Multiple Energy Harvesting Devices Enabled Joint Computation Offloading and Dynamic Resource Allocation for Mobile-Edge Computing Systems

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***Abstract*—A mobile-edge computing (MEC) system integrating energy harvesting (EH) techniques is a promising paradigm for supporting computation-intensive and delay-sensitive mobile applications. While computation offloading reduces users' perceived latency, EH techniques mitigate the limitation of mobile devices' battery capacity. However, when considering a scenario with multiple EH devices, the advantages of MEC systems with EH devices may be compromised due to the competition among multiple devices for available computational resources and wireless bandwidth. In this paper, the joint computation offloading and dynamic resource allocation (JCODRA) that minimizes the long-term average execution cost is formulated as a stochastic optimization problem. In particular, both the long-term average execution delay and the penalty delay are included in the optimization objective. The former intends to handle the competition and random and uncontrollable EH processes properly and the latter aims to reduce the ratio of dropped tasks. An online algorithm based on Lyapunov optimization is proposed to transform the original problem into a per-time slot deterministic problem. The results of experiments demonstrate that our algorithm significantly outperforms three representative baseline approaches.**

***Keywords*-mobile edge computing; multi-mobile devices; energy harvesting; long-term average execution cost; Lyapunov optimization**

I. Introduction

Many mobile applications with complex features, like face recognition, demand powerful computation resources and low latency [1]. As resource-limited mobile devices cannot afford such burdens, mobile edge computing (MEC) systems with energy harvesting (EH) techniques have been proposed [2]. Compared to MEC systems with battery-powered devices, MEC systems with EH-enabled devices relieve the need to recharge batteries frequently and support green computing [2]. In the MEC environment, energy harvesting enabled by EH techniques is a random and nondeterministic process [3], which will dramatically affect the computation offloading and resource allocation strategies.

Existing research on computation offloading commonly assumes only one EH device available. This is not valid in most, if not all, real-world scenarios. In this paper, in order to address the new issues raised by the co-existence of multiple EH devices, we investigate a joint computation offloading and dynamic resource allocation problem for MEC systems with multiple EH devices. To stabilize multiple virtual energy queues for multiple mobile devices and minimize the average execution costs are main challenges. The main contributions of this paper are as follows:

- A realistic scenario with one MEC server and multiple EH devices is introduced for investigation. The competition for limited resources among devices is handled by the joint offloading decision and adaptive resource allocation.
- The long-term average execution cost is adopted as the optimization objective. It is measured by the weighted sum of the long-term average execution delay and the penalty delay, to accommodate the competition among mobile devices and the dropped tasks, respectively.
- To obtain the optimal solution, the joint computation offloading and dynamic resource allocation is formulated as a stochastic optimization problem. An online algorithm is proposed to transform the original problem to a per-time slot deterministic problem.
- Extensive experiments are conducted to evaluate the effectiveness and efficiency of our algorithm against three representative heuristic baseline algorithms.

The remainder of the paper is organized as follows. Section II reviews the related work. Section III presents the system model. Section IV formulates our joint offloading and dynamic resource allocation problem. Section V presents the online algorithm for finding the solution. Section VI evaluates the proposed algorithm experimentally. Section VII concludes this paper.

978-1-7281-2717-0/19/$31.00 ©2019 IEEE
DOI 10.1109/ICWS.2019.00035

II. RELATED WORK

The topic of joint computation offloading and resource allocation has attracted many researchers' attention in recent years. Several typical scenarios have been investigated and various approaches have been proposed to optimize the MEC system with different objectives.

Several solutions to the joint computation offloading and resource allocation problem for MEC systems without EH techniques have been investigated [4], [5]. However, existing approaches are not suitable for an MEC system with multiple EH devices because of the new challenges raised by the EH technologies.

Mao et al. considered MEC systems that support one single mobile device with EH techniques [2]. Nevertheless, the scenario considered in [2] is rare, if not unrealistic, in the real world. A multi-user and single-server MEC system is considered in [6]. However, the stochastic nature of renewable energy is not considered in [6]. The amount of energy that is harvested by an EH device is usually nondeterministic in a real-world scenario, which is disregarded in [6]. Thus, a new approach is needed to accommodate MEC systems that support multiple users with EH devices.

III. SYSTEM MODEL

We consider an MEC system consisting of N mobile devices equipped with EH components and a multi-core MEC server. The coverage area of the MEC server is collectively determined with d_{min} and d_{max}. $T \triangleq \{0, 1, 2, \cdots\}$ represents the index of the time slot. τ is the length of the time slot. $U \triangleq \{1, 2, \cdots, N\}$ and $S \triangleq \{1, 2, \cdots, R\}$ represent the index set of mobile devices and the index set of the the MEC's CPU cores, respectively. d_i^t represents the distance to the antenna of the BS in the tth time slot.

A. Task Model

Delay-sensitive computation tasks are considered. $A_i(L_i, \tau_d)$ denotes the computation task of the ith mobile device, where L_i is the task size and τ_d is the execution deadline. The computation task is generated with probability ρ at the beginning of each time slot, $0 \leq \rho \leq 1$. $\xi_i^t = 1$ indicates that the ith mobile device has a computation task arriving within the tth time slot, or $\xi_i^t = 0$ otherwise. Binary offloading for the task is assumed, similar to [2], [6]. We use X_m and X_s to denote the number of CPU cycles required for mobile devices and the MEC server to execute one bit of computation task, respectively. $I_{i,m}^t = 1$ indicates the task of the ith mobile device within tth time slot is executed locally, or $I_{i,m}^t = 0$ otherwise. Similarly, $I_{i,s}^t = 1$ and $I_{i,d}^t = 1$ indicate the computation task is executed remotely and dropped, respectively. Thus,

$$I_{i,m}^t + I_{i,s}^t + I_{i,d}^t = 1, i \in U, t \in T. \tag{1}$$

B. Local Execution Model

f_i^t denotes the ith mobile device's CPU-cycle frequency within tth time slot, and $f_{i,max}$ represents the upper bound CPU-cycle frequency. Thus, the delay $D_{i,m}^t$ and the energy consumption $E_{i,m}^t$ of the mobile device in executing task $A_i(L_i, \tau_d)$ are expressed as

$$D_{i,m}^t = (L_i \cdot X_m)/f_i^t, i \in U. \tag{2}$$

$$E_{i,m}^t = k(L_i \cdot X_m)(f_i^t)^2, i \in U, \tag{3}$$

where k is the effective capacitance coefficient [7].

C. MEC Server Executing Model

The total bandwidth resources of the MEC server is denoted as W, w_{min} is the minimum bandwidth of each wireless channel. The channel bandwidth allocated to the ith mobile device in the tth time slot is denoted as w_i^t. So

$$w_i^t \in \{0\} \cup [w_{min}, W], i \in U, t \in T, \tag{4}$$

$$\textstyle\sum_{i=1}^{N} w_i^t \leq W, t \in T. \tag{5}$$

According to the Shannon-Hartley formula, the achievable data rate $r_i^t(w_i^t, h_i^t)$ is:

$$r_i^t(w_i^t, h_i^t) = w_i^t \log_2\left(1 + h_i^t p_i/\sigma\right), i \in U, \tag{6}$$

where p_i is the wireless transmit power of the ith mobile device, σ denotes the noise power at the receiver, and h_i^t denotes the channel power gain at the tth time slot . h_i^t is given by $h_i^t \sim F(d_i^t) = g_0(d_i^t)^{-4}$ [4]. The downlink transmission delay is ignored due to the powerful communication capabilities of the MEC server. Thus, the uplink transmission delay $D_{i,ts}^t$ and the relevant energy consumption $E_{i,s}^t$ of the mobile device are given by:

$$D_{i,ts}^t = L_i/r_i^t(w_i^t, h_i^t), i \in U. \tag{7}$$

$$E_{i,s}^t = p_i \cdot D_{i,ts}^t = (p_i \cdot L_i)/r_i^t(w_i^t, h_i^t), i \in U. \tag{8}$$

$S_i^t = 1$ indicates that the ith mobile device occupies a CPU core of the MEC server in the t time slot, or $S_i^t = 0$ otherwise. Then:

$$\textstyle\sum_{i=1}^{N} S_i^t \leq R, t \in T. \tag{9}$$

The frequency of the MEC server's core is denoted as f_s. The computing delay $D_{i,cs}^t$ of executing $A_i(L_i, \tau_d)$ is

$$D_{i,cs}^t = (L_i \cdot X_s)/f_s, i \in U. \tag{10}$$

Therefore, the total delay $D_{i,s}^t = D_{i,ts}^t + D_{i,cs}^t$ if $I_{i,s}^t = 1$.

D. Energy Harvesting Model

The EH process is modeled as successive arrivals of energy packets [2], where e_i^t denotes the energy harvested by the ith mobile device at the tth time slot, which is uniformly distributed with the maximum value of E_H^{max} and fulfills:

$$0 \leq e_i^t \leq E_H^{max}, i \in U, t \in T. \tag{11}$$

The battery energy level of the ith mobile device at the beginning of the tth time slot is denoted as B_i^t, and C_i as the battery capacity.The energy consumed is expressed as $\varepsilon_i(I_i^t, f_i^t, w_i^t) = I_{i,m}^t E_{i,m}^t + I_{i,s}^t E_{i,s}^t$, which satisfies

$$\varepsilon_i(I_i^t, f_i^t, w_i^t) \leq B_i^t \leq C_i, i \in U, t \in T. \tag{12}$$

We assume that $B_i^0 = 0$ and $C_i < +\infty, i \in U$. In addition, the harvested energy cannot be used in the current time slot. The battery energy level is evolved according to

$$B_i^{t+1} = \min\{B_i^t - \varepsilon_i(I_i^t, f_i^t, w_i^t) + e_i^t, C_i\}. \tag{13}$$

IV. PROBLEM FORMULATION

In this research, the long-term average execution cost is measured by the weighted sum of the average execution delay and the penalty delay. The penalty delay is included for reducing task dropping rate. $cost_{avg}^t$ and $cost_i^t$ denote the average execution cost of an MEC system and the execution cost of the ith mobile device in the tth time slot, respectively.Thus $cost_{avg}^t = \frac{1}{N}\sum_{i=1}^N cost_i^t$, and

$$cost_i^t = D_i(I_i^t, f_i^t, w_i^t) + \Psi \cdot \xi_i^t I_{i,d}^t. \tag{14}$$

where Ψ is the penalty cost for dropping task, $\Psi \geq \tau_d$. $D_i(I_i^t, f_i^t, w_i^t)$ is the the execution delay experienced by the ith mobile device in the tth time slot,

$$D_i(I_i^t, f_i^t, w_i^t) = \xi_i^t \cdot (I_{i,m}^t D_{i,m}^t + I_{i,s}^t D_{i,s}^t) \leq \tau_d. \tag{15}$$

Consequently, the optimization problem is defined as:

$$\begin{aligned}
\mathcal{P}_1: \min_{I^t, f^t, w^t} \lim_{T\to\infty} & \frac{1}{T}\mathbb{E}\left[\textstyle\sum_{t=0}^{T-1} cost_{avg}^t\right] \\
s.t. \quad & (1), (4), (5), (9), (11), (12), (15). \\
& \varepsilon_i(I_i^t, f_i^t, w_i^t) \leq E_{i,\tau}, i \in U, t \in T. && (16)\\
& 0 \leq f_i^t \leq f_{i,max}, i \in U, t \in T. && (17)\\
& S_i^t \in \{0,1\}, i \in U, t \in T. && (18)\\
& \xi_i^t, I_{i,m}^t, I_{i,s}^t, I_{i,d}^t \in \{0,1\}, i \in U, t \in T, && (19)
\end{aligned}$$

where $I^t \triangleq \{I_1^t, I_2^t, \cdots, I_N^t\}$,$f^t \triangleq \{f_1^t, f_2^t, \cdots, f_N^t\}$, and $w^t \triangleq \{w_1^t, w_2^t, \cdots, w_N^t\}$ represent the offloading decision, CPU-cycle frequency decision and bandwidth allocation in the tth time slot, respectively. Eq. (16) incarnates the upper bound of battery discharging. Eq. (17) incarnates the mobile devices' CPU-cycle frequency constraints. Eq. (18) and Eq. (19) represent the zero-one indicator constraints.

V. ALGORITHM DESIGN

A. JCODRA Algorithm based on Lyapunov Optimization

The strong coupling among various constraints makes it difficult to solve $\mathcal{P}_1$. Solving $\mathcal{P}_2$ which is the tightened version of $\mathcal{P}_1$ is a promising method. $\mathcal{P}_2$ is formulated as:

$$\begin{aligned}
\mathcal{P}_2: \min_{I^t, f^t, w^t} \lim_{T\to\infty} & \frac{1}{T}\mathbb{E}\left[\textstyle\sum_{t=0}^{T-1} cost_{avg}^t\right] \\
s.t. \quad & (1), (4), (5), (9), (11), (12), (15), (18), (19). \\
& f_i^t \in 0 \cup [(L_i \cdot X_m)/\tau_d, f_{i,max}]. && (20)\\
& \varepsilon_i(I_i^t, f_i^t, w_i^t) \in 0 \cup [E_{i,min}, E_{i,max}]. && (21)
\end{aligned}$$

$E_{i,min} = \min\{\frac{k(L_i \cdot X_m)^3}{\tau_d{}^2}, \frac{L_i \cdot p_i}{r_i^t(W, F(d_{min}))}\}$ and $E_{i,max} = \min\{\max\{k(L_i \cdot X_m)(f_{i,max})^2, p_i\tau\}, E_{i,\tau}\}$.

Lyapunov optimization is effective in maintaining the system stability, which can be used to solve $\mathcal{P}_2$.

θ_i is denoted as the perturbation parameter of the ith mobile device. The virtual energy queue of the ith mobile device in tth time slot is defined as Q_i^t, which is given by $Q_i^{t+1} = B_i^{t+1} - \theta_i$.

Based on Lyapunov optimization, the long-term stochastic optimization problem can be transform into a deterministic optimization problem in each time slot. First, the Lyapunov function and drift function are constructed according to $\mathcal{P}_2$. Then, the Lyapunov drift-plus-penalty function is defined according to functions. Finally, minimizing the upper bound of the drift-plus-penalty function, we can obtain the optimal solution of $\mathcal{P}_2$. The pseudo-code of the Joint Computation Offloading and Dynamic Resource Allocation (JCODRA) algorithm is presented in Algorithm 1. In *Lemma* 2, we will prove that the constraint (11) is also satisfied JCODRA.

Algorithm 1 The JCODRA Algorithm

Input: Information about MEC server and mobile devices.
Output: $\{I^t, f^t, w^t\}$, which are the offloading decision, CPU-cycle Frequency decision and bandwidth allocation in each time slot.

At the beginning of the tth time slot, obtain the information of all mobile devices.

Obtain I^t,f^t,w^t by solving the following deterministic problem:

$$\begin{aligned}
\mathcal{P}_3: \min_{I^t, f^t, w^t} & \textstyle\sum_{i=1}^N \left[Q_i^t(e_i^t - \varepsilon_i(I_i^t, f_i^t, w_i^t)) + V \cdot cost_i^t\right] \\
s.t. \quad & (1), (4), (5), (9), (11), (15), (18) - (21).
\end{aligned}$$

Update the virtual energy queue for each mobile device.

Set $t = t + 1$.

We attempt to obtain f^t and w^t as the optimal resource allocation, and I^t of $\mathcal{P}_3$ as the optimal offloading decision.

B. Optimal Resource Allocation

Initially, we assume that a feasible offloading decision has been made. Thus, mobile devices can be divided into three sets, i.e., $i \in A(t)$, $j \in B(t)$ and $k \in C(t)$ if $I_{i,m}^t = 1$, $I_{j,s}^t = 1$ and $I_{k,d}^t = 1$, respectively. Secondly, based on the feasible offloading decision, $\mathcal{P}_3$ is converted to $\mathcal{P}_4$:

$$\begin{aligned}\mathcal{P}_4 : \min_{f^t} & \sum_{i\in A(t)} \left(-Q_i^t \cdot k(L_i \cdot X_m)(f_i^t)^2 + V \cdot \frac{L_i X_m}{f_i^t}\right) \\ & + \min_{w^t} \sum_{i\in B(t)} \left(\frac{-Q_i^t \cdot p_i \cdot L_i + V \cdot L_i}{r_i^t(w_i^t, h_i^t)} + \frac{V \cdot L_i X_s}{f_s}\right) \\ & + \sum_{i\in C(t)} (V \cdot \Psi) + \sum_{i\in U} \left(Q_i^t \cdot e_i^t\right) \\ s.t. \quad & (1), (4), (5), (9), (11), (15), (18) - (21).\end{aligned}$$

Lemma 1: The solution to $\mathcal{P}_4$ is the upper bound of the solutions to $\mathcal{P}_3$. In addition, the solution to $\mathcal{P}_4$ is equivalent to the solution to $\mathcal{P}_3$ when the given offloading decision for $\mathcal{P}_4$ is optimal.

Proof: The proof is omitted due to space limitation. ■

The $\mathcal{P}_4$ is divided into three separate sub-problems:

1) Execute Tasks Locally: $\mathcal{P}_{lo}$ is expressed as:

$$\begin{aligned}\mathcal{P}_{lo} : \min_{f^t} & \sum_{i\in A(t)} \left(-Q_i^t \cdot k(L_i \cdot X_m)(f_i^t)^2 + V \cdot \frac{L_i X_m}{f_i^t}\right) \\ s.t. \quad & (15), (20), (21).\end{aligned}$$

Thus, $I_{i,m}^t = 1$, $w_i^t = 0$ and $f_i^t > 0$ are satisfied for $i \in A(t)$. $\mathcal{P}_{lo}$ is a unary function, the optimal CPU frequency f^{t*} of the mobile devices can be obtained by derivation.

Theorem 1: the optimal CPU frequency f^{t*} satisfy

$$f_i^{t^*} = \begin{cases} f_{i,L}, & Q_i^t < 0, f_{i,0}^t < f_{i,L} \\ f_{i,0}^t, & Q_i^t < 0, f_{i,L} \le f_{i,0}^t \le f_{i,U} \\ f_{i,U}, & Q_i^t \ge 0 \ or \ Q_i^t < 0, f_{i,0}^t > f_{i,U}, \end{cases} \tag{22}$$

where $f_{i,L} = \frac{L_i \cdot X_m}{\tau_d}$, $f_{i,0}^t = (\frac{V}{-2Q_i^t k})^{\frac{1}{3}}$, and $f_{i,U} = \min\{\sqrt{\frac{E_{i,max}}{k(L_i \cdot X_m)}}, f_{i,max}\}$.

Proof: The proof is omitted due to space limitation. ■

2) Remote Task Execution: $\mathcal{P}_{se}$ is expressed as:

$$\begin{aligned}\mathcal{P}_{se} : \min_{w^t} & \sum_{i\in B(t)} \left(\frac{-Q_i^t \cdot p_i \cdot L_i + V \cdot L_i}{r_i^t(w_i^t, h_i^t)} + \frac{V \cdot L_i X_s}{f_s}\right) \\ s.t. \ & (4), (5), (15), (21).\end{aligned}$$

Thus, $I_{i,s}^t = 1$, $w_i^t > 0$ and $f_i^t = 0$ are satisfied for $i \in B(t)$. By solving $\mathcal{P}_{se}$ via KKT condition the optimal bandwidth allocation w^{t*} for mobile devices can be obtained.

Theorem 2: The optimal bandwidth allocation w_i^{t*} of set $B(t)$ satisfy

$$w_i^{t*} = \begin{cases} z_i, & i \in F(t) \\ \frac{(W - \sum_{j\in F(t)} z_j) \cdot \sqrt{g_i^t}}{\sum_{k\in G(t)} \sqrt{g_k^t}}, & i \in G(t), \end{cases} \tag{23}$$

where $g_i^t = \frac{L_i \cdot (V - Q_i^t \cdot p_i)}{\log_2 (1 + (h_i^t p_i)/\sigma)}$, $z_i = \max\{m_i, n_i, w_{min}\}$, and $F(t) \cap G(t) = \varnothing$, $F(t) \cup G(t) = B(t)$.

Proof: The proof is omitted due to space limitation. ■

3) Tasks are dropped: $\mathcal{P}_{dr}$ is expressed as:

$$\mathcal{P}_{dr} : \min \sum_{i\in C(t)} (V \cdot \Psi)$$

If $\xi_i^t = 0$, there is only a single feasible offloading decision for the mobile device with $i \in C(t)$,$f_i^t = 0$, and $w_i^t = 0$. In addition, the solution to $\mathcal{P}_{dr}$ is a fixed non-negative number under the feasible offloading decision.

C. Optimal Offloading Decision

It is obviously impractical to traverse all the possible offloading decisions in $\mathcal{P}_3$. Therefore, we employ the following method. Firstly, $\mathcal{P}_3$ is divided into N sub-problems. Then, each sub-problem builds a $Reward$ function to measure the benefit of offloading a task. Finally, the optimal offloading decision for $\mathcal{P}_3$ is obtained.

The sub-problem of $\mathcal{P}_3$ is denoted as $\mathcal{P}_{sub,i}$, $i \in U$. The objective function of $\mathcal{P}_3$ and that of $\mathcal{P}_{sub,i}$ are denoted as $\mathcal{J}_3^t(I^t, f^t, w^t)$ and $\mathcal{J}_{sub,i}^t(I_i^t, f_i^t, w_i^t)$, respectively. $\mathcal{J}_{sub,i}^t(I_i^t, f_i^t, w_i^t)$ is expressed as:

$$\begin{aligned}\mathcal{J}_{sub,i}^t(I_i^t, f_i^t, w_i^t) = & I_{i,m}^t \cdot \mathcal{J}_{lo,i}^t(f_i^t) \\ & + I_{i,s}^t \cdot \mathcal{J}_{se,i}^t(w_i^t) + I_{i,d}^t \cdot \mathcal{J}_{dr,i}^t,\end{aligned} \tag{24}$$

where $\mathcal{J}_{lo,i}^t(f_i^t)$, $\mathcal{J}_{se,i}^t(w_i^t)$ and $\mathcal{J}_{dr,i}^t$ are the objective functions of $\mathcal{P}_{sub,i}$ when $I_{i,m}^t = 1$, $I_{i,s}^t = 1$ and $I_{i,d}^t = 1$, respectively. It is known that $\mathcal{J}_3^t(I^t, f^t, w^t) = \sum_{i\in U} \mathcal{J}_{sub,i}^t(I_i^t, f_i^t, w_i^t)$. Please note that the values of $\mathcal{J}_{lo,i}^t(f_i^{t*})$ and $\mathcal{J}_{dr,i}^t$ are fixed because they are independent of the offloading decision.

For mobile devices that belong to $B(t)$, we employ the $Reward$ function to evaluate the benefits of offloading their computation tasks to the MEC server. It is expressed as:

$$Reward_i^t = \min\{\mathcal{J}_{lo,i}^t(f_i^{t*}), \mathcal{J}_{dr,i}^t\} - \mathcal{J}_{se,i}^t(w_i^t). \tag{25}$$

A larger the value of Reward function indicates greater benefit for executing the computation task on the MEC server.

Lemma 2: The perturbation parameter is defined as $\theta_i = E_{i,max} + V\Psi(E_{i,min})^{-1}, i \in U$, which ensures that the optimal solution of $\mathcal{P}_3$ obtained is feasible and satisfies constraint (12).

Proof: The proof is omitted due to space limitation. ■

VI. EXPERIMENTAL EVALUATION

A. Heuristic Baseline Approaches

In the experiments, we compare JCODRA against the following three heuristic baseline approaches:

- **Mobile Execution:** Tasks can only be executed locally with the maximum feasible CPU-cycle frequency.

- **MEC Server Execution:** Tasks can only be executed remotely through homogeneous channels. The bandwidth of each channel is $w^* = \frac{W}{R}$.
- **Dynamic Offloading:** Tasks can be executed locally with $f_{i,U}^t$ or remotely through homogeneous channels.

B. Experiment Settings

1) Parameter Settings: Homogeneous mobile devices are used in the simulation. The default parameter values in Table I are used unless otherwise specified later. The values of key parameters used in the experiments in [2] are employed in our experiments, marked with $\star$ in Table I. And the EUA dataset [8], a real-world dataset, is employed to simulate the locations of the mobile devices and the MEC server.

Table I: Parameter Settings

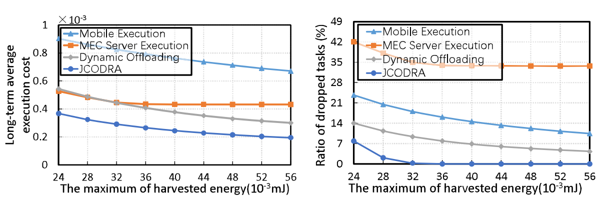
Parameters	**Value**	**Parameters**	**Value**
N	30	f_s	3.5 GHz
R	12	Ψ	2ms $\star$
d_{min}	10 m	σ	10^{-13} W $\star$
d_{max}	200 m	ρ	0.6 $\star$
W	100 Mbps	V	10^{-4}
w_{min}	10^{-3} Mbps	k	10^{-28} $\star$
E_H^{max}	4.8×10^{-2} mJ $\star$	g_0	10^{-4}
τ	2ms $\star$	$L_i, i \in U$	1000 bits $\star$
τ_d	2ms $\star$	$p_i, i \in U$	1W $\star$
X_s	125 cycles/bit	$E_{i,max}, i \in U$	2mJ $\star$
X_m	737.5 cycles/bit $\star$	$f_{i,max}, i \in U$	1.5GHz $\star$

2) Performance Metrics: In the experiments, we evaluate the performance of the approaches by following metrics:

- *Long-term average execution cost:* The lower the better.
- *Ratio of dropped tasks:* The lower the better.

C. Experimental Results and Discussion

Fig. 1 shows both the long-term average execution cost and the ratio of dropped tasks under the four approaches decrease as E_H^{max} increases. As shown in Fig. 1(b), compared to the Mobile Execution, MEC Server Execution and Dynamic Offloading, the JCODRA reduces the ratio of dropped tasks up to 89.9%, 94.6% and 81.7% when the E_H^{max} is 28$\times$10^{-3}mJ, respectively.



(a) Long-term average execution cost (b) Ratio of dropped tasks

Figure 1: System performance vs. E_H^{max}

The other experimental results are omitted due to space limitation.

VII. Conclusion

In this paper, we investigated the MEC system with multiple EH devices. An algorithm named JCODRA is developed based on Lyapunov optimization to solve the joint computing offloading and dynamic resource allocation problem. The performance analysis reveals the asymptotic optimality of the proposed algorithms. The experimental results show that JCODRA outperforms the three heuristic baseline approaches. In particular, the ratio of dropped tasks achieved by JCODRA is almost zero.

Acknowledgment

This research was partially supported by the Ministry of Education Project of Humanities and Social Sciences (No. 16YJCZH014), Australian Research Council Discovery Projects (DP170101932 and DP18010021), the Natural Science Foundation of Hubei Province of China (No. 2016CFB466), and the Open Fund of Hubei Key Laboratory of Transportation Internet of Things (Wuhan University of Technology) (No. 2018IOT005). Qiang He is the corresponding author.

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