Cooperative Offloading Based on Online Auction for Mobile Edge Computing

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Abstract. In the field of edge computing, collaborative computing offloading, in which edge users offload tasks to adjacent mobile devices with rich resources in an opportunistic manner, provides a promising example to meet the requirements of low latency. However, most of the previous work has been based on the assumption that these mobile devices are willing to serve edge users, with no incentive strategy. In this paper, an online auction-based strategy is proposed, in which both users and mobile devices can interact dynamically with the system. The auction strategy proposed in this paper is based on an online approach to optimize the long-term utility of the system, such as start time, length and size, resource requirements, and evaluation valuation, without knowing the future. Experiments verify that the proposed online auction strategy achieves the expected attributes such as individual rationality, authenticity and computational ease of handling. In addition, the index of theoretical competitive ratio also indicates that the proposed online mechanism realizes near-offline optimal long-term utility performance.

Keywords: Online auction strategy · Collaborative computing offloading · Long-term utility

1 Introduction

With the continuous development of advanced wireless communication technology in recent years, the number of mobile devices has also exploded. First, these applications are typically resource-intensive, latency-sensitive, and computationally intensive. Second, the computing power required by mobile devices is still

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severely limited by portability operations [1]. This presents a serious test for the future of mobile devices [2].

Offloading computing tasks is a fundamental solution to the problem of resource constraints [3]. Although cloud computing has made great achievements in the past many years, when users finally offload tasks to the public cloud, there is still the problem of long delay, especially in the environment of severe network congestion. In recent years, MEC has been designed as a promising computing paradigm for mobile services with ultra-low latency [4,5]. Rather than offloading tasks to a remote cloud, mobile users address ultra-low latency issues by cooperating with end users or by performing computationally intensive tasks at the network edge of nearby facilitie [6]. It is precisely because it is known that the MEC system performance can be effectively improved through the untapped resources of a large number of mobile devices, this paper studies the MEC framework of user cooperation [7]. Specifically, some mobile devices could partake these untapped resources to assist other edge users in offloading computing tasks [8].

The existing gage is to guarantee the real reliability of the online strategy proposed in this paper. In addition to request-private conditions such as resource requirements and task evaluation involved in offline policies, this paper also needs to address new obstacles, namely ensuring the authenticity of start times and task durations [9]. False edge users purposefully use false reports of their private information to control market decision-making action to obtain high profits, which will deteriorate the long-term profit system [10,11]. This paper adopts the technical expression social utility, which is determined as the total utility of edge end users and mobile devices. The crucial is to incentivize edge users to claim their realistic details through the right price. Only when users report false conditions will they get less utility than if they report true information. Its early classic work - the vicery-clarke-groves (VCG) strategy was used to develop a mechanism to prove its auction [12,13]. However, the existing VCG algorithm is not suitable for the online situation, because its payment determination requires the optimal distribution results. In the case of uncertain future task requests, this paper cannot obtain those optimal solutions [14].

To address all the above problems and challenges, this paper develops an incentive mechanism for online auctions with the following properties: (1) The arrival and departure of computing tasks and mobile devices are dynamic at any time, and each task will be set up with a bundled resource package in the future; the auction decision-making behavior is matched between dynamic tasks and mobile devices. (2) The auction strategy designed in this paper is conducted in an online manner and does not do any suppositions about the arrival of future request information. Despite the premise that future information is not available, task assignment decision-making must be done instantaneously. The main contributions of the artical are summarized as follows.

In this paper, an online incentive strategy is developed in a collaborative MEC environment for multi-type resource users. This paper deals with the generality of collaborative task execution: (1) Tasks are heterogeneous and need different amounts of diversity resources; (2) The number of tasks a mobile device can perform is limited by its resource capacity; (3) The performance of resource supply and demand can affect its unit resource price. Therefore, two mechanisms are designed in this paper. One is an offline mechanism based on VCG, which is optimal as a benchmark. The other is a true online mechanism that only refers to the current request status to make decisions.

2 System Model

A. Mobile Edge Computing: Referring to here a MEC involving M edge users, indicated by $\mathcal{M} = \{1, 2, ..., M\}$, microbase stations for mobile devices N, indicated by $\mathcal{N} = \{1, 2, ..., N\}$ devices serving the users. Mobile devices can be thought of as smartphones, mobile microclouds, ipads and Internet of Things devices. It is assumed that the system is run in timeslot mode, and each timeslot is represented as $t \in \mathcal{T}$, $\mathcal{T} = \{1, 2, ...T\}$. User i's j-th task is denoted as $\mathcal{T}_{ij} = \{t_{ij}, l_{ij}\}$, where t_{ij} stands for the start time of the task, l_{ij} stands for the length of the task, that is, the amount of timeslots used to accomplish the task. Therefore, the index number required to complete the time slot is expressed as $t'_{ij} = t_{ij} + l_{ij} - 1$. Z-Resources for instance CPU, RAM, and bandwidth are assumed. Define $a^z_{ij}(t)$ be the amount of z-resources required for slottime t, whose variable $a^z_{ij}(t)$ varieties with time, and its varieties will be different due to the heterogeneity of computing tasks. $A_{ij} = \left\{a^1_{ij}, a^2_{ij}, ..., a^Z_{ij}\right\}$ is defined as a computing resource as a specified bundle, where $a^z_{ij} = \left\{a^z_{ij}(t) : \forall t \in [t_{ij}, t'_{ij}]\right\}$.

To give a mode for mobility, set t_n and s_n to the interval time and service duration of mobile devices $n \in N$ respectively. The computing resources of each mobile device are limited. Defining C^z_n indicates the maximum capacity of type z-type resources on mobile device N. Because the microbase station can access the all network state, it is a system controller that controls the decision making of task scheduling.

B. Auction Theory: In this paper, the interaction between edge users and mobile devices is modeled as an auction strategy, which edge users are regarded as bidders and mobile devices as sellers. The microbase-station is a trusted third-party auction manager who manages both parties and makes online decisions. Users on the edge ask nearby mobile devices to assist with tasks and provide some immediate reward when the task is completed. The stages of the auction process are as follows:

Set b^j_i to the bid of task $\mathcal{T}_{ij}$. The bidding prototype of the task $\mathcal{T}_{ij}$ should denoted as $\sigma^j_i = \left\{t_{ij}, l_{ij}, A_{ij}, b^j_i\right\} \in \Sigma_i$, where Σ_i is the bidding group of edge user i. There are $\mathcal{M}, \mathcal{N}$ and $\Sigma = \{\Sigma_1, \Sigma_2, ..., \Sigma_M\}$, the auction manager can control a winning bid set $\mathcal{W}$ and a task assignment scheme, i.e., to search a mapping: $\left\{\sigma^j_i : \sigma^j_i \in \mathcal{W}\right\} \rightarrow \{n : n \in \mathcal{N}\}$ and the payment of each winning bidder $\sigma^j_i \in \mathcal{W}$. Note here that each bid σ^j_i is private info for edge user i.

In a fake auction, the bidder will present the difference between his request and his actual request. For the purpose of distinguishing, the submitted bids are indicated by $\sigma^j_i = \left\{t_{ij}, l_{ij}, A_{ij}, b^j_i\right\}$, and the actual request info is indicated as $\bar{\sigma}^j_i = \left\{\bar{t}_{ij}, \bar{l}_{ij}, \bar{A}_{ij}, q^j_i\right\}$.

C. Offline Revenue Maximization Problem: The entire information about bidding and mobile devices is available in an offline environment. There is a tradeoff between the utility and the cost of completing a task, which in turn creates some utilities for the bidder. The bid assignment variable $y_n(\sigma_i^j)$ is given here, and $y_n(\sigma_i^j) = 1$ when the bid σ_i^j is assigned to the mobile device N. And the overall bid allocation strategy is $\mathcal{Y} = (y_n(\sigma_i^j) : \forall n \in \mathcal{N}, \forall \sigma_i^j \in \Sigma)$.

Bidding allocation strategy $\mathcal{Y}$ is defined, $\Lambda = (\lambda_{ij})$ is a payment rule, and λ_{ij} indicates the payment of task $\mathcal{T}_{ij}$. In order to explore this tradeoff, this paper adopts welfare benefit maximization index, which is mainly characterized via system completion utility and mobile device service cost.

1. Computation Completion Utility: Set bid Σ and bid allocation strategy $\mathcal{Y}$, and the system utility that can be completed by computing the task will be expressed as:

$$U(\mathcal{Y}) = \sum_{\sigma_i^j \in \Sigma} \sum_{n \in \mathcal{N}} y_n(\sigma_i^j) \cdot b_i^j \tag{1}$$

2. Mobile Device Service Costs: The service cost of mobile devices mainly comes from its battery energy consumption. This paper applies a linear energy consumption mould according to resource consumption. It is understood that in the case of not using dynamic voltage frequency scaling, its energy consumption and CPU, RAM usage approximately show a linear relationship. Set $r_n^z(t)$ to represent the z-type resource usage on mobile device N at time t, and its relevanting execution cost can be expressed as

$$E_n^z(r_n^z(t)) = \begin{cases} g_n^z r_n^z(t) & 0 \le r_n^z(t) \le C_n^z \\ +\infty & otherwise \end{cases} \tag{2}$$

which g_n^z indicates the energy consumption required to use unit z-type resource in each slottime on mobile device n.

The total resource consumption in $\mathcal{T}$ is summarized by $\boldsymbol{r} = (r_n^z(t)) : \forall n \in \mathcal{N}, \forall z \in \mathcal{Z}, \forall t \in \mathcal{T}$. Therefore, its operating cost is:

$$\Omega_E(\boldsymbol{r}) = \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} \sum_{z \in \mathcal{Z}} E_n^z(r_n^z(t)) \tag{3}$$

3. Utility Maximization Problem: Set Σ_{-i}^{-j} to the entire set of claimed bid profiles for all tasks except bid σ_i^j. That $(\sigma_i^j, \Sigma_{-i}^{-j})$ stand for the entire bidding situation. The user i's untility function is: $\mu_{ij}(\sigma_i^j, \Sigma_{-i}^{-j}) = b_i^j - \lambda_{ij}(\sigma_i^j, \Sigma_{-i}^{-j})$, when exist $x_n(\sigma_i^j) = 1$. The total utility of a mobile device is to receive the total payment minus the cost of service. Social utility maximization problem (SUM) is the difference between the utility completed after task aggregation and the service cost. In short, the problem of maximizing social benefits in the system model in the article will be converted into the mixed integer programming problem as follows:

$$\max_{\mathcal{Y}, \boldsymbol{r}} SUM(\mathcal{Y}, \boldsymbol{r}) = U(\mathcal{Y}) - \Omega_E(\boldsymbol{r}) \tag{4}$$

$$\sum_{\sigma_i^j \in \Sigma: t_{ij} \leq t \leq t'_{ij}} y_n(\sigma_i^j) a_{ij}(t) \leq r_n^z(t) \qquad \forall n, \forall t, \forall z \tag{4a}$$

$$\sum_{n \in \Psi_{ij}} y_n(\sigma_i^j) \leq 1 \qquad \forall \sigma_i^j \tag{4b}$$

$$y_n(\sigma_i^j) \in \{0, 1\} \qquad \forall \sigma_i^j \quad \forall n \in \Psi_{ij} \tag{4c}$$

which $\Psi_{ij} = \{n \in N : t_n \leq t_{ij}, l_{ij} \leq s_n\}$.

3 Offline Auction Strategy Formed

The objective of the article is to design a VCG enabled offline optimal auction strategy in which the auctioneer has the entire future details situation. The optimal allocation outline is the optimal solution of the precisely maximized mixed integer programming, namely, Eq. (4).

Strategy 1. (VCG-enabled Offline Auction Strategy-VCG-OOA)

(1) The allocation strategy $\boldsymbol{Y}_n^O \triangleq (y_n^O(\sigma_i^j) \quad \forall \sigma_i^j \in \Sigma \quad \forall n \in \mathcal{N})$ is derived by optimal solution to the mixed integer programming problem with a union of global bid Σ.

(2) The payment strategy $\boldsymbol{\Lambda}_n^O \triangleq (\lambda_n^O(\sigma_i^j) \quad \forall \sigma_i^j \in \Sigma \quad \forall n \in \mathcal{N})$, which $\lambda_n^O(\sigma_i^j)$ is descripted as :

$$\lambda_n^O(\sigma_i^j) = SUM(\mathcal{Y}^o(\Sigma), \boldsymbol{r}^o(\Sigma)) - b_i^j - SUM(\mathcal{Y}^o(\Sigma - \left\{\sigma_i^j\right\}), \boldsymbol{r}^o(\Sigma - \left\{\sigma_i^j\right\})) \tag{5}$$

where $\Sigma - \left\{\sigma_i^j\right\}$ indicates all bid sequences except bid b_i^j, and $\mathcal{Y}^o(\Sigma - \left\{\sigma_i^j\right\})$ indicates the optimal solution obtained when $\Sigma - \left\{\sigma_i^j\right\}$ treats as the input.

Algorithm 1. OAP-SUM Strategy

1: **Input:** Current Event;
2: $\tilde{t} \leftarrow Now \quad timeslot$;
3: $N(\tilde{t}) \leftarrow \{n |$the collection of mobile devices participating in the auction at$\tilde{t}\}$;
4: $\Psi(\tilde{t}) \leftarrow \left\{\sigma_i^j |\right.$bid has been authorized but work has not yet been processed within$\left.\tilde{t}\right\}$
5: **if** Event=='Mobile device n reaches' **then**
6: $\quad N(\tilde{t}) \leftarrow N(\tilde{t}) \cup n, \quad (t_n \leq t \leq t'_n)$;
7: **end if**
8: **if** Event=='Bid $\sigma_i^j reaches$' **then**
9: $\quad$ Computing the union Ψ_{ij} for bid σ_i^j based on $N(\tilde{t})$;
10: $\quad \mathcal{Y}(\sigma_i^j), \lambda_{ij} \leftarrow$ OAP-SUM-A $(\tilde{t}, N(\tilde{t}), \sigma_i^j, \Psi_{ij})$
11: $\quad \Psi(\tilde{t}) \leftarrow \Psi(\tilde{t}) \cup \sigma_i^j$
12: $\quad \mathcal{Y} \leftarrow \mathcal{Y} \cup \mathcal{Y}(\sigma_i^j), \Lambda \leftarrow \Lambda \cup \lambda_{ij}$
13: **end ifreturn:** $\mathcal{Y}$ and Λ

4 Online Auction Strategy Formation

OAP-SUM Strategy: According to the applicable rules of Myerson's theorem, this paper mainly describes the scheme implementation and allocation rules of SUM online auction policy (OAP-SWM), as shown in Algorithm 1. This paper first develops an event processing application, which involves the call processing of results for instance bid arrival, bid acceptance, task completion, mobile device arrival and mobile device departure (line 2–4). OAP-SUM computes two collections, $N(\tilde{t})$ indicates the collection of mobile devices available at auction time $\tilde{t}$. $\Psi(\tilde{t})$is the collection of accepted bids for unfinished tasks at $\tilde{t}$ (line 5–6). The union $N(\tilde{t})$ is updated as soon as the new mobile device reaches. In the case of submitting a new bid, OAP-SUM first computes the union Ψ_{ij} of bid σ_i^j based on $N(\tilde{t})$ (line 7–9). OAP-SUM-A is controlled by function based on allocation decision and payment decision at lines 10. The OAP-SUM set is then updated at lines 11–12.

1) Allocation policy: This paper uses the primitive dual technique to develop allocation policy. Firstly, the relaxed integer constraint is adopted in Eq. (4c), and $y_n(\sigma_i^j) \in \{0, 1\}$ is converted to $y_n(\sigma_i^j) \geq 0$. Based on the standard Fenchel duality principle, the cost function or the conjugate function form $\hat{E}_n^z(x)$ of $E_n^z(r_n^z(t))$ is first given.

$$\hat{E}_n^z(x) = \underset{r_n^z(t)\geq 0}{max} \{xr_n^z(t) - E_n^z(x)\} \tag{6}$$

The dual variables $\eta_n^z(t)$ and ν_{ij} are added to the Eqs. (4a) and (4b) in the form of constraint conditions. The duality problem is developed as follows:

$$min \sum_{n\in\mathcal{N}} \sum_{z\in\mathcal{Z}} \sum_{t\in\mathcal{T}} \hat{E}_n^z(\eta_n^z(t)) + \sum_{\sigma_i^j\in\Sigma} \nu_{ij} \tag{7}$$

$$\nu_{ij} \geq b_i^j - \sum_{z\in\mathcal{Z}} \sum_{t_{ij}\leq t\leq t'_{ij}} \eta_n^z(t) a_{ij}^z(t) \qquad \forall n, \forall \sigma_i^j \tag{7a}$$

$$\eta_n^z(t) \geq 0 \qquad \forall n, \forall z, \forall t \tag{7b}$$

$$\nu_{ij} \geq 0 \qquad \forall \sigma_i^j \tag{7c}$$

Based on the principle of complementary relaxation primal duality in the Karush -Kuhn -Tucker (KKT) condition, the primal variable $y_n(\sigma_i^j) = 1$ iff the dual constraint, i.e., Eq. (7a) is valid in the optimal solution. In order to realize the feasibility of the double restriction of formula (7a), for each new bid σ_i^jcase, this paper defines:

$$\nu = [y]^+, \quad y = \underset{n\in\Psi_{ij}}{max}(b_i^j - \sum_{z\in\mathcal{Z}} \sum_{t} \eta_n^z(t_{ij}, t) a_{ij}^z(t)) \tag{8}$$

which $[y]^+$ indicates max $\{y, 0\}$. From this comes the allocation rule. In the case of $\nu_{ij} > 0$, bids σ_i^j will be accepted and $y_{n'}(\sigma_i^j) = 1$, otherwise, they will be rejected.

Algorithm 2. OAP-SUM-A $(\tilde{t}, N(\tilde{t}), \sigma_i^j, \Psi_{ij})$

Initialize: $\mathcal{Y}(\sigma_i^j) = (y_n(\sigma_i^j) \quad \forall n \in \mathcal{N}), \lambda_{ij} = 0$;
for $\forall n \in \mathcal{N}(t)$ **do**
  for $\forall z \in \mathcal{Z}$ **do**
    for $\forall t = \tilde{t} : T$ **do**
      $r_n^z(t, \tilde{t}) = \sum a_{ij}^z(t) \quad \forall \sigma_i^j \in \Psi(\tilde{t})$
      $\eta_n^z(t, \tilde{t}) = \Gamma_n^z(r_n^z(t, \tilde{t}))$
    end for
  end for
end for
Obtaining n' via resolving the Eq. (12);
Computing the dual variable value ν_{ij};
Computing the union Ψ_{ij} for bid σ_i^j based on $N(\tilde{t})$;
$\nu_{ij} \leftarrow b_i^j - \sum_{z \in \mathcal{Z}} \sum_{t_{ij} \le t \le t'_{ij}} \eta_{n'}^z(t, \tilde{t}) a_{ij}^z(t)$
$\Psi(\tilde{t}) \leftarrow \Psi(\tilde{t}) \cup \sigma_i^j$
$\mathcal{Y} \leftarrow \mathcal{Y} \cup \mathcal{Y}(\sigma_i^j), \Lambda \leftarrow \Lambda \cup \lambda_{ij}$
if $\nu_{ij} > 0$ **then**
  $y_{n'}(\sigma_i^j) \leftarrow 1$ and $y_n(\sigma_i^j) \leftarrow 0 \quad \forall n \in \{\mathcal{N} - n'\}$
  $\lambda_{ij} \leftarrow \sum_{z \in \mathcal{Z}} \sum_{t_{ij} \le t \le t'_{ij}} \eta_{n'}^z(t, \tilde{t}) a_{ij}^z(t)$
else
  $\nu_{ij} \leftarrow 0$
  $y_n(\sigma_i^j) \leftarrow 0 \quad n \in \mathcal{N}$
end if
return: $\mathcal{Y}(\sigma_i^j)$ and λ_{ij}

(2) Payment Principle: The dual variable $\eta_n^z(t, \tilde{t})$ is taken as the optimal planned price for a z-type resource in time slot $t \ge \tilde{t}$ on mobile device n. Based on the off-line environment, the dual problem can be easily resolved directly to obtain these prices. However, it is difficult to get these prices when bids change dynamically over time. An auxiliary price function of $r_n^z(t) \in [0, C_n^z]$ is developed to realize online decision as soon as possible.

$$\Gamma_n^z = \frac{P_z - g_n^z}{2Z} \left(\frac{2Z(Q_z - g_n^z)}{P_z - g_n^z}\right)^{\frac{r_n^z(t)}{C_n^z}} + g_n^z \tag{9}$$

which $P_z = \underset{\sigma_{ij}}{min} \frac{b_i^j}{\sum\limits_{t \in [t_{ij}, t'_{ij}]} a_{ij}(t)}$, $Q_z = \underset{\sigma_{ij}}{max} \frac{b_i^j}{\sum\limits_{t \in [t_{ij}, t'_{ij}]} a_{ij}(t)}$ are respectively the lower and upper limits of the bidder's valuation of unit z-type resources, which are obtained from previous information. All explanations are given in the future paper Appendix. In a word, the specific details of the allocation principle appear in OAP-SUM-A of Algorithm 2.

5 Experimental Analysis

A. Experimental Environment Setting: The task data in this paper is taken from Google database, which composed of task start time, implementation time and resource requirement conditions. This article converts the request into a bid, as shown below. This paper assumes two types of resources, namely $Z = 2$. In order to obtain the bidding value of the task, the unit z-type resource valuation is taken from the random selection in P_z, Q_z, whose bidding value corresponds to its resource requirements within the quantization range of the unit valuation. The value range of P_z, Q_z varies with different experiments. $Q_z = 8$ and $P_z = 1$ are the default cases.

Under other default conditions, the edge computing system in this paper contains $N = 20$ mobile devices. In this paper, the cycle T of 300 timeslots is tried to run, and then the trajectory of the mobile device is randomly generated. It is supposed that mobile devices have the property of Poisson process arrival in average arrival interval N/T, and their service time interval s_n is selected uniformly and randomly in $[15, 35]$, and the normalized resource capacity of each mobile device comes from the uniform and random distribution within the range of $[0.25, 0.35]$. g_n^z is uniformly and randomly distributed between the range $[0.6 - 1]$.

B. Actual Acquisition of Competitive Ratio Analysis: This paper adopts online auction strategy to realize the comparison between the actual competition ratio and the corresponding theoretical one. The actual competition ratio is based on the OAP-SUM Algorithm to realize the ratio between the maximum actual social utility and the optimal offline social utility. The value of the theoretical competition ratio is $ln(2Z\gamma)$, which $\gamma = \underset{n,z}{max} \frac{Q_z - g_n^z}{P_z - g_n^z}$.

Figure 1(a) verifies the comparison between the actual and theoretical competition ratios of OAP-SUM Algorithm as the number of tasks grows. $Q_z = 8$, the paper learned that most of the actual competitive ratio is around 1.4, which is far less than the upper limit of the actual theoretical value, which denotes that the online strategy developed shows superior performance. However, the value of the actual competition ratio increased slightly with the grow in the number of tasks. The real reason is that with the grow of tasks, the future uncertainty will be more difficult to control, and the possibility of task allocation will be more and more, and the corresponding decision difficulty will be more and more uncontrollable. Furthermore, it is specifically understood that the theoretical ratio is not correlated with the corresponding number of tasks.

In Fig. 1(b), the functional forms of actual and theoretical competition ratios of OAP-SUM are studied when parameter γ ranges from 6 to 12. The number of tasks given here is 120 and the number of mobile devices is 20. Thus, with the increase of γ, the actual ratio will also increase. This makes sense because higher unit resource prices will lead to real improvements in competitiveness. The theoretical ratio is the same. This verification result is consistent with the analysis that the competition ratio is controlled by the value of $ln(2Z\gamma)$.

C. Individual Rational Analysis: This paper studies the performance of OAP-SUM from the perspective of individual rationality, as illustrated in Fig. 2. Here, 20 successful bids are randomly selected from the winning collection, and the submitted bids, actual payments, and actual execution costs are given. It can be seen from Fig. 2 that the bid submitted is continuously greater than the actual

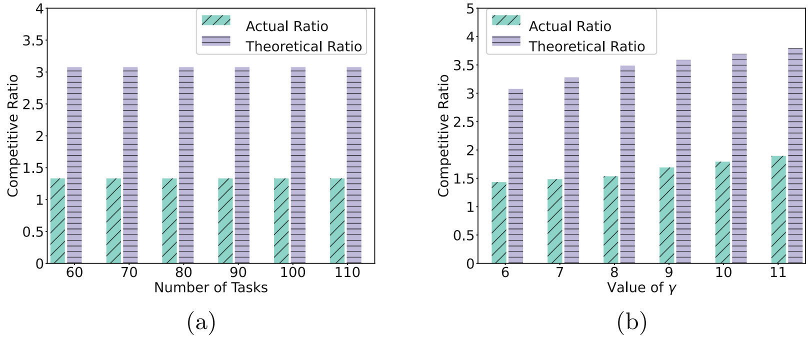


Fig. 1. Competitive Ratio of different number of tasks with γ.

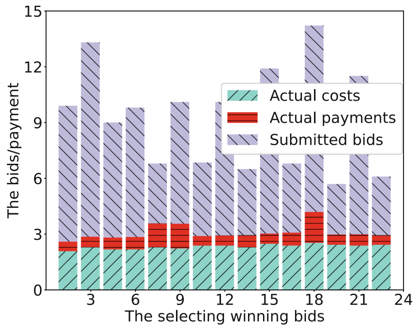


Fig. 2. Individual rational analysis

payment price paid to mobile devices, i.e., the individual rationality is guaranteed by OAP-SUM. **D. True Validity Analysis:** Now we study the analysis of the true validity of OAP-SUM. Figure 3 shows the performance impact of unreal resource requirements and task execution time on user utility respectively. In this paper, a winning bid σ_i^j is randomly selected and its bid situation is adjusted at any time. Meanwhile, the OAP-SUM algorithm is run again with other bids unchanged. It is stated here that the user cannot declare that the execution time is shorter than the actual execution time and the actual resource demand is less. Therefore, this article only applies to the environment where the user claims that the execution time is longer and the resource demand is higher. The value on the x-axis refers to the ratio of claimed resource requirements to actual resource requirements. It follows from this that submitting more bids than actual resource requirements will reduce the user's utility, while the actual resulting true resource requirements will yield the highest utility.

Similarly, the added task execution time in Fig. 3(b) is a bid σ_i^j in the range from 10 to 20, and its real value is 10. As can be seen from the graph, submitting bids with longer execution times than actual times will reduce the user's utility, while actual verified true execution times will yield the highest utility.

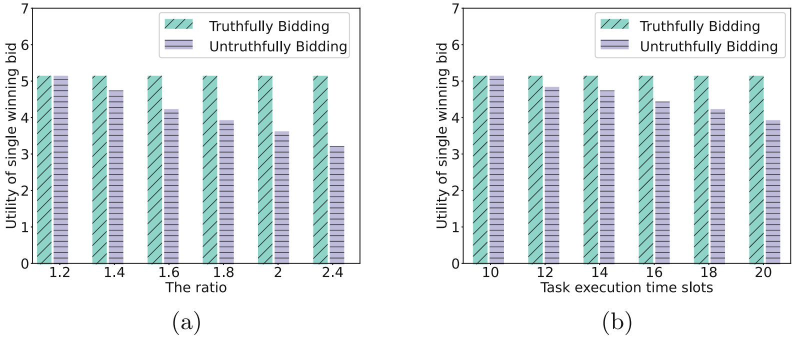


Fig. 3. Authenticity analysis

E. Comparison of the Two Proposed Strategies: The online mechanism OAP-SUM is now compared with the offline one VCG-OOA according to two capability indexes of user utility and winner percentage.

Figure 4 verifies the function comparisons of VCG-OOA and OAP-SUM in the light of user utility and winner percentage, respectively, as the number of tasks grows. It can be concluded that the user utility of OAP-SUM is larger or smaller than that of VCG-OOA in Fig. 4(a). The reason for this is that although there is an allocation optimum, VCG-OOA may not necessarily be the payment optimum. Figure 4(b) verifies the difference in function comparison of winner percentages. It is worth mentioning that the percentage of winners serves as a measure of distribution efficiency. Typically, the allocation strategy of OAP-SUM is close to optimal because its winner percentage is very close to the result of VCG-OOA. It can also be seen from the figure that as the amount of tasks grows, the percentage of winners will decrease. The reason behind this is that owing to the restricted resource capacity of mobile devices, the increased task value is greater than the increased number of winners.

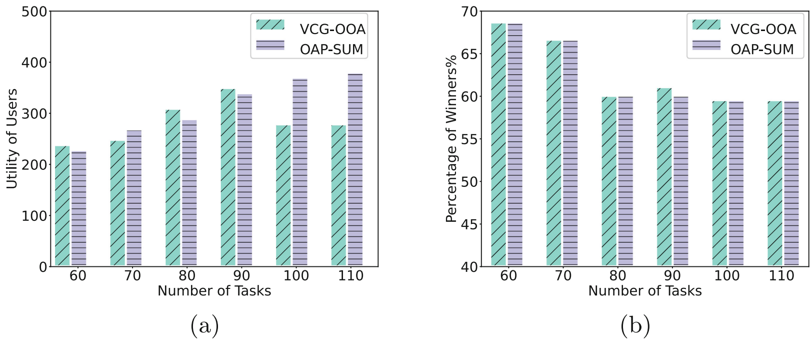
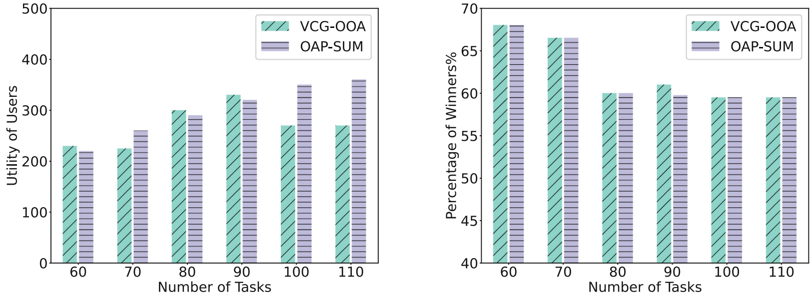


Fig. 4. Analysis and comparison of different number of tasks

Figure 5 verifies how the winner's utility and the winner's percentage are influenced when the ratio γ is increased from 6 to 12. Figure 5(a) shows that the utility of VCG-OOA is to maintain a kind of stability, while the utility of OAP-SUM decreases with the grow of γ value. The major reason is that the ratio σ is only a range of the marginal price function of the OAP-SUM strategy and will not affect the VCG-OOA strategy. OAP-SUM takes advantage of the increasing value of γ, which in turn charges the winner more to reduce user utility. Similarly, as displayed in Fig. 5(b), the percentage of winners shows a decreasing trend with the increase of γ value.



(a) (b)

Fig. 5. Comparative analysis of different γ

6 Conclusion

In this paper, cooperative computing offload performance in MEC is investigated. In this paper, task offloading scheduling is modeled as an NP-hard SUM problem, and an offline optimization strategy is first used as a reference benchmark. This paper further designs an online strategy that does not rely on future details, which not only schedules computing tasks and computing payments in polynomial time without involving future details, but also optimizes the long-term social utility problem in a near-optimal fashion. A large number of theoretical analyses show that the designed online auction achieves such properties as individual rationality, authenticity and computational tractability. Meanwhile, function evaluations on actual world trajectories also validate the valid performance of the online mechanism proposed in this paper.

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