Incentive Mechanism for Edge Cloud Profit Maximization in Mobile Edge Computing

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***Abstract*—Mobile edge computing (MEC) has become a promising technique to accommodate demands of resource-constrained mobile devices by offloading the task onto edge clouds nearby. However, most existing works only focus on whether or where a task is offloaded but ignore the motivation of the edge cloud to offer service. To stimulate service provisioning by edge clouds, it is essential to design an incentive mechanism that charges mobile devices and rewards edge clouds. In this paper, we utilize market-based pricing model to establish a relationship between the resources provided by edge clouds and the price paid by the mobile devices in a non-competitive environment. Furthermore, we design a profit maximization multi-round auction (PMMRA) mechanism for the resource trading between edge clouds as sellers and mobile devices as buyers in a competitive environment. The mechanism can effectively determine the price paid by the buyers to use the resources provided by the sellers and make the corresponding match between edge clouds and mobile devices. Finally, numerical results show that proposed mechanism outperforms other existing algorithms in maximizing the profits of resource providers.**

***Index Terms*—Mobile edge computing, incentive mechanism, auction mechanism, profit maximization**

I. Introduction

In the era of mobile computing and Internet of Things, the explosive growth of resource-hungry applications puts forward higher requirements for mobile devices. Due to the physical size, mobile devices usually have the limited processing capacity and battery life. Mobile edge computing (MEC) is such a promising technology that narrows the distance between mobile devices and the clouds by turning any potential resource-abundant device into edge cloud. Unlike mobile cloud computing (MCC), mobile devices do not need to offload tasks to a distant central cloud but the edge clouds nearby in MEC. Reduced transmission distance brings ultra-low latency and longer battery lifetime of mobile devices [1], [2].

MEC utilizes task partitioning and offloading technique to enhance the performance significantly and create a shared atmosphere that when a mobile device needs to help, other devices nearby can share their extra resources with the device and vice versa. But very few efforts in recent years have been taken on the motivation for sharing resources. We consider the edge clouds as resources providers (RP) and the mobile devices which need help as users. Intuitively, the motivation for sharing resources is how many economic benefits a resource provider can obtain from each service while guaranteeing users' quality of experience (QoE). Therefore, it is essential to model the profit maximization incentive mechanism for resource providers. Besides, the characteristics of economic markets need to be considered. MEC network is an open environment, thus one of the most important features is competition. If you can offer more powerful processing capacity with lower prices, more users are intended to enjoy your service. Thus it is important to match resource providers with corresponding users in a competitive environment.

Some existing works proposed some incentive mechanisms for MEC or crowd sensing networks [3], [4]. In [3], Zhang et al. proposed a joint coalition-and-pricing based data offloading approach to arrange data offloading of mobile devices (MDs) as well as depict the offloading relationship between MDs and MEC servers. However they ignored the computing energy consumption on edge clouds. In fact, it is an imperative factor of making pricing policies since edge clouds are also mobile devices rather than central cloud with unlimited resources. In other words, the previous works ignored the characteristics that edge clouds have distinct capabilities and the limited resources in MEC networks. This motivates us to formulate the more reasonable total cost on edge cloud.

In addition, open auction mechanism have been studied to establish the relationship between sellers and buyers in MCC. In [5], Samimi et al. proposed a new market model called the Combinatorial Double Auction Resource Allocation (CDARA) to address the problem how to design an optimal market-based resource allocation in cloud computing services. But it is unrealistic in the MEC network because the global information of edge clouds is not readily available. Another key factor influencing auction mechanism is winner determining. And they set the bid level submitted by sellers as the only criterion for determining winner. This is unfair to the buyers, because we cannot exclude that the sellers intentionally raise the price for their own profits.

Therefore, it is critical how to design a more persuasive auction mechanism to maximize the profit of resource providers on the premise of satisfying user demands with the participation of users. The objective of this paper is to propose an incentive mechanism for resource providers to maximize their profits in mobile edge computing by utilizing market-based pricing and auction model. Compared with the previous work, this paper has several contributions. *First*, we

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formulate the incentive mechanism into a profit maximization problem based on market pricing model by considering both the utility of resource providers and the constraint on user benefits in the non-competitive environment. And we utilize the convex optimization method to get the optimal solution. *Second*, we design an efficient PMMRA mechanism to match the users with resource providers and determine the final payment in the competitive environment. The mechanism consists of three parts: bidding strategy, user matching and payment determination. Then we prove several properties of the proposed auction mechanism. *Third*, we evaluate the performance of our proposed auction mechanism by taking the auction results in the non-competitive environment as a benchmark. Experimental results show that compared with other existing algorithms, our proposed PMMRA mechanism is more effective in ensuring the profits of resource providers and the benefits of mobile users.

II. System Model

A. Network Model

As illustrated in Fig. 1, we consider a mobile edge computing architecture with one trusted third party, I edge clouds and J mobile devices/users. The edge cloud includes the fixed edge gateway and and some mobile phones with abundant resources, which assists mobile devices to offload computing tasks. The edge cloud is the resource provider (RP) and mobile devices are the users who use these resources. The users can offload their tasks onto RPs if their connections are available. The processing capacity of RP i is quantified by the clock frequency. We assume that the resource status of RP i are the 2-tuple (f_i, W_i), where f_i and W_i are the clock frequency and channel bandwidth owned by RP i, respectively.

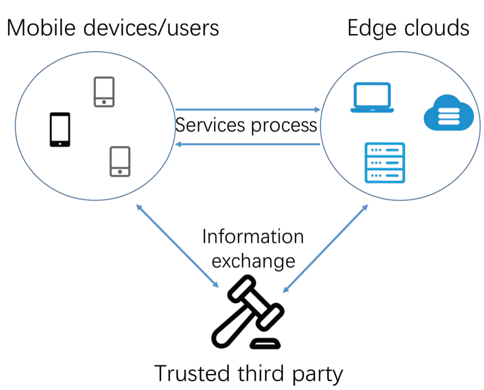


Fig. 1. A typical MEC architecture in an auction environment.

Each user has multiple different computation tasks to be offloaded onto the RP. The task of user j can be expressed by (f_j, d_j, Cy_j), where f_j is the clock frequency of user j, d_j denotes the data size of the offloaded task and Cy_j is total CPU cycles of computing task.

B. Computing Model

Intuitively, the tasks with smaller size may be more suitable for being processed on local device. According to [6], smart mobile devices can adjust their clock frequency to deal with different tasks to save energy by utilizing dynamic voltage and frequency scaling (DVFS) technique. Let $T_{j,l}$ and $E_{j,l}$ denote the execution time and the energy consumption when the task is executed locally, then we have

$$T_{j,l} = \frac{Cy_j}{f_j} \tag{1}$$

$$E_{j,l} = \kappa Cy_j f_j^2 \tag{2}$$

where κ denotes the effective switched capacitance depending on the chip architecture. And similar to the literature [7], in this paper we set $\kappa = 10^{-11}$.

Since resource providers are made up of a number of resource-rich mobile devices, the computation execution time and energy consumption by edge cloud are similar to Eq.(1) and Eq.(2), respectively. Different with local computing, however, edge computing needs to consider the transmission delay and transmission energy consumption when users offload their tasks onto edge cloud. According to Shannon formula, we can formulate the data rate of the task offloaded to RP i as

$$r_i = W_i log_2(1 + \frac{P_j H_{ji}}{N}) \tag{3}$$

where P_j is the transmission power of user j offloading task, and H_{ji} denotes the channel gain between user j and RP i. N is the background noise power.

Thus when offloading the task onto edge clouds, the completion time and energy consumption can be computed by respectively

$$T_{i,j} = \frac{d_j}{r_i} + \frac{Cy_j}{f_i}, \tag{4}$$

$$E_{i,j} = (\frac{d_j}{r_i})P_j + \kappa Cy_j f_i^2 \tag{5}$$

C. Auction Model

There are three important components in auction theory: sellers, buyers and auctioneer. In this paper, we suppose that the resource providers $\mathcal{I} = \{1, 2, ..., I\}$ are sellers, the users $\mathcal{J} = \{1, 2, ..., J\}$ are buyers and the trusted third party is considered as the auctioneer. Each RP i submits its bids for the users' tasks $B_i = \{b_{i1}, b_{i2}, ..., b_{iJ}\}$ to the auctioneer. Each $b_{ij} \in B_i$ shows the bid claimed by RP i for processing task offloaded by user j. All the bids claimed by the sellers in $\mathcal{I}$ are expressed as $\mathcal{B} = \bigcup_{i=1}^{I} B_i$. Because the completion time and energy consumption of each user's task may be different, the bids to different tasks may be different.

In a competitive environment, in order to determine the price and match sellers with buyers effectively, a trusted third party auctioneer is indispensable. Due to the diversity of edge networks, the choice of the auctioneer is diversified. Both the central cloud with powerful computing capacity, certified edge clouds and specialized auction agency have the opportunity to become a trusted third party. In this paper, the auctioneer needs to collect the information about users' tasks including data size, CPU cycles and so on. Then the auctioneer initiates the auction and receives the bid claimed by sellers to ensure that the bid of each seller is not known by others. Finally, based on the bids and information, the auctioneer determines the price and matches the sellers with buyers according to the proposed auction mechanism.

III. Incentive Mechanism in Non-competitive Environment

A. Problem Formulation

The profit-maximization problem aims to determine the service (i.e. the clock frequency of RPs) and the corresponding price so as to achieve the highest profit of resource providers. The profit of a resource provider is given by

$$\Pi_{ij} = R_{ij}(f_i) - C_{ij}(f_i, W_i) \tag{6}$$

where $R_{ij}(f_i)$ is the total revenue with respect to (w.r.t) f_i and $C_{ij}(f_i, W_i)$ is the total cost w.r.t f_i and W_i.

The total cost may involve a fixed cost and a variable cost. We define the total cost as the expenses that RP spends in executing the task, which can be given by

$$C_{ij}(f_i, W_i) = p_e \kappa C y_j f_i^2 + p_t \frac{C y_j}{f_i} + p_w W_i \tag{7}$$

where p_e, p_t, p_w are the the economic cost of energy, time and bandwidth per unit respectively. The first two items are variable costs since they are function of f_i. The last item in Eq.(7) is independent of f_i and it is taken as the fixed cost.

In Economics, demand curve depicts the relationship between the price of a certain commodity and the amount of the commodity that consumers are willing to buy. However, due to the complexity and irregularity of demand affected by price, it is difficult to accurately characterize the complex supply-demand relationship curve by a standard curve. Thus without loss of generality, we can utilize a straight line to represent the demand curve in economics and use a linear function to reflect the revenue of the RP [8]. Fees charged to user j by resource provider i include a fixed connection price α and a price β charged per unit of resource used. Therefore the revenue can be expressed by

$$R_{ij}(f_i) = \alpha + \beta f_i \tag{8}$$

In addition, we need to take the user experience into consideration. The QoE of user j is defined as the gain by offloading the task onto edge clouds, which is given by

$$O_{ij} = p_e(E_{j,l} - E_{i,j}) + p_t(T_{j,l} - T_{i,j}) - \eta R_{ij} \tag{9}$$

where η is a weight, which indicates that the user emphasizes more on performance or price.

For the entire MEC environment the profit-maximization problem can be formulated as

$$\mathbf{OPT-1}: max \sum_{i=1}^{I}\sum_{j=1}^{J}\Pi_{ij} = \sum_{i=1}^{I}\sum_{j=1}^{J}(R_{ij}(f_i) - C_{ij}(f_i, W_i)) \tag{10}$$

Subject to $(\forall i \in \{1, 2, ..., I\}\ \forall j \in \{1, 2, ..., J\})$

$$\begin{aligned} C1 &: \ \Pi_{ij} > 0 \\ C2 &: \ O_{ij} - U_0 \geq 0 \end{aligned}$$

The constraint C1 guarantees that the profit of user j that matches with the RP i is greater than the total cost. Constraint C2 specifies that if the gain of user j is smaller than a threshold U_0, the user may not offload the task onto the edge cloud.

B. Problem Solving and Algorithm Design

In this subsection, we will first prove the convexity of optimization problem $\mathbf{OPT-1}$ by the following theorem.

Theorem 1: The optimization problem $\mathbf{OPT-1}$ with constraints (C1 and C2) is concave with respect to (w.r.t) the optimization variables f_i,

Proof: Due to space limit, we omit the detailed proof. ■

Theorem 1 demonstrates that the problem $\mathbf{OPT-1}$ has a zero duality gap and satisfies the Slaters constraint qualification. Thus we can employ the convex method to solve this problem. The Lagrange function of optimization problem $\mathbf{OPT-1}$ is expressed as

$$\begin{aligned} L(f_i, \theta, \omega) = &\sum_{i=1}^{I}\sum_{j=1}^{J}(R_{ij}(f_i) - C_{ij}(f_i, W_i)) \\ &+ \theta((R_{ij}(f_i) - C_{ij}(f_i, W_i)) + \omega((O_{ij} - U_0) \end{aligned} \tag{11}$$

where the θ and ω are Lagrange multipliers.

According to KKT conditions [9], the optimal CPU clock frequency can be given by

$$f_i^* = u + v - \frac{1}{3}\gamma_1 \tag{12}$$

where $u = \sqrt[3]{\frac{-m+\sqrt{\Delta}}{2}}$, $v = \sqrt[3]{\frac{-m-\sqrt{\Delta}}{2}}$, $\gamma_1 = -\frac{2X(1+\theta+\omega)}{\beta(1+\theta-\omega\eta)}$ and $X = p_e \kappa C y_j$ and $Y = p_t C y_j$.

It is not difficult to find that the time complexity of the proposed algorithm is $\mathcal{O}(J{*}Iter_{max})$, where $Iter_{max}$ denotes the maximum number of iterations. In this section, we utilize the market-based profit-maximization price model to achieve the optimal price in the non-competitive environment. However, in practice, it is quite unrealistic. Therefore in next section, we will design an incentive mechanism in the competitive environment.

IV. Incentive Mechanism in Competitive Environment

A. Problem Formulation

As aforementioned in II-C, we has given auction model, which includes the definitions of buyers, sellers and auctioneer. We define the RP-users matching matrix as $\mathbf{A} = \{a_{ij}\}_{I \times J}$, where $a_{ij} \in \{0, 1\}$ is the matching factor revealing whether RP i wins its bid for user task j. If the RP i wins the bids and serves the user j, then we have $a_{ij} = 1$, otherwise, $a_{ij} = 0$.

If the task of user j is allowed to execute on RP i, then the user should pay p_{ij} to RP i. We represent the profit as the utility of RP i from selling resources to user j, which can be expressed by

$$U_{ij} = a_{ij}(p_{ij} - C_{ij}(f_i, W_i)) \tag{13}$$

where $C_{ij}(f_i, W_i)$ is the total cost defined in III-A and p_{ij} is the final payment offered to i for bid $b_{i,j}$.

According to the above analysis, our profit-maximization problem in the competitive environment can be formulated as

$$\textbf{OPT-2}: max \sum_{i=1}^{I}\sum_{j=1}^{J} U_{ij} = \sum_{i=1}^{I}\sum_{j=1}^{J} a_{ij}(p_{ij} - C_{ij}(f_i, W_i)) \tag{14}$$

Subject to ($\forall i \in \{1, 2, ..., I\}$ $\forall j \in \{1, 2, ..., J\}$)

$$\begin{aligned} C1 &: \sum_{i=1}^{I} a_{ij} \leq 1, \forall j \in \{1, 2, ..., J\} \\ C2 &: a_{ij} f_i \leq f_j, \forall i \in \{1, 2, ..., I\} \end{aligned}$$

The objective of problem **OPT-2** is to maximize the sum of utility for resource providers. Constraint C1 means that each task can only be served by at most one RP. Constraint C2 reflects that the overall amount of resources required by users should be no more than that of resources owned by edge cloud.

In the following we will design an auction mechanism to determine the matching factor a_{ij} and the final payment p_{ij} to maximize the utility for resource providers in a competitive environment.

B. Auction Mechanism

In the designed profit maximization multi-round auction (P-MMRA) mechanism, users submit their resource requirement to the auctioneer and the RPs submit their bids according to the broadcast information received from the auctioneer firstly. After receiving the bid information from RPs, the auctioneers perform the following operations: user matching, checking their computational resources and calculating the utilities. Finally, when matching matrix is determined, the auctioneer determines the final price based on the match. An effective auction mechanism should have the following properties:

- **Individual rationality**: The reward of no winner seller is less than its cost, which means the utility of each RP should be nonnegative. With respect to the auction model, we have $U_{ij} \geq 0$ for $\forall i \in \{1, 2, ..., I\}$.
- **Efficiency**: The auction algorithm, which consists of bidding strategy, user matching and payment determination, should be solved with a polynomial time complexity.
- **Incentive compatibility**: No resource providers can improve its profit (utility) by submitting a bid different from its true cost. In other words, the bid should be truthful, i.e., $b_{ij} = C_{ij}$. This property is also called as Truthfulness.

In the auction mechanism, the bidding strategy, user matching and payment determination play significant roles. The bidding strategy is designed as a standard to measure which seller is more suitable for buyers. The user matching decides which user can be served by edge cloud. The payment determination intends to calculate the final price of users paid to the resource providers.

1) Bidding strategy: Most auction mechanisms determine who wins the bid based on the bid submitted by sellers. However, different from the most existing auction mechanisms, the auctioneer should calculate the Bid Performance Ratio (BPR) before determining who is the winner. BPR is defined as the ratio of bids submitted by sellers to the buyer's processing capacity (clock frequency of buyer). We use a parameter γ_{ij} to represent the BPR, which is given by

$$\gamma_{ij} = \frac{b_{ij}}{f_j} \tag{15}$$

According to the definition of BPR, we choose the edge cloud from the user's perspective. We only determine which seller is more suitable for buyers initially. Hence, in order to maximize the benefits of edge clouds, we need to design a user matching algorithm to solve the matching problem between sellers and buyers from the perspective of the edge clouds.

2) User matching: The user matching problem can also be called as winner determination problem and the goal of user matching is to decide whether one RP intends to serve the user. Similar to the BPR, we define Price Performance Ratio (PPR) as the ratio of the payment paid by the buyer to the capacity increment provided by the seller, which is given by

$$\zeta_{ij} = \frac{p_{ij}}{f_i - f_j} \tag{16}$$

It is clear that the seller would like to choose the buyer with relatively high PPR to provide services. The unselected buyers enter the loser group and this process is repeated until all buyers are served by the seller. Then the auction is stopped. We let $\bar{J}$ denote the set of buyers that have been assigned to sellers, and $\bar{B}$ represent the set of bids.

3) Payment rule determination: The final price paid by buyers is determined by payment rule we propose. The payment rule determination has a crucial influence on the properties of the auction mechanism. Hence, we adopt the Vickrey auction, in which the auctioneer sets the second-highest bid as the final payment [10]. The key of payment rule determination is how to achieve the second-highest bid. The main idea of our payment rule is to remove the winner's bid selected in section IV-B2 from the set of bid and repeat the previous step until finding out a new winner. The new winner's bid is the final price the buyer needs to pay.

The detailed procedure of PMMRA mechanism is presented in Algorithm 1.

C. Analysis of Properties

We now analyze the properties of the PMMRA mechanism discussed in IV-B, including individual rationality, efficiency and incentive compatibility.

Lemma 1: The proposed PMMRA mechanism is incentive compatibility.

Proof: During the design of the PMMRA mechanism, we have added an auctioneer to collect information, match and decide the final payment. More importantly, the auctioneer has

Algorithm 1 PMMRA algorithm

Input: :$\bar{J}$, $\bar{B}$;
Output: :The optimal matching matrix $\mathbf{A}^* = \{a_{ij}\}_{I\times J}$, the optimal final price p_{ij}.

Initialize: $a_{ij}^{'} = 0$ for $\forall i, j$, $\bar{J} = \varnothing$, $\bar{B} = \bigcup_1^J B_i$
while $\bar{J} \neq \mathcal{J}$ **do**
  for j=1 to J **do**
    Calculate γ_{ij} for each b_{ij} by Eq. (15);
    Select the bid b_{ij} with the smallest γ_{ij};
    Set $a_{ij} = 1$;
    if b_{ij} makes the constraints C1 and C2 unsatisfied **then**
      Remove the bid b_{ij};
    end if
    Set $\bar{B} = \bigcup_1^J B_i \setminus b_{ij}$;
    Select the sub-optimal bid $b_{ij}^{'}$;
    Set $a_{ij}^{'} = 1$ and $p_{ij} = b_{ij}^{'}$;
  end for
  for i=1 to I **do**
    if $\sum_1^J a_{ij} > 1$ **then**
      Calculate ζ_{ij} by Eq.(16);
      The seller chooses the buyer with biggest ζ_{ij} to serve;
      The remaining buyers enter the loser group;
    end if
  end for
end while

the function of dispatch and supervision. When the auctioneer detects that the seller's bid (b_{ij}) is higher than the actual cost (C_{ij}), it has the right to cancel the seller's bid (i.e. $b_{ij} = 0$). Hence, we effectively ensure the incentive compatibility ($b_{ij} = C_{ij}$) of the PMMRA mechanism by adding a regulatory mechanism. ■

Lemma 2: The proposed PMMRA mechanism can achieve individual rationality.

Proof: According to the definition of profit in Eq. (13), the profit of RP i without winning bid ($\alpha_{ij} = 0$) is 0. For a RP i that has winning bids, its profit can be calculated by Eq.(13). Because we have proved that the proposed PMMRA mechanism is incentive compatibility, we can transform the formula into

$$U_{ij} = p_{ij} - b_{ij} \tag{17}$$

As aforementioned, we set the sub-optimal bid as the final payment. In other words, when RP i wins the bid, the b_{ij} must be smaller than its payment $p_{ij} = b_{ij}^{'}$, otherwise, $b_{ij}^{'}$ will win the bid instead of b_{ij}. Thus the utility is non-negative ($p_{ij} - b_{ij} \geq 0$). ■

Lemma 3: The proposed PMMRA mechanism is computationally efficient.

Proof: To select each winning bid, we need to sort all the bids and the time complexity of the sorting algorithm for each task is $\mathcal{O}(IlogI)$. Furthermore, when the edge cloud selects the task to serve, we also need to sort the PPR, thus the time complexity for each edge cloud is $\mathcal{O}(JlogJ)$. It is worth noting that, we must ensure that every task that can be offloaded is serviced by an edge cloud in our PMMRA algorithm.

To sum up, the overall time complexity of PMMRA in Algorithm 1 is $\mathcal{O}(J(JIlogI + IJlogJ))$, which means that the PMMRA algorithm converges in a polynomial time with respect to I and J. ■

V. Performance Evaluation

In this section, we will evaluate the performance of PMMRA mechanism. We first describe the simulation settings and then give experimental results to demonstrate the advantages of our proposed PMMRA mechanism.

A. Simulation Setting

In the experiments, we consider the scenario where the number of edge clouds varies from 3 to 10 and the number of users varies from 5 to 25, both of which are randomly deployed. The CPU clock frequency of each user is set from 1 GHz to 1.5 GHz randomly. We assume that the transmission power is between 257 and 325 mW and the background noise is $-50dBm$. We set the channel gain $H_{ji} = D^{(-\delta)}$, where $\delta = 4$ is the path loss factor and D is the distance between users and edge clouds. The total bandwidth varies from 10 to 20 Mbps. Since different tasks have different execution features, Cy_j is set from 200 to 2000 Mega cycles and d_j is from 10 kB to 1 MB [11].

B. Performance on Individual Rationality

To validate Lemma 2, we first investigate the performance on individual rationality. In this simulation, we assume that there are 20 users (buyers) and 3 resource providers (sellers). We try to reveal the relationship between bids and final payments. It is worth noting that we choose the optimal price in the non-competitive environment as a benchmark.

Fig. 2 depicts the bids and payments for different number of users. Clearly, we can observe that each RP can get a payment not less than its bid submitted to the auctioneer. In other words, our PMMRA mechanism is individual rationality. The results demonstrate that the utility of successfully matched edge cloud is non-negative. In addition, the difference between the final payment given by PMMRA mechanism and the optimal price in the non-cooperative environment is very small. In other words, the PMMRA mechanism not only meets the needs of users but also maximizes the profits of resource providers.

C. Comparison of Different Strategies

In this subsection, we compare the utility of resource providers with [12] and the number of offloaded tasks with [13]. In [12], Chen et al. formulated the offloading decision problem as a multi-user offloading game and maximized the number of offloaded users by designing a distributed algorithm, which is denoted as Chen's algorithm. In [13], Zhang et al. formulated the matching problem as a utility maximization problem and adopted a combinational auction to solve the matching problem, which is denoted as Zhang's algorithm.

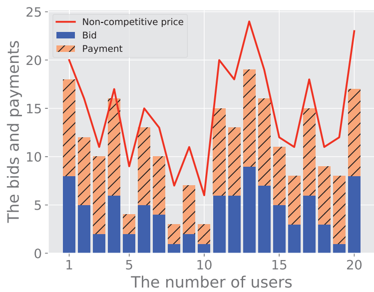


Fig. 2. Performance on individual rationality

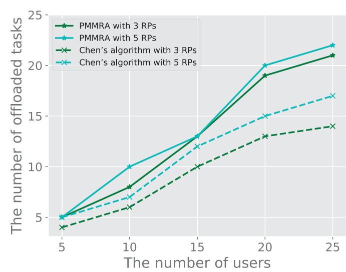
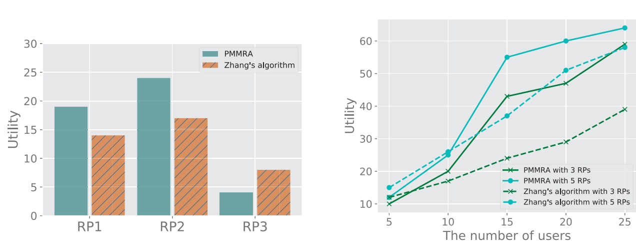


Fig. 3. The performance of the PMMRA and Chen's algorithms on the number of offloaded tasks.

Fig. 3 reveals the performance comparison of the PMMRA and Chen's algorithms for different RPs and the variable users. We can find from Fig. 3 that in general, the number of offloaded tasks increases as the number of users increases. Nevertheless, as the number of users increases, the gap between Chen's algorithm and PMMRA becomes bigger. Furthermore, we can see from the Fig.3 that our PMMRA algorithm improves performance by 29% in the number of offloaded tasks compared with Chen's algorithm. The reason is that Chen's algorithm works in the TDM system, and the users are easily interfered by other users signals in TDM model. However, our PMMRA is from an economic perspective, which makes our mechanism more scalable in any system and the number of offloaded tasks will not be reduced due to interference between users.

Fig. 4(a) and Fig. 4(b) show that the PMMRA mechanism outperforms Zhang's algorithm in both individual (the utility of each resource provider) and holistic perspectives (the utility of all resource providers). We can observe from Fig.4(b) that our mechanism can increase the utility by 30% evenly. The resource provider's utility can be maximized by setting PPR when the edge clouds are matched with users. Although in some cases Zhang's algorithm is slightly better than our PMMRA, they do not take into account the resource provider's computation energy consumption.



(a) (b)

Fig. 4. The comparison between the PMMRA and Zhang's algorithms

VI. Conclusions

In this paper, we propose the profit maximization incentive algorithms of resource providers in non-competitive and competitive environment. In the non-competitive environment, we formulate the incentive mechanism into a profit maximization problem based on market price model by considering not only the utility of resource providers but the constraint on user gain. In the competitive environment, we design a profit maximization multi-round auction (PMMRA) mechanism to match the users with resource providers and determine the final payment. Simulation results show that our mechanism can obtain larger utility for resource provider and increase the number of served users as much as possible.

VII. Acknowledgement

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