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A Truthful Double Auction Framework for Promoting Femtocell Access

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ABSTRACT With the explosive growth of mobile data traffic in cellular networks, indoor users are always suffering poor data services. Femtocells are widely accepted as an effective way to solve this problem by providing better coverage. In this way, the user quality of service (QoS) can be significantly enhanced. However, a major obstacle to implement the fashion is lacking market-driven mechanisms to incentivize femtocell owners to trade their access permissions (ACPs). Therefore, designing a robust auction mechanism for ACP trading has attracted lots of attention. A critical challenge of designing such an auction mechanism is to ensure the economic property of truthfulness. Most of the prior works on this issue focus on single-sided scenario, where there is only one seller or one buyer. However, multiple femtocells and multiple macrocell users equipments (MUEs) are always involved in practical systems. In this paper, we study a general market model where multiple femtocells can trade with multiple MUEs and show that designing such a truthful auction mechanism for this scenario is challenging. Therefore, we propose a truthful double auction for access permission (TDAP) allocation. We show analytically that our auction mechanism is economic robust (i.e., satisfying three economic properties including truthfulness, individually rationality, and budget balance) and computationally efficient. Moreover, through extensive simulation experiments, we show TDAP can highly improve auction efficiency outperforming prior auction design.

INDEX TERMS Double auction, femtocell network, mechanism design, truthfulness.

I. INTRODUCTION

Currently, as all kinds of demands for data is increasing explosively, the users' access activities (like multimedia streaming) are becoming mobilized. In this situation, the cellular network operators have to address the explosive traffic demands of mobile users which exceed the network capacity. Otherwise, the users' experience will be adversely affected [1], [2]. The femtocells, also known as home base stations (HBSs), have been launched by many mobile operators [3] since they provide a cost-effective way to alleviate the cellular congestion. Especially, they improve the Quality of Service (QoS) of indoor users and reduce the power consumption. Femtocells connect with the operators' macrocell networks through optical fiber or other connections, which provide a short-range service for indoor users and thus improve the network performance.

In a conventional two-tier network, where wireless service provider (WSP) runs macrocell network and femtocells are run by home owners, the *hybrid access* has been widely accepted as one of the most potential access control mechanism [4], [5]. In hybrid access architecture, certain macrocell users equipments (MUEs) are allowed to access to the nearby femtocells. In other words, the femtocells can increase the total network capacity by serving nearby MUEs. However, a main obstacle to implement the fashion is lacking the

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incentives for these femtocells to serve the MUEs. A popular approach to solve this obstacle is designing certain market-driven schemes to stimulate the self-serving femtocell owners to share available resources.

Auction is known as an efficient market-driven mechanism where resources can be efficiently distributed between sellers and buyers [6], and thus auction-based incentive mechanisms for allocating resources have been well studied in many research areas, *e.g.,* spectrum auction designs [7], [8] and cloud auction designs [9], [10]. When designing an efficient auction mechanism, a critical property of *truthfulness* is required [6]. However, only a few works address the issue of designing truthful mechanism for femtocell networks, *e.g.,* [11]–[15]. These works considered different aspects to design auctions. Chen *et al.* [11] considered a reverse auction mechanism. In contrast, Wang *et al.* [14] proposed a forward multi-object auction. From a different aspect, the access time slots between femtocells and MUEs are auctioned, and a single-sided auction mechanism which involves one seller and multiple buyers is designed in [12]. In [13] and [15], auction mechanisms are proposed to motivate femtocells yet the truthfulness is not considered.

Different from prior works, we consider a more practical scenario where multiple femtocells trade their ACcess Permissions (ACPs) to multiple MUEs. As a result, a *double* auction mechanism is needed. However, designing such a truthful double auction for ACP transaction is challenging due to the unique features of ACP allocation (ACPs of different sellers are heterogeneous). We firstly show that the classic truthful double auctions, including VCG [16] and McAfee [17], cannot be applied here directly. In addition, we show the double auction mechanism proposed in prior works like [18] will lose truthfulness when applied to ACP allocation. As a result, we need to address the heterogeneity of ACPs novelly when designing the auction. To cope with these challenges, we propose a **T**ruthful **D**ouble **A**uction for access **P**ermission allocation (TDAP) in this paper. The basic idea of TDAP is to treat a buyer as multiple *virtual buyers* supposing they participate in the auction independently, which is crucial to guarantee the truthfulness and enhance the system efficiency.

To this end, the main technical contributions of this paper can be summarized as follows:

1) We study a general market model for promoting femtocell access where multiple femtocells compete to trade their ACPs to multiple MUEs. We show designing such a truthful double auction for this model is challenging and propose TDAP, a **T**ruthful **D**ouble **A**uction for access **P**ermission allocation.
2) TDAP is economic-robust, *i.e.,* it is *truthful*, *individually rational* and *budget balanced*. Truthfulness is essential to ensure auction fairness and resist market manipulation. The individual rationality guarantees that bidders' utilities are non-negative, which provides participating incentives for bidders. Budget balance is to make sure that the auctioneer has motivations to initiate auctions.
3) TDAP is computationally efficient, which incurs a polynomial time complexity of $O(NM\log(NM) + NM^2)$, where N is the number of buyers and M is the number of sellers.
4) Through extensive simulations, it is shown that TDAP is effective and efficient for ACP trading.

We organize the rest of the paper as follows. Section II reviews related works. The preliminaries are presented in Section III. The technique challenges are investigated in Section IV. The detailed auction design is proposed in Section V. Performance evaluations of the proposed auction design are shown in Section VI. Finally, conclusions and future work are given in Section VII.

II. RELATED WORKS

In the economics literature, the VCG auction [19]–[21] is one of the most famous truthful auction mechanism. However the VCG auction is single-sided and the VCG-based double auction [16] cannot been applied to ACP allocation due to the heterogeneity of ACP trading. In [17], McAfee double auction is designed to allocate homogeneous commodities. In another word, there is no preference over commodities for buyers. This feature of McAfee limits its application to ACP trading. Other double auction designs like [22] and [23] do not guarantee the truthfulness.

Auction-based approaches has been widely used in many research areas. Truthful auction mechanism is proposed in [7], in which selfish users share downloading capacity for video streaming. In [8], a truthful online double auction mechanism focusing on privacy-preserving is constructed for spectrum allocation. In cloud computing area, previous studies on allocation and pricing of computing resources in cloud market designed truthful combinatorial double auction-based mechanisms [9], [10]. Recently, some literature starts to focus on auction-based approaches for virtualization in 5G [24] and mobile data offloading [25]–[27].

There are a few studies on the auction design for ACP transaction in the femtocell network [11]–[15], [28]. The authors in [28] proposed a refunding framework using Stackelberg Game for MUEs and femtocells. The hybrid access is motivated by the auction mechanism proposed in [13]. However, it maximizes both utilities of the macrocell and femtocells, regardless of truthfulness. Similarly, Xing *et al.* [15] focus on revenue maximization of the macrocell without considering the truthfulness. Hua *et al.* [12] pay a close attention to the truthful cooperation among all agents in designing a single-sided VCG-based auction mechanism. The auction mechanism in [11] is a reverse one in which femtocells trade the ACP to the WSP with one buyer and multiple sellers. And a forward multi-object auction based on package bidding is proposed in [14]. In other words, the mechanisms proposed in the above works either lose truthfulness or cannot be applied to double-sided scenario. Most importantly, the double mechanisms proposed in other literature like cooperative communications [18] will lose truthfulness when applied to ACP trading, and the other double auctions used in cloud computing like [9] and [10] are also not suitable here.

III. PRELIMINARIES

In this section, we describe the system model and the targets of designing a robust auction mechanism.

A. SYSTEM MODEL

We consider a typical two-tier macro-femtocell network of one WSP and M femtocell owners. There are N MUEs competing for the ACPs of femtocells. We consider a system of discrete-time, where femtocell owners and MUEs submit their bids to the WSP respectively in each time period. The WSP acts as the auctioneer and runs the designed auction mechanism to allocate the ACPs of M femtocell owners to N MUEs. Therefore, the femtocell owners are the *sellers* in this auction, while MUEs are *buyers*. The products to be auctioned are the ACPs. For easy description, we denote the buyer set as $\mathbb{B} = \{1, \cdots, N\}$ and the seller set as $\mathbb{S} = \{1, \cdots, M\}$.

A sealed-bid auction is studied here in which bidders privately submit their bids to the auctioneer, with no information of others' bids. In this situation, bidders do not know the bids of others and thus do not collude.

Now we describe the bids of buyers and asks of sellers. For buyers, the MUEs have preferences over femtocell owners since the quality of ACP is varied by the femtocell capacity and location information. The bids of buyers are different to that of sellers. This is the key characteristic of ACP heterogeneity. Therefore, for a buyer $n \in \mathbb{B}$, we use a bid vector $\mathbf{B}_n = (B_n^1, B_n^2, \cdots, B_n^M)$ to denote its bid, where B_n^m is the bid valuation of buyer n for ACP of seller m, $m \in \mathbb{M}$. We denote the bid matrix consisting of all buyers' bid vectors as $\mathbf{B} = (\mathbf{B}_1, \cdots, \mathbf{B}_N)$. While for sellers, because they only care about the amount of payments for using their resources, their asks do not differentiate among buyers. Therefore, we denote ask of seller m as A_m, and the ask vector of all sellers as $\mathbf{A} = (A_1, \cdots, A_M)$.

B. DESIGNING TARGETS

The general problem of double auction design can be described as follows: "Given asks from sellers and bids from buyers, design algorithm to select winning sellers and buyers, assign the auctioned products of winning sellers to selected winning buyers, and design algorithm to determine the prices for paying/charging auction winners to maximize system efficiency."

Based on the above definition, we can give out the double auction model. Firstly, the sellers $\mathbb{S}$ submit their asks $\mathbf{A}$ to an auctioneer, at the same time, the auctioneer also collects the information of bids $\mathbf{B}$ provided by the buyers $\mathbb{B}$. Following that, the auctioneer selects the winning sellers and buyers based on all asks and bids, and then generates *market-clearing prices* for winners. The market-clearing price for a winning seller m is his actual *payment* received, denoted as P_m^s. The market-clearing price for a winning buyer n is the *price* he paid, denoted as P_n^b. Let $\mathcal{B}_w \subset \mathbb{B}$ be the set of winning buyers, and $\mathcal{S}_w \subset \mathbb{S}$ be the set of winning sellers. The allocation of ACPs between winning buyers and wining sellers can be defined as a mapping function $\delta : \{n : n \in \mathcal{B}_w\} \rightarrow \{m : m \in \mathcal{S}_w\}$, and $\delta(n) = m$ indicates that the buyer n wins the ACP of seller m.

Now we define the utilities of the bidders. The utilities of the buyers are dependent on the charged prices and the valuations of the required ACPs, and the utilities of the sellers are dependent on the collected payment and the true valuations (or costs) of sellers for providing the services. Let V_n^m be the valuation of buyer n for obtaining the ACP from seller m. Then the valuation vector of buyer n can be denoted as $\mathbf{V}_n = (V_n^1, \cdots, V_n^M)$. For a buyer-seller mapping $\delta(n) = m$, the *utility* of buyer n is $U_n^b = V_n^m - P_n^b$ if it wins the auction, and equals 0 otherwise. Similarly, let V_m^s be the true valuation of the seller m for selling its ACP. Then the utility of seller m is $U_m^s = P_m^s - V_m^s$ if it wins the auction, and equals 0 otherwise. Some notations frequently used in this paper are summarized in Table 1.

TABLE 1. Some frequently used notations.

Symbol	Definition
M	the number of femtocells (sellers)
N	the number of MUEs (buyers)
$\mathbb{B}$	the set of buyers
$\mathbb{S}$	the set of sellers
B_n^m	the bid valuation of buyer n for ACP of seller m
$\mathbf{B}_n$	the bid vector of buyer n
A_m	the ask of seller m
$\mathbf{A}$	the ask vector of all sellers
$\mathcal{B}_w$	the winning buyer set
$\mathcal{S}_w$	the winning seller set
$\mathcal{B}_c$	the winning virtual buyer candidates
$\mathcal{S}_c$	the winning seller candidates

The designed auction mechanism should satisfy the following four desirable properties.

1) TRUTHFULNESS

A double auction is *truthful* if no buyer n or seller m can improve its own utility by bidding untruthfully (*i.e.*, $\mathbf{B}_n \neq \mathbf{V}_n$ or $A_m \neq V_m^s$), regardless of other players' bids.

Truthfulness, also called as incentive computability, is essential to ensure auction efficiency and resist market manipulation. Otherwise, selfish bidders can game the auction by manipulating their bids, and thus favor themselves but hurt others. In contrast, the truthful auctions ensure that bidders' utilities will be maximized when bidding its true valuation. In this way, the auctioneer will assign ACPs to the buyers who set the highest value on them efficiently.

2) INDIVIDUAL RATIONALITY

A double auction is *individually rational* when winning buyer pays no more than its ask and winning seller is paid no less than its bid. This means that for every winning mapping $\delta(n) = m$, we have $P_n^b \leq B_n^m$ and $P_m^s \geq A_m$.

This property guarantees that the utilities of bidders are non-negative, and thus providing the participating incentives.

3) BUDGET BALANCE

A double auction is *budget balanced* when the profit of auctioneer is guaranteed to be non-negative, which is defined as the difference between the revenue collected from buyers and the expense paid to sellers, *i.e.,* the following equation holds where $\mathcal{B}_w$ and $\mathcal{S}_w$ denote the winning buyer set and winning seller set, respectively.

$$\phi = \sum_{i\in\mathcal{B}_w} P_i^b - \sum_{j\in\mathcal{S}_w} P_j^s \geq 0 \tag{1}$$

The property ensures that the auctioneer is willing to set up auctions.

4) COMPUTATIONAL EFFICIENCY

Conventionally, the auction mechanism is required to be run in a polynomial time complexity.

IV. DESIGN CHALLENGES

Now we illustrate designing such an economic-robust double auction for ACP allocation is a challenging problem, due to the unique features of ACP allocation. To better understand these challenges, we firstly show the traditional truthful double auctions (including VCG [16] and McAfee [17]) failed when applied to the ACP auction directly. Then we also show prior works of auction design like [12] and [18] would lose the truthfulness when directly extended to the ACP auction.

A. VCG-BASED DOUBLE AUCTION

The Vickrey-Clarke-Groves (VCG) scheme [19]–[21] is the most well-known truthful auction scheme. The sketch of the VCG-based double auction scheme [16] can be described as follows. (1) When determining the winners and the assignment between buyers and sellers, the scheme must maximize the social welfare $W = \sum_{i\in\mathcal{B}_w}(B_i^{\delta(i)} - A_{\delta(i)})$. When the scheme is applied to ACP allocation, we can obtain the optimal value by solving the maximum weighted matching in the bipartite graph $G = (\mathbb{B}, \mathbb{S}, \varepsilon, \theta)$, where edge $(i, j) \in \varepsilon$ if $B_i^j > 0$ and $\theta(i, j) = B_i^j - A_j$ is the weight on edge (i, j). (2) Then the price charged from each buyer $i \in \mathcal{B}_w$ is

$$P_i^b = B_i^{\delta(i)} - (W^* - W^*_{\mathbb{B}\setminus i}) \tag{2}$$

where W^* denotes the optimal social welfare, and $W^*_{\mathbb{B}\setminus i}$ denotes the optimal value when buyer i is excluded. Similarly, each seller $j \in \mathcal{S}_w$ receives a payment of

$$P_j^s = A_j - (W^* - W^*_{\mathbb{S}\setminus j}) \tag{3}$$

The VCG-based double auction is shown to be truthful and individually rational [16]. However, it is also shown that the mechanism is not budget balanced in [18].

B. MCAFEE DOUBLE AUCTION

The key characteristic of the McAfee double auction [17] is that the auctioned items are homogeneous, *i.e.,* there is no preference among these items for buyers. As a result, each seller j submits one ask A_j and each buyer i only submits one bid B_i. (1) The bids are then sorted in a non-increasing order as well as the asks are sorted in a non-decreasing order: $B_1 \geq \cdots \geq B_N$ and $A_1 \leq \cdots \leq A_M$. The auctioneer then obtains the largest k such that $B_k \geq A_k$ and $B_{k+1} < A_{k+1}$. Let $t = \frac{B_{k+1}+A_{k+1}}{2}$. (2) The clearing prices are determined as follows:

$$\begin{cases} P^b = P^s = t, & \text{if } A_k \leq t \leq B_k, \\ P^b = B_k, & P^s = A_k \quad \text{otherwise.} \end{cases} \tag{4}$$

where P^s is the received payment of each winning seller and P^b is the charged price of each winning buyer. It has been shown that the McAfee double auction satisfies all the described three economic properties [17]. However, the requirement of homogeneous auction items makes it inappropriate for the ACP auction without further development.

C. PRIOR AUCTION DESIGNS

A double auction TASC for cooperative communication is proposed in [18]. TASC consists of three main stages. Firstly, TASC chooses the relay assignment algorithm (*e.g.,* maximum weighted matching algorithm) to match sellers and buyers. Secondly, it sorts all the matched buyers such that $B_{i_1}^{\delta(i_1)} \geq B_{i_2}^{\delta(i_2)} \cdots$, and sorts all the matched sellers such that $A_{j_1} \leq A_{j_2} \cdots$. Then it finds the largest k such that $B_{i_k}^{\delta(i_k)} \geq A_{j_k}$. Finally, it finds the largest β such that $B_{i_k}^{\delta(i_k)} \geq A_{j_\beta}$ and the largest α such that $B_{i_\alpha}^{\delta(i_\alpha)} \geq A_{j_k}$. Then it uses buyer-seller pair (α, j_k) or (i_k, β) as boundary pair to determine the winning buyer-seller pairs and market-clearing prices, respectively. At last, it compares the results of the two choices and makes the better one as the final auction result. A key characteristic of TASC is that it sacrifices one seller and one buyer to guarantee the truthfulness [18].

TABLE 2. The bid matrix of buyers.

	s_1	s_2	s_3	s_4	s_5	s_6	s_7
r_1	10	4	4	0	0	0	0
r_2	0	0	7	3	4	0	8
r_3	9	0	7	4	6	0	0
r_4	0	6	0	10	4	6	8
r_5	0	0	8	0	0	9	4

TABLE 3. The asks of sellers.

seller	s_1	s_2	s_3	s_4	s_5	s_6	s_7
ask	3	2	5	6	4	1	7

TASC is shown to guarantee the above three economic properties. However, we use an example to show that TASC will lose truthfulness when applied to ACP allocation. Table 2 illustrates the bid matrix of 5 buyers, and Table 3 presents

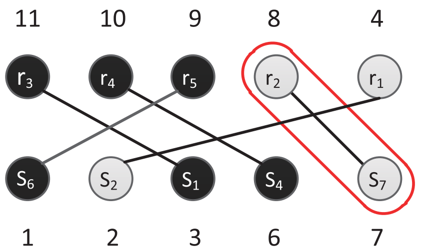

FIGURE 1. A bipartite graph showing the auction result of TASC.

the true ask vector of 7 sellers. We suppose the maximum weighted matching algorithm is executed in the first stage and the matched buyer-seller pairs can be described in Fig. 1. The auctioneer finds that $k = 4$ and examines the (r_2,s_7) pair and the (r_3,s_4) pair, and selects (r_2,s_7) as the boundary pair. Therefore the winning pairs contain (r_1,s_1), (r_4,s_4) and (r_5,s_6). The price each winning seller accepts is $P^s = A_7 = 7$. The price for each winning buyer is $P^b = B_2^7 = 8$.

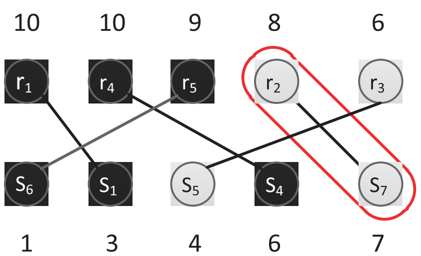

FIGURE 2. Assignment result when buyer r_3 increases its bid B_3^6 to 11.

Now if buyer r_3 changes its bid B_3^1 from 7 to 11, we obtain the new assignment result shown in Fig. 2. Then the winning pairs become (r_3, s_1), (r_4, s_4) and (r_5, s_6). The pair (s_2, r_7) becomes the boundary pair, and the price for each winning buyer is $P^b = B_2^7 = 8$. Then the new utility of buyer r_3 becomes $V_3^1 - P^b = 9 - 8 = 1$. This means that buyer r_3 can improve its utility (from 0 to 1) with untruthful bid.

Similarly, we can also prove the double auction in [12] cannot be applied to ACP trading directly.

V. OUR AUCTION DESIGN

Based on the above observations, it is needed to design a new double auction scheme which is suitable for ACP transaction while satisfying all the desired economic properties. In this section, we propose TDAP, a **T**ruthful **D**ouble **A**uction for access **P**ermission allocation. Nevertheless, the *Impossibility Theorem* [29] explains that designing a double auction that simultaneously achieves all three economic properties as well as system efficiency maximization is impossible. Since the three economic properties are critical to implement the auction, we focus on designing the double auction mechanism satisfying the economic properties primarily while maximizing efficiency approximately. As a conventional approach, this kind of trade-off has also been applied in other double auction mechanisms [18], [30].

A. MAIN ALGORITHMS

The basic idea behind TDAP comes from the spectrum auction design ALETHEIA [31] where the authors treat one bidder as multiple virtual bidders to tackle fasle-name bids. Motivated by the auction design ALETHEIA, we here treat one buyer as multiple *virtual buyers* assuming they participate in the auction independently to address the heterogeneity of ACPs. This scheme is crucial to ensure the truthfulness and improve the efficiency.

TDAP consists of two main procedures. Firstly, the auctioneer deals with the buyers. Each buyer is treated as multiple virtual buyers. It determines the winning player candidates, and maps each winning seller candidate with one winning virtual buyer candidate. For easy description, in the following sections, we still use the buyer instead of virtual buyer to describe the auction design. Secondly, it determines the wining buyer-seller maps and charges a clearing price from each winning buyer candidate and collects a clearing payment to the winning seller candidate.

1) WINNER DETERMINATION

In this step, TDAP treats each buyer $i \in \mathbb{B}$ as multiple *virtual buyers*. In other words, for buyer i, if $B_i^j > 0$, it creates a new virtual buyer denoted as i^j with unique bid B_i^j. In this way, a buyer with multiple positive valuations can arise a number of times mapping to the sellers. Let $\mathbb{B}'$ be the set of virtual buyer set and $x = |\mathbb{B}'|$, and we get $x \leq N \times M$.

Following that, virtual buyer set is sorted in a non-increasing order of bids, and seller set is sorted in a non-decreasing order of asks. Let $\mathbb{B}''$ and $\mathbb{S}'$ be the sorted virtual buyer set and sorted seller set, respectively.

$$\mathbb{B}'' : B_{p_1}^{q_1} \geq B_{p_2}^{q_2} \geq \cdots \geq B_{p_x}^{q_x}$$
$$\mathbb{S}' : A_1 \leq A_2 \leq \cdots \leq A_M.$$

We now select a fixed value $k \in [1, M]$ (e.g., $\lceil \frac{M}{2} \rceil$), and we can find μ as the last profitable trade:

$$\mu = \text{argmax}_\mu B_{p_\mu}^{q_\mu} \geq A_k \tag{5}$$

Then a virtual buyer p^q is a winning candidate if $B_p^q \geq B_{p_\mu}^{q_\mu}$ and its matching seller q with $A_q < A_k$. A seller q is a winning candidate if its ask $A_q < A_k$ and there are at least one winning virtual buyer bids for seller q. Let $\mathcal{B}_c$ and $\mathcal{S}_c$ denote the winning virtual buyer candidate set and winning seller candidate set, respectively. The detailed algorithm is described in Algorithm 1.

2) COMPUTING PRICES

In this procedure, we determine the assignment and the prices. As shown in Algorithm 2, the auctioneer first checks each winning seller candidate j and after that decides the winning buyer mapping with each seller j. There are two cases to be considered. **Case I:** If there are only one virtual buyer candidate i^j bids for seller j, the virtual buyer i^j is winning and then added into the winning buyer set $\mathcal{B}_w$, and the charged price is $B_{p_\mu}^{q_\mu}$. **Case II:** If there are more than one virtual buyer

Algorithm 1 DetermineWinners ($\mathcal{B}, \mathcal{S}, \mathbf{V}, \mathbf{A}$)

$\mathcal{B}_c \leftarrow \emptyset, \mathcal{S}_c \leftarrow \emptyset$;
Construct a new buyer set
$\mathbb{B}' = \{p^q : B_p^q > 0, p \in \mathbb{B}, q \in \mathbb{S}\}$;
$\mathbb{B}''$ = sorted $\mathbb{B}'$ in a non-increasing order of bids;
$\mathbb{S}'$ = sorted $\mathbb{S}$ in a non-decreasing order of asks;
$M = |\mathbb{S}'|, k = \lceil \frac{M}{2} \rceil$;
$\mu = \mathrm{argmax}_\mu B_{p_\mu}^{q_\mu} \geq A_k$;
for *each* $p^q \in \mathbb{B}'$ **do**
  if $B_p^q \geq B_{p_\mu}^{q_\mu}$ *and* $A_q < A_k$ **then**
    $\mathcal{B}_c \leftarrow p^q$;
for *each* $j \in \mathbb{S}'$ **do**
  if $A_j \leq A_k$ **then**
    $\mathcal{S}_c \leftarrow j$;
return ($\mathcal{B}_c, \mathcal{S}_c, B_{p_\mu}^{q_\mu}, A_k$);

Algorithm 2 Pricing ($\mathcal{B}_c, \mathcal{S}_c, B_{p_\mu}^{q_\mu}, A_k, \mathbf{V}, \mathbf{A}$)

$\mathcal{B}_w \leftarrow \emptyset, \mathcal{S}_w \leftarrow \mathcal{S}_c$;
for *each* $j \in \mathcal{S}_c$ **do**
  $P_j^s = A_k$;
  for *each* $i \in \mathcal{B}_c$ **do**
    if $\delta(i) == j$ **then**
      $\mathcal{B}^j \leftarrow \mathcal{B}^j \cup \{i\}$;
  if $|\mathcal{B}^j| == 1$ **then**
    $\mathcal{B}_w \leftarrow \mathcal{B}_w \cup \{i\}$;
    $P_{i^j}^b = B_{p_\mu}^{q_\mu}$;
  else
    Sort $\mathcal{B}^j$ to an ordered list $\mathbb{B}^j$ such that $B_{i_1}^j \geq B_{i_2}^j \geq \cdots \geq B_{p_\mu}^{q_\mu}$;
    Select the first buyer i_1^j from $\mathbb{B}^j$ with the highest bid;
    $\mathcal{B}_w \leftarrow \mathcal{B}_w \cup \{i_1^j\}$;
    $P_{i_1^j}^b = B_{i_2}^j$;
return ($\mathcal{B}_w, \mathcal{S}_w, \delta, P^b, P^s$);

candidate bid for seller j, the virtual buyer candidate who has the highest bid wins the ACP, and then is included into the winning buyer set. We charge it the second highest bid of those who bid for seller j. For each winning seller j, its payment is the ask A_k. Note that, a buyer with multiple virtual buyers can win multiple ACPs from different sellers. The case which one buyer can match only one seller will be discussed in our future work.

B. AN ILLUSTRATIVE EXAMPLE

We still use the example in Section III. According to Algorithm 1, we construct $\mathbb{B}'$ and obtain the sorted set $\mathbb{B}'' = \{1^1, 4^4, 3^1, 5^6, 5^3, 2^7, 4^7, 2^3, 3^3, 3^5, 4^2, 4^6, 1^2, 1^3, 2^5, 3^4, 4^5, 5^7, 2^4\}$. And we get the sorted set $\mathbb{S}' = \{s_6, s_2, s_1, s_5, s_3, s_4, s_7\}$, then determine winner candidate according to algorithm 1.

- Select $k = 4$, and $A_k = 4$; Then find $\mu = 16$ and $B_{p_{16}}^{q_{16}} = 4$.
- Obtain $\mathcal{B}_c = \{1^1, 3^1, 5^6, 4^2, 4^6, 1^2\}$, $\mathcal{S}_c = \{s_6, s_2, s_1\}$ naturally.

According to pricing algorithm, we determine matching and prices for winning buyers and sellers.

- The set of winning buyers: $\mathcal{B}_w = \{1^1, 5^6, 4^2\}$.
- The set of winning sellers: $\mathcal{S}_w = \{s_6, s_2, s_1\}$.
- The matching between winning buyers and sellers: $\delta(1) = 1, \delta(5) = 6, \delta(4) = 2$.
- The charged price from winning buyers: $P_{1^1}^b = B_5^6 = 9$, $P_{5^6}^b = B_4^6 = 6$, $P_{4^2}^b = B_1^2 = 4$.
- The rewarded payment for each winning seller: $P^s = 4$.

C. AUCTION PROPERTIES

Theorem 1: TDAP is individually rational.

Proof: Two cases for winning buyers are considered.

- Case I: buyer i^j wins seller j without competition, *i.e.*, no other buyers in $\mathcal{B}_c$ bid for seller j. Then the charged price satisfies $B_{p_\mu}^{q_\mu} \leq B_i^j$ according to Algorithm 1.
- Case II: buyer i^j wins seller j with competition, *i.e.*, there are more than one buyer in $\mathcal{B}_c$ bid for seller j. The charged price is the second highest bid in $\mathcal{B}^j$ which is less than or equal to B_i^j.

Therefore, the buyers are individually rational.

For winning sellers, the payment rewarded is A_k for any winning seller j, and $A_j \leq A_k$ according to the Algorithm 1. Therefore, the sellers are individually rational.

Therefore, TDAP is individually rational. ■

Theorem 2: TDAP is budget balanced.

Proof: According to the pricing Algorithm 2, we know that for each winning seller $j \in \mathcal{S}_w$ there is a corresponding winning buyer $i^j \in \mathcal{B}_w$ bidding for j. The charged price for i^j is $P_{i^j}^b \geq B_{p_\mu}^{q_\mu}$, and the payment for j is $A_k \leq B_{p_\mu}^{q_\mu}$, and thus the following equation holds.

$$\phi = \sum_{i \in \mathcal{B}_w} P_i^b - \sum_{j \in \mathcal{S}_w} P_j^s \geq 0 \tag{6}$$

This completes the proof and thus TDAP is budget balanced. ■

To prove TDAP is truthful, we firstly illustrate that the winner determination is monotonic, in the mean time the pricing rule is bid-independent.

Lemma 1: Given the buyers' bid set and the sellers' ask set, if buyer i wins the auction by bidding B_i^j, buyer i can also win by bidding $\hat{B}_i^j > B_i^j$ when the bid set except only B_i^j and the ask set are the same.

Proof: Since $\hat{B}_i^j > B_i^j$, then i^j will also be included in the winning buyer candidate set $\mathcal{B}_c$ when bidding $\hat{B}_i^j$ according to Algorithm 1. Then there are two cases to be considered.

- Only one virtual buyer $i^j \in \mathcal{B}_c$ bids for seller j, and it wins directly.
- More than one buyer in $\mathcal{B}_c$ bid for seller j. Since the buyer wins by bidding B_i^j, it is the highest bid in $\mathcal{B}^j$. Now $\hat{B}_i^j > B_i^j$ and thus it is still the highest bid in $\mathcal{B}^j$. Therefore, the buyer also wins.

This completes the proof. ■

Similarly, the following lemma holds and we omit the proof here.

Lemma 2: Given the buyers' bid set and the sellers' ask set, if seller j wins the auction by bidding A_j, seller j can also win by bidding $\hat{A}_j > A_j$ when the bid set and the ask set except A_j are the same.

Next, we show the pricing method is bid-independent.

Lemma 3: If the buyer i wins the auction by bidding $\hat{B}_i^j$ or B_i^j, when the bid set except only B_i^j and the ask set are the same, the clearing price charged from i^j is the same for both bidding cases.

Proof: There are two cases to be considered.

- Only one virtual buyer $i^j \in \mathcal{B}_c$ bids for seller j, and the charged price is $B_{p_\mu}^{q_\mu}$ for both bidding cases.
- More than one virtual buyer in $\mathcal{B}_c$ bid for seller j. The charged price is the second highest bid in $\mathcal{B}^j$, which is the same for both bidding cases.

This completes the proof. ■

Similarly, we obtain the following lemma.

Lemma 4: In the auction, if the seller j wins via bidding $\hat{A}_j$ or A_j, when the bid set and the ask set except only A_j are the same, the payment rewarded to seller j is the same for both bids.

Now we prove the truthfulness of TDAP for buyers as well as sellers.

Theorem 3: TDAP is truthful for buyers.

Proof: Suppose V_i^j is the truthful bidding for buyer i^j, and let $\hat{B}_i^j$ be the deceptive bidding when $\hat{B}_i^j \neq V_i^j$. The following cases are to be considered, corresponding to whether buyer i^j wins or loses.

- Case I: Buyer i^j loses by bidding $\hat{B}_i^j$, then his utility is 0. If buyer i^j provides its truthful bid, we know his utility will be non-negative (≥ 0) by Theorem 1.
- Case II: Buyer i^j wins by bidding $\hat{B}_i^j$. (1) If he also wins by bidding V_i^j, then the utilities for both cases are the same because the charged price does no change by Lemma 3. (2) Now if buyer i^j loses by bidding V_i^j. If i^j loses in stage I (Algorithm 1), we have $(V_i^j < B_{p_\mu}^{q_\mu})$ or $(V_i^j \geq B_{p_\mu}^{q_\mu} \& A_j > A_k)$. In the former situation, the charged price for i^j is no less than $B_{p_\mu}^{q_\mu}$ by Lemma 3, and thus his utility will be negative when bidding $\hat{B}_i^j$. In the latter situation, no matter how buyer i^j changes the bid, he cannot win by Algorithm 1 and thus this situation does not exist. If i^j loses in stage II (Algorithm 2), it must be the situation where the bid V_i^j is less than or equal to the highest bid in $\mathcal{B}^j$. Let $B_{i_{(1)}}^j$ be this highest bid. Now if buyer i^j wins by bidding $\hat{B}_i^j$, the charged price will be $B_{i_{(1)}}^j$, and thus the utility will be ≤ 0.

In summary, in both cases, no other bidding is better than the bidding of truthful valuation. ■

Theorem 4: TDAP is truthful for sellers.

Proof: The proof is similar to that in Theorem 3 and thus we omit here to save the paper space. ■

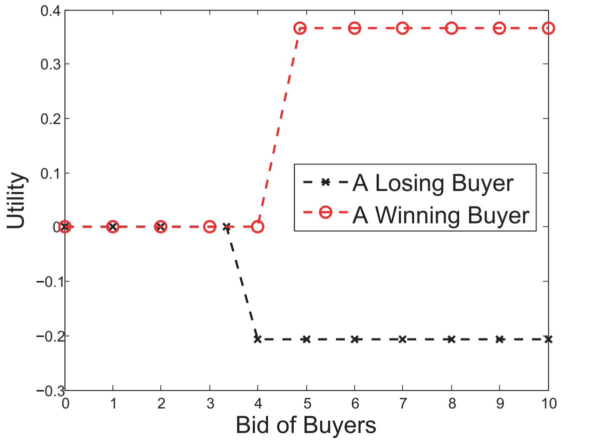

FIGURE 3. The utilities of a buyer in auction.

Based on Theorem 3 and 4, we directly get:

Theorem 5: TDAP is truthful.

Now we analyze the computational complexity of TDAP.

Theorem 6: TDAP runs in time $O(NM \log(NM) + NM^2)$, where N is the number of buyers and M is the number of sellers.

Proof: In the first stage, the number of virtual buyer in $\mathbb{B}'$ is at most NM. Thus sorting $\mathbb{B}'$ takes $O(NM \log(NM))$ time, and sorting $\mathbb{S}$ takes $O(M \log M)$. The two for loops in line 8 and line 11 takes $O(NM)$ and $O(M)$, respectively. In the second stage, there are at most $\lceil \frac{M}{2} \rceil$ sellers in $\mathcal{S}_c$ and at most $N\lceil \frac{M}{2} \rceil$ virtual buyers in $\mathcal{B}_c$. Then the first for loop in line 4 takes $O(N\lceil \frac{M}{2} \rceil \lceil \frac{M}{2} \rceil) = O(NM^2)$ time. For the sorting process in line 11, it takes $O(\lceil \frac{M}{2} \rceil N \log N) = O(NM \log N)$ time. In summary, TDAP takes $O(NM \log(NM) + NM^2)$ time in total. ■

VI. PERFORMANCE EVALUATION

In this section, we conduct comprehensive simulations to evaluate the performance of the proposed auction mechanism.

A. SIMULATION SETUP

We assume femtocell access points scatter within an area of 100×100. MUEs intend to purchase ACPs within this area. In practical system, the bid valuation of MUEs for different femtocells is dependent on the location information and the quality of access. However, in this section, the bids are randomly distributed over $(0, V_{max}]$, where V_{max} is set to 4 in most of experiments. Similarly, we assume the sellers' asks are randomly distributed over (0,2]. We implement the mechanism in Windows 7 with Intel Core i5-2520 CPU 2.5GHz using Matlab 2011b. And we select $k = \lceil \frac{M}{2} \rceil$.

We evaluate the performance of TDAP from different aspects, including *truthfulness*, *system efficiency* and *computational cost*.

B. TRUTHFULNESS

To verify the truthfulness of TDAP, we need to show no bidders can improve their utilities by bidding untruthfully.

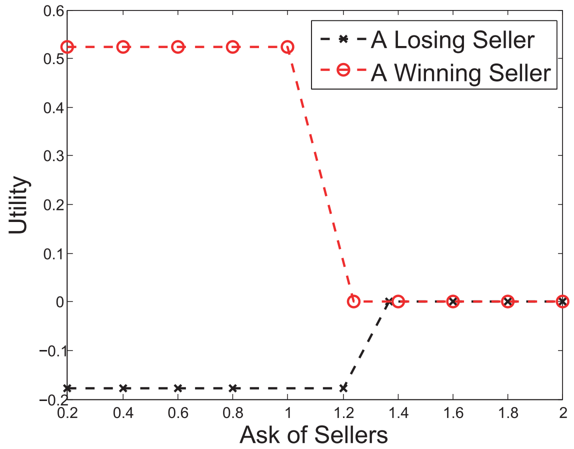

FIGURE 4. The utilities of a seller in auction.

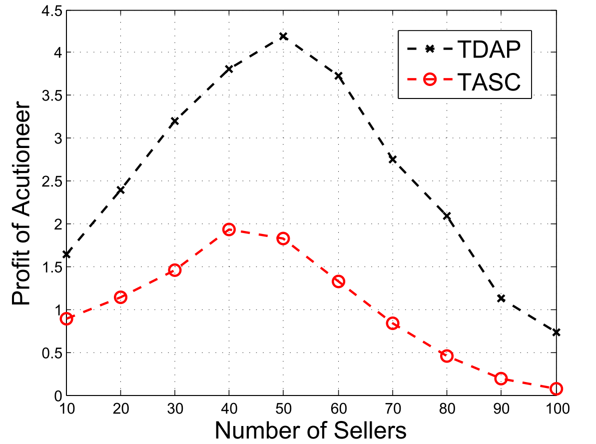

FIGURE 6. Evaluate the system efficiency in terms of auctioneer's profit.

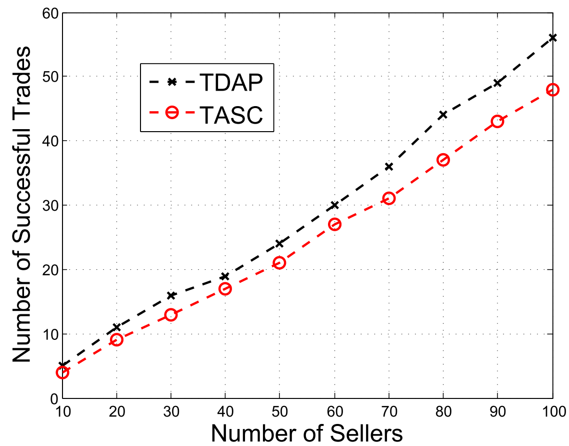

FIGURE 5. Evaluate the system efficiency via examining the number of successful trades.

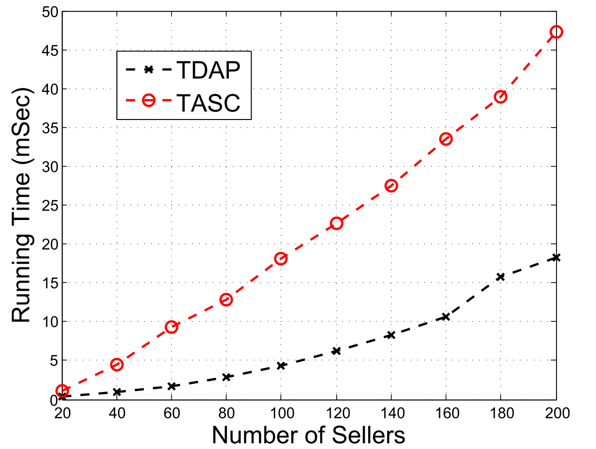

FIGURE 7. The running time of TDAP and TASC varies on the number sellers.

Therefore, one buyer and one seller is randomly picked (we repeat this examination over 100 times), and then examine how their utilities change with his bid or ask. We show the results in Fig. 3 and Fig. 4. In Fig.3, a buyer will obtain positive utility when bidding higher than its truth valuation, but cannot improve its utility by bidding untruthfully. Another losing buyer will get negative utility when bidding higher than its true valuation. In summary, no matter what other bids it takes, buyers cannot improve the utility. Similar observation can be also found for sellers from Fig. 4

C. SYSTEM EFFICIENCY

The system efficiency of TDAP is evaluated in the aspect of the total auctioneer's profit as well as the number of successful trades. We implement the proposed TASC [18] for our scenario and compare TDAP with TASC for better understanding the system efficiency of TDAP. For a fair comparison, in this evaluation, the bids and asks are uniformly distributed over (0, 1]. Fig.5 shows the number of successful trades of two mechanisms. The results show that TDAP outperforms TASC. This is because TDAP includes much more winning buyer candidates and creates competition between buyers, while TASC needs to sacrifice one buyer-seller pair to guarantee the truthfulness [18].

In addition, we compare TDAP with TASC in terms of the auctioneer's profit, which is defined as the difference between sum of winning buyers' prices and sum of winning sellers' payments. The results in Fig.6 show that TDAP can significantly improve the profit of the auctioneer when compared with TASC. This is because the charged price for each buyer and the payment for each seller is equal for all buyer-seller pairs in TASC, and they are the same in most cases. In addition, when the number of sellers increases, the profit is approaching 0 since with more sellers joining in the auction, the probability that $P^b = P^s$ is becoming higher. While in TDAP, competition between winning virtual buyer candidates increases the charged prices.

D. COMPUTATIONAL EFFICIENCY

We now evaluate the computational cost of TDAP and TASC by computing the running time in different scenarios. The time complexity of TASC is $O(\mathcal{T} + l^3)$, where $\mathcal{T}$

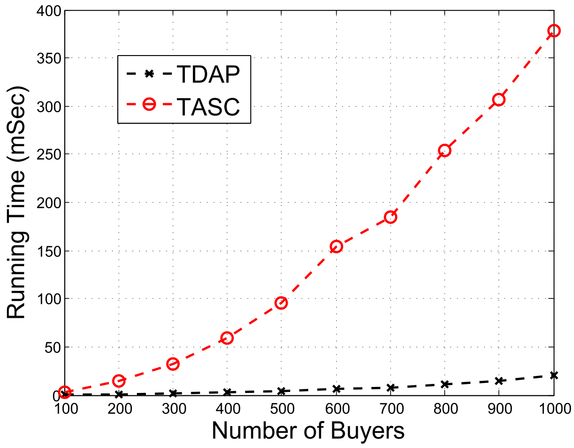

FIGURE 8. **The running time of TDAP and TASC varies on the number buyers.**

is the time complexity of relay assignment algorithm and $l = \min\{N, M\}$. We implement TASC choosing the maximum weighted matching algorithm with time complexity of $O((N+M)^2 \log(N+M) + (N+M)NM)$ [32]. Firstly, we fix the number of buyers $N = 100$, and then vary the number of sellers. The results are shown in Fig.7. We observe that TDAP performs better than TASC since TASC takes time to run the relay assignment algorithm. Secondly, we consider the different situation of fixing the number of sellers $M = 20$, then vary the number of buyers. The results are shown in Fig.8. From the results, we observe that TASC takes much more time when N increases quickly. In both cases, the results show that TDAP runs in a polynomial time concerning N and M, and performs better.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, after studying the general market model for promoting femtocell access where multiple femtocells compete to trade their ACPs to multiple MUEs, we propose TDAP, a truthful double auction mechanism for access permission allocation to promote the system performance. TDAP is shown to be economic-robust and efficient. In addition, through extensive experiments, we show that TDAP can highly improve the auctioneer's profit and the number of successful trades, as compared to the state of the art of double auction mechanism. TDAP adopts a novel strategy where each buyer is treated as multiple virtual buyers, and a buyer with multiple virtual buyers can win multiple ACPs from different sellers. In our future work, we will make TDAP cover the case where one buyer can only match one seller.

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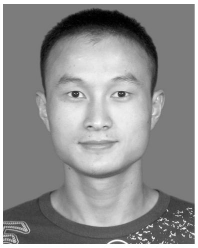

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