$$

Duo to (12b), $F_i \le \sum_{t=1}^{M} a_i[t]T^C[t]f_{\max}$ can always be achieved, thus

$$\mu_{i,c}^* = \frac{2\kappa_i F_i f_{\max}}{T_i^C[t]} \tag{25}$$

Therefore, the optimal solution to $\boldsymbol{F}^*$ can be obtained by

$$f_i^*[t] = \arg\max_{f_i^*[t],\ \mu_i^*} \{g(f_{i,a}^*[t],\ \mu_{i,a}^*),\ g(f_{i,b}^*[t],\ \mu_{i,b}^*),\ g(f_{i,c}^*[t],\ \mu_{i,c}^*)\} \tag{26}$$

We introduce the computing resource allocation between the UAV and IoTDs as Algorithm 1.

Algorithm 1 Computing resource allocation algorithm

1: Use eq. (22-24) to obtain $\mu_{i,x}^*$ $\forall i \in \mathcal{N}$, $\forall x \in \{a, b, c\}$;
2: Obtain $f_{i,x}^*[t]$ in accordance with eq. (19) $\forall i \in \mathcal{N}$, $\forall t \in \mathcal{M}$, $\forall x \in \{a, b, c\}$;
3: Use eq. (26) to obtain $f_i^*[t]$ $\forall i \in \mathcal{N}$, $\forall t \in \mathcal{M}$;
4: **Return:** The optimal computing resource allocation $\boldsymbol{F}^*$.

B. Joint IoTDs Selection and Hovering Duration Optimization

Given any computing resource allocation scheme $\boldsymbol{F}$, we can obtain the following IoTDs selection and hovering duration optimization problem

$$\underset{\boldsymbol{A},\boldsymbol{T}}{\text{minimize}} \; \sum_{i=1}^{N}\sum_{t=1}^{M} \kappa_i F_i a_i[t](f_i[t])^2 + \phi P^h \sum_{i=1}^{N}\sum_{t=1}^{M} T_i[t] \tag{27a}$$

$$\text{s.t. } T_i[t] \ge a_i[t](\frac{F_i}{f_i[t]} + \frac{D_i}{r_i[t]}),\ \forall i \in \mathcal{N},\ \forall t \in \mathcal{M} \tag{27b}$$

(13), and (12f)

Given any $f_i[t]$ and using eq. (7), constraint (12b) can be replaced by (12f). Constraint (27b) is non-convex because the optimization variable $T_i[t]$ is directly divided by the other optimization variable $a_i[t]$. Notice that the object function of problem (27) consists of two independent parts, including computing energy and hovering energy. As for the hovering energy saving purpose, the equality of the time constraint holds for (27b), thus we obtain

$$T_i^*[t] = a_i[t](\frac{F_i}{f_i[t]} + \frac{D_i}{r_i[t]}) \tag{28}$$

And the total optimal hovering duration of each *t*-th time slot can be obtained by eq. (4). Hence we obtain

$$\underset{\boldsymbol{A}}{\text{minimize}} \; \sum_{i=1}^{N}\sum_{t=1}^{M} [\kappa_i F_i (f_i[t])^2 + \phi P^h (\frac{F_i}{f_i[t]} + \frac{D_i}{r_i[t]})] a_i[t] \tag{29}$$

s.t. (13), and (12f)

Problem (29) is a linear programming (LP) problem, which can be solved by the well established optimization toolbox, e.g., CVX [14] optimally and efficiently. Fortunately, for each *i*-th IoTD, given $f_i[t]$, $a_i[t] = 1$ if and only if $\kappa_i F_i (f_i[t])^2 + \phi P^h (\frac{F_i}{f_i[t]} + \frac{D_i}{r_i[t]})$ is minimum, otherwise, $a_i[t] = 0$. Consequently, the optimal solutions $\boldsymbol{A}$ to the LP problem (29) can all be obtained at $\boldsymbol{A}$'s boundary, thus the optimal solution $\boldsymbol{A}$ of subproblem (29) is binary, and there's no need to reconstruct a binary solution to the original $\mathcal{P}$.

C. Overall Algorithm

Algorithm 2 Overall algorithm for joint optimization problem

1: **Initialize:** $\boldsymbol{A}^0$, $\boldsymbol{T}^0$ and let k = 1;
2: **Repeat:**
3: Use algorithm 1 to obtain $\boldsymbol{F}^k$;
4: Use CVX tool box, and (28) to obtain $\boldsymbol{A}^k$, $\boldsymbol{T}^k$;
5: Update k = k+1;
6: **Until:** the fractional decrease of E is below a threshold ε or a maximum number of iterations ($k_{\max}$) is reached;
7: **Return:** The optimal IoTDs selection scheme $\boldsymbol{A}^*$, computing resource allocation $\boldsymbol{F}^*$, and hovering durations $\boldsymbol{T}^*$ in each time slot.

In general, we first use the Lagrange dual method to optimize the UAV computing resource allocation scheme $\boldsymbol{F}$

under the given IoTDs selection scheme $\boldsymbol{A}$ and the UAV hovering durations $\boldsymbol{T}$, then for given computing resource allocation scheme $\boldsymbol{F}$, we use the LP optimization technique to obtain $\boldsymbol{A}$ and $\boldsymbol{T}$. Fortunately, the optimal solution to the LP subproblem is obtained at $\boldsymbol{A}$'s boundary, and there's no need to reconstruct a binary solution to the original $\mathcal{P}$. In general, we introduce the overall iterative algorithm to solve $\mathcal{P}$ as Algorithm 2.

IV. Simulation Results

In this section, simulation results are presented to show the effectiveness of the proposed joint optimization design. We suppose an UAV flies over $N = 100$ IoTDs, which are distributed within a geographic area of size 1×1 km^2, and hovers $M = 3$ times at the given locations. Moreover, the UAV maximum total computation capacity is set to 10 G CPU cycles per second and the UAV flies and hovers at a fixed altitude H = 40 m. We set the bandwidth as B = 1 MHz, the channel power gain at the reference distance of 1 m as - 40 dB and the noise power at each IoTD as - 60 dBm. The transmission power of each IoTD is set as 2.82 mW. The maximum transmission rate is below 250 kbps. We set the effective switched capacitance $\kappa_i = 10^{-27}$. The UAV hovering power consumption is set as P^h = 59.2 W [15]. We set the weight ϕ as 8.4×10^{-4}.

In Fig.2 and Fig.3, we show the energy-effectiveness and the time-effectiveness of our proposed algorithm, respectively. We compare our proposed solutions with random selection and fixed frequency benchmarks. The random selection means that the IoTDs select UAV's hovering locations randomly, while the fixed frequency benchmark means that the UAV sets its computing frequency as 1/2 f_{max} for all the IoTDs.

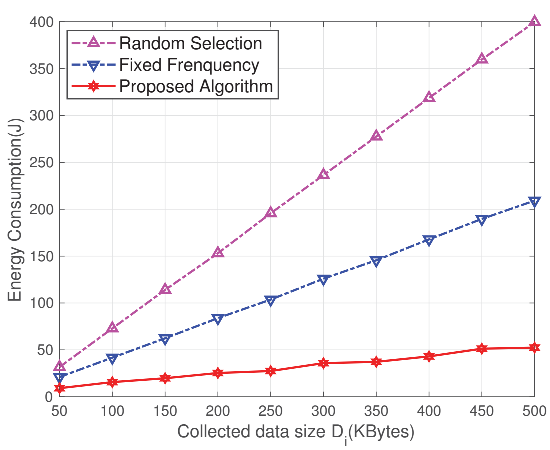

Fig. 2. The UAV energy consumption versus the IoTD sensed data size D_i.

In Fig. 2, one can see that with the increase of the transmitted data from each IoTD, the UAV's energy consumption rises correspondingly.

Next, we show the total hovering time including the required time for data processing at the UAV and the transmission time from all IoTDs to the UAV.

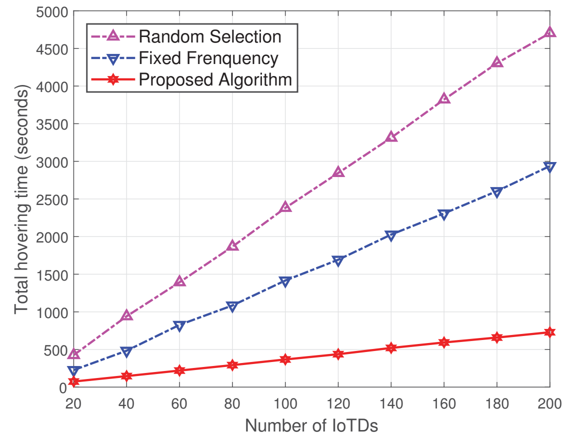

Fig. 3. The UAV total hovering time versus the number of IoTDs.

In Fig. 3, with the increase of the number of IoTDs, the UAV hovering time rises as well, as expected. One can also see that in both figures, our proposed algorithm outperforms the other two benchmarks.

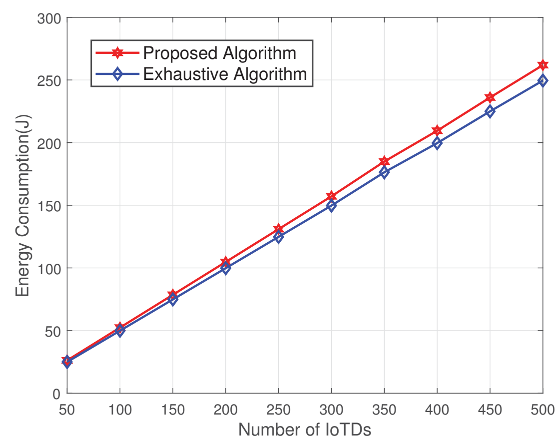

Fig. 4. The gap between the optimal solution and our proposed suboptimal solution.

In Fig. 4, we set the data size as 500 KBytes and compare our proposed algorithm with the exhaustive search. The exhaustive search can be considered as the optimal solution. However, it just searches all the feasible solutions, which has the lowest efficiency. One can see that the performance of our algorithm is very close to the exhaustive algorithm but we have much less complexity.

V. Conclusion

In this paper, we propose an UAV based MEC system, in which we assume the UAV with cloud computing enhanced system, hovering at several places to receive data from the IoTDs and to process data for them. We formulate the whole process as an mixed-integer non-convex optimization problem. To solve this problem, an efficient iterative algorithm has been proposed, by jointly optimizing the resource allocation, scheduling and UAV's hovering time. Simulation results show that our proposed design has better performance than other benchmarks.

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