Collaborative Computing Based on Truthful Online Auction Mechanism in Internet of Things

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Abstract. With the increasingly diverse and complex demands of the Internet of Things (IoT) devices, terminal equipments have been unable to effectively meet their quality of service (QoS). To resolve this issue, the resource allocation strategy for edge-cloud collaborative computing has been seen as a promising scheme by offloading computation-intensive tasks from IoT devices to edge servers or cloud data center. In this paper, we study the resource collaborative scheduling problem and formulate a truthful online auction mechanism in the mobile edge computing (MEC) system. We propose the objective problem of maximizing the long-term average revenue, subjecting to the task queue stability constraint. Furthermore, we apply Lyapunov optimization techniques to deal with this objective problem, which can be solved without prior information. So as to derive subproblems optimal solutions and obtain effective resource allocation strategy, a revenue maximization online auction (RMOA) algorithm is designed. Theoretical analysis shows that the RMOA algorithm can achieve optimal system revenue approximately while ensuring the stability of the MEC system. In addition, simulation results indicate the effectiveness of the RMOA algorithm and verify the influence of various parameters.

Keywords: Collaborative computing · Internet of Things · Resource allocation · Auction mechanism · Lyapunov optimization

1 Introduction

Nowadays, with the rapid development of wireless communication technology and Internet of Things (IoT) technology, a variety of new network services such as automatic driving and augmented reality are constantly emerging. The demands for IoT devices are becoming increasingly complex and diverse, and the processing of these computation-intensive tasks require powerful data processing capacity [1]. Nevertheless, most of the IoT devices have limited battery and computing capacity, which can not satisfy the processing performance requirements of tasks [2].

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It is recommendable to expand computing and services to near the data generation. As an emerging technology, mobile edge computing (MEC) has received widespread attention from academia, which can reduce delay and energy consumption by deploying edge servers close to IoT devices [3,4]. However, the resources of the edge servers are limited, if all of the computing tasks are offloaded to the edge servers, the service performance and execution efficiency of IoT devices will be reduced [5]. In addition, too many service requests compete with limited computing resources, which will make the system unstable. In order to improve the processing efficiency of IoT devices, considering the edge-cloud collaborative computing framework is an effective resource allocation scheme [6].

The framework of edge-cloud collaboration can provide fast and flexible supply of computing resource for IoT devices, which has sparked interest in market based dynamic resource allocation mechanism. As a fast and effective method of market resource allocation, online auction mechanism has been widely applied. It can dynamically reflect supply-demand relationship of computing resources and offer desirable resource scheduling strategies for edge consumers and auctioneers at the same time [7]. Hence, it is a crucial research issue to devise a truthful online auction mechanism, which can not only make IoT devices compete for computing resources fairly, but also increase the overall revenue of the system.

The problem of server resource allocation in MEC was studied by [8,9], which assigned user requests based on utility function. [10] constructed the optimal power allocation problem for base station to maximize the overall throughput delivered to mobile user. [11] presented an online resource scheduling framework to minimize task delays in MEC system. [12,13] designed a real auction mechanism to get the appropriate allocation policy. Nevertheless, these works gave little insight into the dynamic nature of channel condition and task processing. We study collaborative computing scheme based on auction mechanism, and propose the problem of stochastic optimization.

In this article, we construct the framework of edge-cloud collaboration and investigate the problem of computing resources online auction based on Vickrey-Clarke-Groves (VCG) auction mechanism. In addition, we apply Lyapunov optimization techniques to solve this issue while guaranteeing the queue and system stability. A truthful revenue maximization online auction (RMOA) algorithm is proposed, which considers the randomness of task arrival and channel conditions. The main works and contributions of this article can be summarized as follows,

- The framework of edge-cloud collaboration is constructed for resource allocation based on online auction in radio access network. We apply the Lyapunov optimization technology to solve stochastic optimization problem, which maximizes the long-term revenue in the MEC system.
- We propose the RMOA algorithm and truthful online auction mechanism to obtain effective resource allocation strategy. Dispatcher can balance system revenue and queue length by setting parameter based on RMOA algorithm, and make auction decision dynamically.
- Theoretical analysis shows that the RMOA algorithm can reach to the approximate optimal system revenue while ensuring the stability of MEC system, and simulation experiments prove the effectiveness of RMOA algorithm.

2 System Model and Problem Formulation

We formulate a MEC system in radio access network, where N IoT devices with computation-intensive tasks are offloaded by a MEC server or a cloud data center. Let $\mathcal{I}$ denote the collection of the IoT device. There is a small base station (SBS) with a MEC server in this system, which can be regarded as a dispatcher or auctioneer, and the cloud data center connects to the edge via a wired channel. Owing to the limited processing capacity of edge server, when too many IoT devices arrive at the same time, edge server will offload computing tasks to the cloud. The system operates tasks with a slot length ι, there exist $t \in \{0, 1, ..., T-1\}$ [14,15].

We assume that all of the IoT devices are heterogeneous, they have different specifications and no prior knowledge. IoT devices submit their own bidding profiles to the dispatcher, which can be denoted by a 3-tuple parameter $\theta_i(t) = <u_i(t), c_i(t), b_i(t)>$, where $\theta_i(t) \in \theta_i, \varPhi = \{\theta_1, \theta_2, ..., \theta_{\mathcal{I}} | i \in \mathcal{I}\}$. $u_i(t)$ represents the profit of completing this calculation task, $c_i(t)$ denotes the CPU cycles required to complete the unit data computation task, $b_i(t)$ represents bid value of IoT device i. Auctioneer will make a computing resource scheduling policy based on the received bidding profiles.

Due to the transmission speed of downlink is much faster than that of uplink, the transmission cost of downlink could be ignored. The transmission rate of device i is given as follows

$$r_i(t) = w_l log_2(1 + \frac{p_i h_i(t)}{w_l \sigma^2}), \tag{1}$$

where w_l represents channel bandwidth between SBS and terminal equipments, σ^2 denotes the noise power spectral density. p_i and $h_i(t)$ are defined as transmission power and channel gain, respectively. Let $a_i(t)$ (bits) indicate the number of the offloaded computing task requests at time slot t with a time average rate $\lambda_i = \mathbb{E}\{a_i(t)\}$ [16].

We define that $f_e(t)$ is the edge server CPU-cycle frequency, and it has an upper bound denoted by f_e^{max}, which can be written as

$$f_e(t) \leq f_e^{max}. \tag{2}$$

Let $d_i^s(t)$ is the data execution quantity of edge server for IoT device i. For edge server, given the CPU-cycle frequency $f_e(t)$, the allocated computation tasks have an upper bound, which is

$$\sum_{i \in \mathcal{I}} c_i(t) d_i^s(t) / f_e(t) \leq \iota. \tag{3}$$

We assume that the winner of the bid is identified as $\mathcal{X}(t) = \{x_i(t) | i \in \mathcal{I}\}$, which can be expressed as

$$x_i(t) = \begin{cases} 1, & \text{if IoT device } i \text{ is winning bid at slot } t, \\ 0, & otherwise. \end{cases} \tag{4}$$

We assume each IoT device's computing task should be completed in only one time slot, so they can only win a maximum of one bid, the constraint is

$$\sum_{t\in\mathcal{T}} x_i(t) \leq 1, \forall i \in \mathcal{I}. \quad (5)$$

We adopt $Q_i(t)$ to represent the queue length of tasks not being processed in SBS, and $d_i^c(t)$ denotes the number of offloaded data from SBS to cloud server. Then, the queue backlog $Q_i(t)$ is

$$Q_i(t+1) = max\{Q_i(t) - d_i^s(t) - d_i^c(t), 0\} + a_i(t). \quad (6)$$

In order to ensure system stability and reduce queue backlog, we define a limit condition on the average queue backlog. q_i denotes the time average queue backlog, which can be described in

$$q_i = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\left\{Q_i(t)\right\} < \eta, \exists\eta \in \mathbb{R}^+. \quad (7)$$

2.1 Cost Model

In this article, we consider the costs of energy consumption when IoT devices win the bidding, which includes the transmission energy consumption from IoT devices to SBS, the computing energy consumption of MEC server and cloud server. The transmission energy consumption $E_i^{tra}(t)$ is

$$E_i^{tra}(t) = p_i \frac{d_i^s(t) + d_i^c(t)}{r_i(t)}. \quad (8)$$

We define κ as the influence coefficient of relating to capacitor execution, and the computation energy consumption of MEC server is

$$E_i^e(t) = \kappa c_i(t) d_i^s(t) f_e^2(t). \quad (9)$$

Let μ represent the energy consumption coefficient in cloud data center, the computation energy consumption in cloud is defined as

$$E_i^c(t) = \mu d_i^c(t). \quad (10)$$

Since the transmission capacity of wired channels is limited, the constraint should be satisfied when offloading computing tasks from SBS to cloud

$$\sum_{i\in\mathcal{I}} d_i^c(t)/w_c \leq \iota, \quad (11)$$

were w_c is the wired channel bandwidth between SBS and cloud, and w_c has an upper bound, which can be expressed as $w_c \leq w_c^{max}$.

According to the above description, the total cost of energy consumption in the whole system as follows

$$\psi(t) = \sum_{i \in \mathcal{I}} g_i(t)\{E_i^{tra}(t) + E_i^e(t) + E_i^c(t)\}, \tag{12}$$

where $g_i(t)$ is the unit cost of energy consumption for device i, which may vary from different IoT devices. Then, the time average of cost function of the MEC system is

$$\varphi = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\left\{\psi(t)\right\}. \tag{13}$$

2.2 Utility Model

In this model, we introduce the system utility that contains two parts: the utility $U_l(t)$ of IoT devices win the bidding and the revenue $U_e(t)$ of completing the calculation task for MEC system. Hence, the $U_l(t)$ is formulated as

$$U_l(t) = \sum_{i \in \mathcal{I}} [b_i(t) - \pi_i(t)]. \tag{14}$$

Meanwhile, $u_i(t)$ represents the evaluation of the system revenue from the completing the calculation task. Denote the payment to edge server by $\pi_i(t)$. Then, the revenue of edge server is written as

$$U_e(t) = \sum_{i \in \mathcal{I}} [\pi_i(t) + u_i(t)] \tag{15}$$

According to the above formulas, we can get the utility function in this MEC system

$$\begin{aligned} U(t) &= U_l(t) + U_e(t) - \psi(t) \\ &= \sum_{i \in \mathcal{I}} x_i(t)\{[b_i(t) + u_i(t)] - g_i(t)[E_i^{tra}(t) + E_i^e(t) + E_i^c(t)]\}. \end{aligned} \tag{16}$$

2.3 Optimization Problem

In this article, we think about the problem of system revenue maximization (SRM). An optimization problem to maximize the time average revenue in the MEC system with the queue stability constraints is proposed, which is as follows

$$\textbf{(SRM)} \max_{d^s(t), d^c(t)} U = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\left\{U(t)\right\}. \tag{17}$$

$$s.t. \, (2), (3), (4), (5), (7) \, and \, (11).$$

The wireless channel conditions, and information of bidding files are dynamic in our modle. In addition, the MEC system has no prior knowledge and can not obtain future information about IoT devices. An online auction mechanism based on Lyapunov techniques is put forward, which can transform stochastic optimization problem into deterministic optimization problem.

3 Revenue Maximization Online Auction Algorithm Design

To effectively resolve this optimization problem, we propose a truthful online auction mechanism and the revenue maximization online auction (RMOA) algorithm. In the auction, IoT devices could submit real bids through the following pricing strategy to compete computing resource effectively. Then, auctioneer determines the winner and resource allocation strategy.

3.1 Pricing Strategy

Because of the selfishness of IoT device, they might submit bidding information untruthfully in order to maximize own profit. To solve this problem, we have introduced the VCG auction mechanism [17], which can make the system achieve a truthful auction process. The strategy for determining the winner can be effectively solved by Hungarian algorithm [15].

We pay attention to the problem of collaborative computing in IoT after successful bidding of IoT devices with Hungarian algorithm. Then, the task of the IoT device i is performed on the server, where $x_i(t) = 1$. After the winner is determined, the auctioneer needs to determine the payment according to the VCG pricing scheme to ensure the authenticity of the bid. Therefore, the payment charged by auctioneer to IoT device i can be given as

$$\pi_i(t) = [SRM(\varPhi) - SRM(\varPhi \setminus \theta_i(t))], \tag{18}$$

where $SRM(\varPhi)$ is the maximum achievable objective function value, $SRM(\varPhi \setminus \theta_i(t))$ denotes the optimal objective function value without IoT device i participation. Due to pricing strategy of VCG auction mechanism contents authenticity of the whole system and the payment $\pi_i(t)$ depends on the bids of other IoT devices, which can encourage the bidders to bid truthfully.

3.2 Evaluation of Computation Tasks

We use Lyapunov optimization technology to transform the problem above. $\varTheta(t) = (Q_i(t))$ can be expressed as the queue backlog matrix in MEC system. Then, the *Lyapunov function* is

$$L(\varTheta(t)) = \frac{1}{2}\sum_{i \in \mathcal{I}}[Q_i^2(t)] \tag{19}$$

where $L(\varTheta(t))$ represents the congestion status of the IoT devices. Then, we set the *conditional Lyapunov drift* $\varDelta(\varTheta(t))$ is

$$\varDelta(\varTheta(t)) = \mathbb{E}\{L(\varTheta(t+1)) - L(\varTheta(t))|\varTheta(t)\}. \tag{20}$$

By keeping the Lyapunov function $\varDelta(\varTheta(t))$ at a small value sate, the revenue function can be maximized. Hence, combining the queue length and scheduling revenue, the *drift plus revenue* is $\Delta(\Theta(t)) - V\mathbb{E}\{U(t)|\Theta(t)\}$, where V is a non-negative number, which is the weight parameters on revenue function and queue length.

Theorem 1. *Under any scheduling algorithm, suppose that the upper bound of* $a_i(t)$ *is* a_i^{max}*, for arbitrary values of* V *and* $\Theta(t)$*, the drift plus revenue will be satisfied the following inequality*

$$\begin{aligned}\Delta(\Theta(t)) - V\mathbb{E}\{U(t)|\Theta(t)\} &= \frac{1}{2}\sum_{i\in\mathcal{I}}[Q_i^2(t+1) - Q_i^2(t)] - V\mathbb{E}\{U(t)|\Theta(t)\}\\ &\le C - V\sum_{i\in\mathcal{I}}\mathbb{E}\{b_i(t) + u_i(t) - g_i(t)[E_i^{tra}(t) + E_i^e(t) + E_i^c(t)]|\Theta(t)\}\\ &+ \sum_{i\in\mathcal{I}}Q_i(t)\mathbb{E}\{a_i(t) - [d_i^s(t) + d_i^c(t)]|\Theta(t)\},\end{aligned} \tag{21}$$

where $C = \frac{1}{2}\sum_{i\in\mathcal{I}}[(a_i^{max})^2 + (\frac{f_e^{max}\iota}{c_i} + w_c^{max}\iota)^2]$ is a constant.

Proof: Combining with the fact $(\max[A-B,0])^2 \le A^2 + B^2 - 2AB(A, B \ge 0)$ and taking square on (6), which as follows

$$\begin{aligned}Q_i^2(t+1) \le\ & Q_i^2(t) + a_i^2(t) + [d_i^s(t) + d_i^c(t)]^2 - 2Q_i(t)[d_i^s(t) + d_i^c(t)]\\ &+ 2a_i(t)\max\{Q_i(t) - [d_i^s(t) + d_i^c(t)], 0\}.\end{aligned} \tag{22}$$

Then, we assume $\bar{d}_i(t) = d_i^s(t) + d_i^c(t)$ represents the number of request from IoT device i to edge server, which is

$$\bar{d}_i(t) = \begin{cases} d_i^s(t) + d_i^c(t), & d_i^s(t) + d_i^c(t) \le Q_i(t),\\ Q_i(t), & otherwise.\end{cases} \tag{23}$$

Owing to $\max\{Q_i(t) - [d_i^s(t) + d_i^c(t)], 0\} = Q_i(t) - \bar{d}_i(t)$, and according to the formula (22), (23) above, and taking the expectations and summing over all the IoT devices,

$$\begin{aligned}\Delta(\Theta(t)) \le\ & \frac{1}{2}\sum_{i\in\mathcal{I}}\mathbb{E}\{a_i^2(t) + [d_i^s(t) + d_i^c(t)]^2|\Theta(t)\}\\ &+ \sum_{i\in\mathcal{I}}Q_i(t)\mathbb{E}\{a_i(t) - [d_i^s(t) + d_i^c(t)]|\Theta(t)\}.\end{aligned} \tag{24}$$

Due to $f_e(t) \le f_e^{max}$ and $w_c \le w_c^{max}$, we can get $d_i^s(t) \le \frac{f_e^{max}\iota}{c_i}$ and $d_i^c(t) \le w_c^{max}\iota)$. In addition, according to the fact that $a_i(t) \le a_i^{max}$, Adding $V\mathbb{E}\{U(t)|\Theta(t)\}$ to inequality (24). Let $C = \frac{1}{2}\sum_{i\in\mathcal{I}}[(a_i^{max})^2 + (\frac{f_e^{max}\iota}{c_i} + w_c^{max}\iota)^2]$, we can get

$$\begin{aligned}&\Delta(\Theta(t)) - V\mathbb{E}\{U(t)|\Theta(t)\}\\ &\quad\le C - V\mathbb{E}\{U(t)|\Theta(t)\}\\ &\quad+ \sum_{i\in\mathcal{I}}Q_i(t)\mathbb{E}\{a_i(t) - [d_i^s(t) + d_i^c(t)]|\Theta(t)\}.\end{aligned} \tag{25}$$

Substituting (12) into (25), therefore, inequality (21) could be obtained. ■

3.3 Online Algorithm

Our RMOA algorithm can make the long-term average revenue achieve to the optimal approximately while keeping the whole system stability, through transforming optimization problem SRM into two independent subproblems. The optimization problem can be rewritten as

$$\max_{d^s(t),d^c(t)} VE\{\{u_i(t)+b_i(t)-g_i(t)[E_i^{tra}(t)+E_i^e(t)+E_i^c(t)]\}|\Theta(t)\} + \sum_{i\in\mathcal{I}} Q_i(t)[d_i^s(t)+d_i^c(t)]. \tag{26}$$

$$s.t. (2), (3), (7)\ and\ (11).$$

Considering the constraint conditions of formulas (2) and (3), we define the first subproblem **P1** and get the optimal edge computation $d^s(t)$ by solving as

$$\mathbf{P1:} \min_{d^s(t)} \sum_{i\in\mathcal{I}} \{V[g_i(t)\frac{p_i}{r_i(t)} + g_i(t)\kappa c_i(t)f_e^2(t)] - Q_i(t)\}d_i^s(t). \tag{27}$$

$$s.t. \quad \sum_{i\in\mathcal{I}} c_i(t)d_i^s(t)/f_e^{max} \le \iota.$$

Since the amount of tasks by computing in edge $d_i^s(t)$ is the decision variable and weighted by $V[g_i(t)\frac{p_i}{r_i(t)}+g_i(t)\kappa c_i(t)f_e^2(t)]-Q_i(t)$, the optimal solution $d_i^s(t)$ is expressed as

$$d_i^s(t) = \begin{cases} \frac{f_e^{max}\iota}{c_i(t)}, & i=i^{'}, \\ 0, & otherwise, \end{cases} \tag{28}$$

where $i^{'} = \text{argmin}_{i\in\mathcal{I}}\{V[g_i(t)\frac{p_i}{r_i(t)} + g_i(t)\kappa c_i(t)f_e^2(t)] - Q_i(t)\}$. Therefore, the optimal resource scheduling strategy according to (28) can be obtained.

Considering the relevant constraint conditions, the second subproblem **P2** can be defined as (29), the optimal resource allocation strategy $d^c(t)$ solves as

$$\mathbf{P2:} \min_{d^c(t)} \sum_{i\in\mathcal{I}} \{V[g_i(t)\frac{p_i}{r_i(t)} + g_i(t)\mu] - Q_i(t)\}d_i^c(t) \tag{29}$$

$$s.t. \quad \sum_{i\in\mathcal{I}} d_i^c(t)/w_c \le \iota.$$

We assume that $d_i^s(t)$ is constant, and the decision variable $d_i^c(t)$ is weighted by $V[g_i(t)\frac{p_i}{r_i(t)} + g_i(t)\mu] - Q_i(t)$, which is

$$d_i^c(t) = \begin{cases} w_c\iota, & i=i^{'}, \\ 0, & otherwise, \end{cases} \tag{30}$$

Where $i^{'} = \text{argmin}_{i\in\mathcal{I}}\{V[g_i(t)\frac{p_i}{r_i(t)} + g_i(t)\mu] - Q_i(t)\}$. Hence, the optimal computation allocation $d^s(t)$, $d^c(t)$ can be determined. Furthermore, the queue length $Q_i(t)$ updates according to (6).

Algorithm 1. Revenue Maximization Online Auction Algorithm (RMOA)

Get the current queue length $Q_i(t)$ of all the IoT devices
for all $i \in \mathcal{I}$ **do**
  Using Hungarian algorithm to get $x^*(t)$
  if $x_i^*(t) == 1$ **then**
    Compute $\pi_i(t)$ based on (18)
  end if
end for
for all $i \in \mathcal{I}$ **do**
  Search for index i_1^* with the minimum value of $V[g_i(t)\frac{p_i}{r_i(t)} + g_i(t)\kappa c_i(t) f_e^2(t)] - Q_i(t)$
  Set $d_i^s(t)$ based on (28)
end for
for all $i \in \mathcal{I}$ **do**
  Search for index i_2^* with the minimum value of $V[g_i(t)\frac{p_i}{r_i(t)} + g_i(t)\mu] - Q_i(t)$
  Set $d_i^c(t)$ based on (30)
end for

Remark: In the MEC system, there is a tradeoff V between resource allocation revenue and queue backlog. The RMOA algorithm can reach the tradeoff with the different times and queue backlog. In time slot t, combining the resource scheduling cost with auction profit, the RMOA algorithm can obtain the optimal resource scheduling policy to maximize the whole system revenue. The details of RMOA is shown in Algorithm 1.

4 Algorithm Analysis

We perform the theoretical analysis of the RMOA algorithm and analysis results indicate that our algorithm can reach the approximate optimal while ensuring the stability of the MEC system. $\bar{Q}$ represents the long-term time average queue backlog, which is

$$\bar{Q} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{i=1}^{\mathcal{I}} \mathbb{E}\left\{Q_i(t)\right\}. \tag{31}$$

Lemma 1. *For arbitrary tasks arrival rate ϑ ($\vartheta > 0$) , there is an optimal randomized policy ρ, which is irrespective of the current queue length and satisfies as follows*

$$\mathbb{E}\{U^{\rho^*}(t)\} = U^*(\vartheta), \tag{32}$$

$$\mathbb{E}\{a_i(t)\} \le \mathbb{E}\{d_i^{s\rho^*}(t) + d_i^{c\rho^*}(t)\}. \tag{33}$$

Proof: **Lemma** 1 can be proved by using Caratheodory's theorem. In order to simplify the paper and enhance the readability, we have omitted the proof. The proof process in detail is just from [18]. ■

Theorem 2. *If there exists nonnegative ϵ satisfies $\vartheta + \epsilon \in \Omega$, where Ω denotes capacity region of the MEC system. The arbitrary value of V, time average system revenue U^{RMOA} under the assumptions in Lemma 1, which has lower bounded*

$$U^{RMOA} \geq U^* - \frac{C}{V}, \tag{34}$$

C is defined in (21), and U^* is the maximum average system revenue.

Proof: By applying **Lemma** 1, arbitrary tasks arrival rate $\vartheta + \epsilon$, there is an optimal randomized strategy $\rho^{'}$ satisfies

$$\mathbb{E}\{U^{\rho^{'}}(t)\} = U^*(\vartheta + \epsilon), \tag{35}$$

$$\mathbb{E}\{a_i(t)\} \leq \mathbb{E}\{d_i^{s\rho^{'}}(t) + d_i^{c\rho^{'}}(t)\} - \epsilon. \tag{36}$$

According to **Theorem** 1, we can get that the lower bound of *drift plus revenue* could be maximized by our RMOA algorithm. Therefore, applying **Lemma** 1 to formula (25), replacing the random strategy with $\rho^{'}$, and bring (35) and (36) into formula (37), the following inequality holds

$$\begin{aligned} &\Delta(\Theta(t)) - V\mathbb{E}\{U(t)|\Theta(t)\} \\ &\quad \leq C - VU^*(\vartheta + \epsilon) - \epsilon \sum_{i \in \mathcal{I}} Q_i(t). \end{aligned} \tag{37}$$

Taking expectation on both sides in formula (37), considering the over time slot and making use of iterating expectations, there exist formula (38)

$$\begin{aligned} &\mathbb{E}\{L(\Theta(T))\} - \mathbb{E}\{L(\Theta(0))\} - V\sum_{t=0}^{T-1}\mathbb{E}\{U(t)\} \\ &\quad \leq CT - VTU^*(\vartheta + \epsilon) - \epsilon \sum_{t=0}^{T-1}\sum_{i \in \mathcal{I}}\mathbb{E}\{Q_i(t)\}. \end{aligned} \tag{38}$$

Since $L(\Theta(T)) \geq L(\Theta(0))$, ϵ and $Q_i(t)$ are both positive. Dividing both sides of the above formula by VT at the same time, the relaxation method is used for the previous formula, it can be obtained as

$$\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{U(t)\} \geq U^*(\vartheta + \epsilon) - \frac{C}{V}, \tag{39}$$

according to (39), when $T \to \infty$ and $\epsilon \to 0$, in equation (34) can be proved. ■

5 Experiments Results

In this paper, we formulate a network model of collaborative computing which is consist of 50 IoT devices. The arrival rate $a_i(t)$ of service request is generated

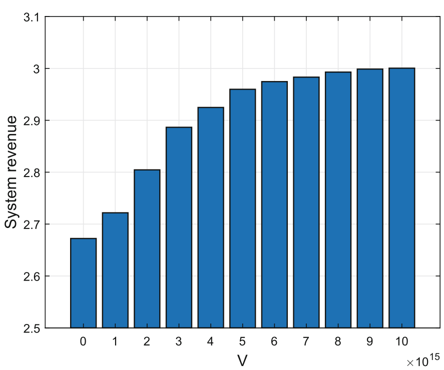

Fig. 1. The system revenue with different values of V.

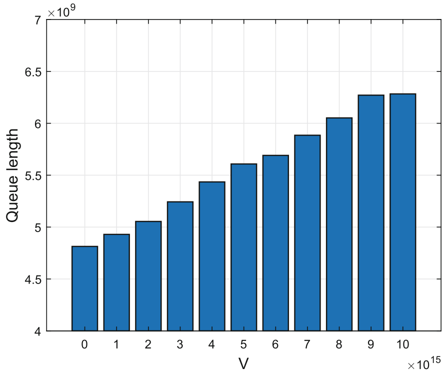

Fig. 2. The queue length with different values of V.

randomly with [2,6] Mbits. The slot length $\iota = 1$ and the transmit power is $p_i \sim U[1, 10]$ W. Then, w_l is 1 MHz and w_c is 10 MHz. Besides, for each IoT device, CPU cycle required for calculating unit data tasks $c_i(t)$ follows uniform distribution with $U[1200, 1800]$. We assume the channel gain $h_i(t)$ is $h_i(t) \sim E(1)$, which follows an exponential distribution. Then, the noise power spectral density σ^2 is 10^{-7} W/Hz. Furthermore, the price of unit energy consumption cost $g_i(t)$ follows normal distribution $N[0, 3]$.

Figures 1 and 2 depict the impact of parameter V on system revenue and queue length. The system revenue increases with V as shown in Fig. 1, this is because the higher the value of V is, the greater the weight of system revenue will be. The reason is that the RMOA algorithm maximizes the revenue of the system by reducing the scheduling cost. Meanwhile, the stability of the task queue is guaranteed as shown in Fig. 2. From Figs. 1 and 2, system revenue and the queue length grow slower and slower as V augments, which follows **Theorem** 2 that system revenue and the queue length have an definite upper bound. Therefore, it is clear that our RMOA algorithm can adjust queue length and system revenue by changing the V value.

In Fig. 3 and 4, we present the influence of different service request arrival rates $\delta \cdot \vartheta$ on system revenue and queue length. System revenue decreases gradually with the increase of the tasks arrival rate in Fig. 3. The reason is that with the growing of arrival rate, the number of uncalculated tasks will also increase, which leads to system revenue reduce. In Fig. 4, since uncalculated tasks accumulate in the system, queue length increases with arrival rate. From the two figures, we can know that system revenue and task queue length converge eventually with different arrival rates. This indicates that the RMOA algorithm can ensure the stability of the whole system.

In Figs. 5 and 6, we compare the other two auction algorithms with our RMOA algorithm in terms of system revenue and queue length. Random allocation algorithm executes the auction decision in a random way. Queue-weighted makes auction decision according to the weighted the task queue length. From

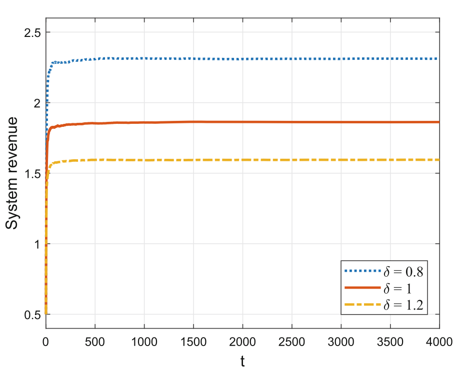

Fig. 3. The system revenue with different arrival rates.

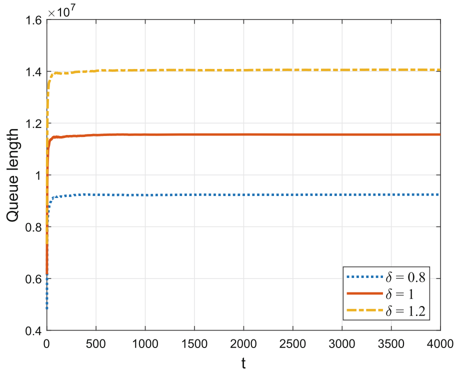

Fig. 4. The queue length with different arrival rates.

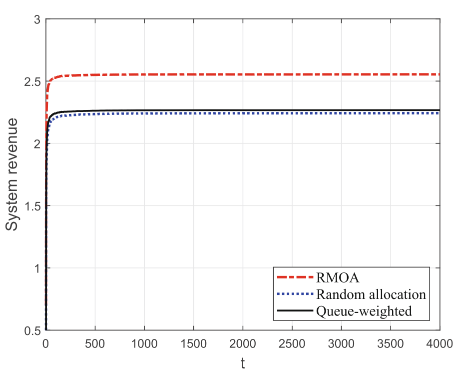

Fig. 5. The system revenue with different algorithms.

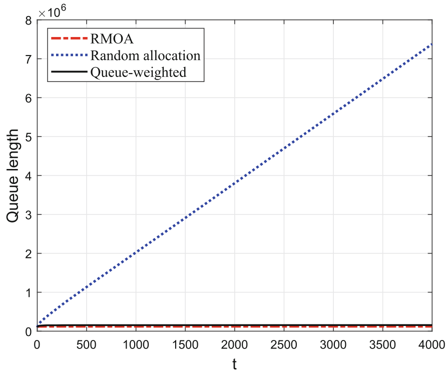

Fig. 6. The queue length with different algorithms.

Fig. 5 and 6, it is obvious that our RMOA algorithm could achieve maximum system revenue and the lowest queue length apparently. Although the queue lengths between RMOA and Queue-weight algorithm are approaching, the Queue-weight algorithm does not consider the dynamic of channel state, so that the system revenue is lower than ours. In conclusion, according to Figs. 5 and 6, our RMOA algorithm has good performance and advantage in optimizing system revenue while ensuring system stability.

6 Conclusion

In this paper, we develop a collaborative computing framework for IoT and a dynamic optimization model is formulated to maximize system revenue while providing performance guarantees. Then, we design a truthful online action mechanism to obtain resultful resource allocation strategy in the MEC system. In addition, the RMOA algorithm is proposed, which can make effective auction strategy according to the bidding files. The theoretical analysis shows that the RMOA algorithm can achieve the approximate optimal system revenue while ensuring the stability of queue length, and simulation results verify the effectiveness of the RMOA algorithm.

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