Service Enterprise Integration, Cheng Hsu (ed.), Kluwer, New York, 2006, pp. 131-156

Chapter 8

AUCTIONS AS A DYNAMIC PRICING MECHANISM FOR E-SERVICES

Juong-Sik Lee and Boleslaw K. Szymanski
Optimaret Inc. and Department of Computer Science, Rensselaer Polytechnic Institute, 110 8th Street, Troy, NY 12180, USA

Abstract: Increasing role of services in developed economies around the world combined with ubiquitous presence of computer networks and information technologies result in rapid growth of e-services. Markets for e-services often require flexible pricing to be efficient and therefore frequently use auctions to satisfy this requirement. However, auctions in e-service markets are recurring since typically e-services are offered repeatedly, each time for a specific time interval. Additionally, all e-services offered in an auction round must be sold to avoid resource waste. Finally, enough bidders must be willing to participate in future auction rounds to prevent a collapse of market prices. Because of these requirements, previously designed auctions cannot work efficiently in e-service markets. In this chapter, we introduce and evaluate a novel auction, called *Optimal Recurring Auction (ORA),* for e-services markets. We present also simulation results that show that, unlike the traditional auctions, ORA stabilizes the market prices and maximizes the auctioneer's revenue in e-service markets.

Key words: e-commerce; e-services; dynamic pricing; recurrent auction; bidder drop.

1. INTRODUCTION

In recent years, expansion of electronic markets (abbreviated as e-markets) triggered an increase in the role and importance of efficient pricing mechanism. In many existing e-markets, fixed pricing or static time-differential pricing mechanisms are used because of their simplicity. There is, however, a natural variation in buyer's demand over time. For this reason, such pricing mechanisms are inefficient as they result in under-utilization of resources when demand is low and under-pricing when demand is high.

A static time differential pricing mechanism in which two or more tiers of on/off peak rates are used can improve efficiency by partially matching lower (higher) demand with lower (higher) price. However, this mechanism still remains inflexible, since demands of buyers do not follow a step function, but rather gradually shift from on- to off-peaks and back[15].

A continuously adjustable dynamic pricing mechanism that adapts to changing market conditions constantly is more efficient. It maintains high resource utilization and the seller's revenue in variety of market conditions. The low price invoked by the adaptive pricing increases competition during the low utilization period. High prices imposed during the high demand period increase the seller's revenues. Moreover, with such a mechanism, the price itself becomes an important signal for controlling fair allocation of resources. Hence, by ensuring that prices match the current market conditions, fully adjustable dynamic pricing mechanisms creates optimal outcomes for both buyers and sellers. At the same time, this very dynamism of pricing makes seller's pricing decisions and buyers' budget planning difficult. An auction mitigates such difficulties, since prices emerge from the buyer's willingness to pay[4]. Additionally, using auction as a dynamic pricing mechanism in e-markets, thanks to their well defined rules and procedures, eases the difficulty and cost of the implementation of the automated negotiations in electronic environments[3]. As a result, the portion of the e-commerce markets that use auction is rapidly increasing.

Thanks to auction's inherent negotiation nature, there have been several attempts to extend application domain of auctions to newly arising markets for e-service, including computational services, bandwidth and network resource allocation, Internet advertisements and so on. However, because of idiosyncrasies of e-service markets, applying traditional auctions in these markets creates several problems. In this chapter we identify such idiosyncrasies and discuss their consequences and we introduce a novel auction design that addresses these idiosyncrasies. Consequently, the chapter is organized as follows. In section 2, we survey existing types of auctions and their use in e-markets. Section 3 describes emerging e-service markets and analyzes their properties together with the requirements for designing optimal auctions for those markets. A novel auction satisfying these requirements is introduced in Section 4. The simulation based verifications of this mechanism are given in Section 5. We conclude the chapter with the summary of its content in Section 6.

2. AUCTIONS AND RELATED WORK

Auctions have been widely used from ancient times have been one of the most popular market mechanism used to match supply with demand. They achieve this goal by allowing buyer and seller to agree on a price of a resource following the well defined rules and procedures[4]. There are two types of players in an auction. One is a bidder and the other is an auctioneer.

Bidder reports bid information to the auctioneer in order to buy or obtain the rights for resources traded in auction. The bid information may consist of price alone or price combined with other attributes such as quality of goods, time of their delivery, etc. Usually, the bid information is mapped onto a single value that we will refer to as 'bid value'. Auctioneer is an agent that creates and clears an auction. Hence, auctioneer opens the auction for bidding and then collects the bids, closes the auction and then selects the winners, and finally distributes resources to the winners and collects the payments.

In General Auction, buyers become bidders and the seller is an auctioneer. In Reverse Auction this is the single buyer that becomes an auctioneer while many sellers become bidders.

2.1 Classification of auction types

Based on number of bidding sides, auctions can be classified as single or double ones[3,6,7]. In a single auction, participants can take part only in one side of an auction (e.g., as a buyer). In a double auction, participants are free to take part in both side of an auction. The single auctions can be further subdivided open-cry and sealed bid. For open-cry auctions the common types are English and Dutch auctions, while sealed bid auction are further classified into First Price (FPSB) and Second Price (SPSB) auctions based on pricing. In English, Dutch and FPSB auction, a winner pays his bidding price. On the other hand, in SPSB auction, also known as Vickrey auction, a winner pays the second highest bidding price. Auctions with multiple units of resources traded are classified based on pricing rules differently. In Discriminatory Price Sealed Bid (DPSB) auction, winners pay their bid price. In Uniform Price Sealed Bid (UPSB) auction, all winners pay the same price which is the highest bidding price of losers. Finally, in Generalized Vickrey Auction (GVA), the price of a winner k is computed by deducting the sum of payments of all other bidders in the current resource allocation from the sum of the payments that would be obtained from those other bidders in the optimum allocation where the bidder k removed from the allocation[18]. GVA is an incentive compatible, direct auction in which true valuation bidding is a dominant strategy (i.e., the strategy that, when followed, maximizes each bidder's expected utility).

English auction is widely used to sell various tangible resources such as art, collectables, electronic devices, and so on. The Dutch auction is used for selling traditional perishable resources such as fresh-cut flowers and fish. The sealed bid auction type that includes FPSB, SPSB, DPSB, and UPSB auctions is widely used in procurement that employs reverse auction.

Double auctions allow multiple buyers and sellers to be present concurrently in the market. Thus, double auction must match bid prices on both sides of the market. Double auctions can be divided into Call Market and Continuous Double Auction (CDA) based on their clearing time and bidding methods. In Call Market, bids are collected for a specific time interval from both sellers and buyers in a sealed manner. Then, bids are matched at the auction clearing time. In contrast, in CDA, auction is continuously cleared each time a new bid (which is delivered in an open-outcry manner) is delivered. The Call Market and CDA are common mechanisms for financial markets, such as stock exchange.

All the above auction types use bids that comprise only of price. In contrast, Multiple-Attribute Auction, also called Multidimensional Auction, allows bidders to bid on various attributes beyond the price. Since the auctioneer selects winners based on all bidding attributes, the overall utility of a bid must be computed and vast number of utility functions has been proposed for such computation. Generic procedures for multi-attribute auction in electronic procurement have been described in references 3 and 8.

Finally, so far we discussed the auctions in which each bidder bids for a single unit of the resource. In Combinatorial Auction, each bidder offers a bid price for a collection of goods (of the bidder's choosing), rather than placing a bid on each item separately. This enables the bidder to express dependencies and complementarities between goods. The auctioneer selects such a set of these combinatorial bids that result in the most revenue without assigning any object to more than one bidder**.** However, the computational complexity of optimal winner selection that maximizes auctioneer's revenue is very high[9].

Table 2-1. Classification of types of auctions

Criterion	**Types**
Number of items per bid	Single; Many (**Combinatorial**)
Bid Attributes	Price; Many (**Multi-attribute**)
Number of winners	One; Many
Bidding method	Open-cry; Sealed; Sealed
	English; **Dutch**
Pricing	**First**; **Second**; **DPSB**; **UPSB**; **VCG**

2.2 General procedure of an auction

A typical auction execution can be described by the six-step processes shown in Figure 2-1.

1) Bid Collection and Validation collects the bids that could be either firm (i.e., not revisable or cancelable) or changeable under predefined rules. Any set of predefined rules can be used for eligibility of the bid and bidder to participate in relevant auction, including but not limited to, legal restrictions, credit limits on particular bidders, bidders' budget limits, bid expiry, minimum/maximum bid amounts and sizes, etc. Cancellation of bids that do not meet such requirements comprises the validation portion of the procedure.

2) Auction Close occurs once a specific set of circumstances are met, as defined by the auctioneer. These could include time elapsed, receipt of sufficient bids, availability of resource, or any other conditions relevant to the specific application. Once an auction closes, bids are not be changeable.

3) Valuation and Bid Ranking operates after the auction round closes. The bid ranking procedure computes bid value for each bid collected and eligible for participation according to any specific rules. The most basic auctions equate the bid value with the price of the bid. The final result of this

procedure is the list of bidders ranked according to the values assigned to their bids.

4) Resource Ranking ranks all resources available for allocation in the given round according to their intrinsic value, which may be identical or different for each resource. A resource can be placed in any arbitrary order with respect to other items from which its intrinsic value cannot be differentiated. Although generally, the ranking reflects differences in intrinsic value of each individual unit of the resources, any relevant factors can be used to assign rank order to the resources based on the specific application. An example is a seat in the theater, where the distance from the stage and the visibility of the stage impacts the intrinsic value of a seat.

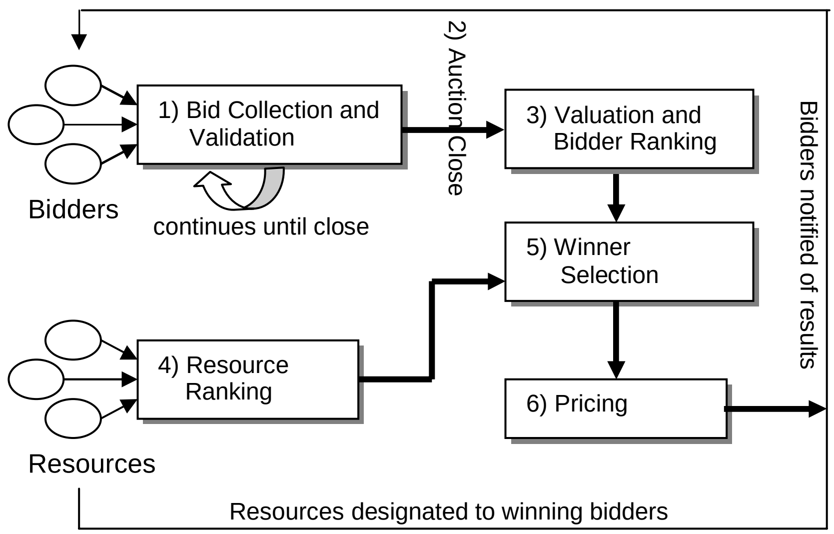


Figure 2-1. General procedures of auction

5) Winner Selection defines the way of allocating or mapping ranked resources offered in the market with specific bidders based on predefined rules. The most general winner selection method is to allocate available resources from the highest bid value bidder up to the number of available resource in decreasing order of bid values.

6) Pricing computes the payments that are charged to the winners for the allocated resources, after the winners are selected in the winner selection procedure. As discussed above, the two main variants of pricing method in the current state of the art are to pay the bid price (also known as first

pricing) or the bid price of the next highest bidder (also known as second pricing).

2.3 Auction design requirements

One of the important design requirements for the basic auctions is to maximize seller's revenue. An auction that satisfies this requirement is called the '*optimal auction*'[10]. In designing auction for e-markets, the following additional requirements should be considered[3].

- Incentive compatibility: An auction is incentive compatible if bidding true valuation maximizes the expected utility for the bidder (i.e., it is the dominant strategy). This property makes implementation of agent-based automated negotiations simple.

- Efficiency: In an efficient auction, the resources are allocated to the bidders who value them the most.

- Individual rationality: The expected payoff of each bid made by a bidder is nonnegative.

- Low cost convergence to the agreement: In an electronic auction, the communication overhead of conducting negotiations and arriving at the agreement should be minimized. An auction in which a bidder can communicate with the auctioneer directly (i.e., via the sealed bids) will be called direct. Direct auctions have low communication overhead.

SPSB and UPSB auctions are incentive compatible, efficient and direct, so they are well-suited for various applications in e-markets.

2.4 Auctions in current e-markets

Recently, a vast number of auctions have been conducted over the Internet. Forester Research forecasts that auctions in e-markets will grow from $13 billion in 2002 to $54 billion in 2007[17]. Current e-markets can be classified as B2C (Business to Customer), C2C (Customer to Customer), B2G (Business to Government), and B2B (Business to Business) markets. In B2C and C2C market, English auction is the most popular auction type since it provides simple negotiation structure, and is particularly well suited for negotiation for short time period. Additionally, bidders enjoy placing bids in competition with others, and this entertainment value of the online English auction is an important feature in customer oriented markets[3]. In B2G and

B2B markets, sealed bid auction types (i.e., FPSB, SPSB, DPSB, or UPSB auctions) are widely used. Those markets rely on a procurement process that requires ‘Reverse Auction’.

Typically, resources traded in those e-markets are physical goods such as collectibles including antiques, stamp, coins, electronic equipments, real estate, used equipments, etc[13].

3. EMERGING E-SERVICE MARKETS

E-service is defined as a modular, nimble, Internet-based service that most often requires various computational resources such as bandwidth, computational cycles or memory to guarantee the Quality of Service (QoS)[15,19,20]. Wide-spread access to the Internet and dominance of service-oriented segment make e-services a fast growing segment of economy. Customer-centric nature of e-service[19], favors auction as a pricing mechanism for e-services markets.

3.1 Markets for application computing services

Recently, the interests in and demands for application computing services (ACS), including on-demand computing, utility computing, grid computing and so on, have been growing rapidly[12,21]. With the development of grid computing infrastructures, the fully implemented application computing services provide a transparent access to a wide variety of large scale geographically distributed computational resources (i.e., CPU, memory, storage, etc.). Hence, markets for ACS are the one of the most important e-markets.

The ACS buyers demand desired computing services, and the ACS providers temporarily allocate the necessary computer hardware and software resources to the buyer’s application to produce the desired results[22]. This is radically different from the traditional approach in which the customer buys the hardware and licenses the software for lifetime ownership. Hence, application computing services bring new business model of outsourcing computer operations. For efficient contracting in such a market, the ACS providers need a tool for expressing their pricing polices and mechanisms that can maximize their profits and the computational resource utilization. Various auction based mechanisms, based either on reverse or general auctions, have been proposed for this role[11,12].

In reverse auction, a ACS buyer (i.e., auctioneer) invites sealed (or open-outcry) bids from several ACS providers by advertising his desired application computing service and the required quality of service, such as time constraints, including the deadlines for receiving the results. The buyer selects the bid that offers lowest service cost and satisfies all the constraints. The selected winner provides the computing service and then returns the computing result to the buyer at his bid price.

In general auction, an ACS provider invites bids from many ACS buyers (i.e., bidders) for application computing services. Based on the auction mechanism used and on the current conditions of distributed computational resources, the ACS provider selects the winners and clears the auction. Auctions used in this area often require that the bid based proportional resource sharing model is followed, in which the amount of computing resources allocated to each bidder is proportional to the value of his bid[11].

3.2 Analysis of emerging e-services markets

Different market structures and properties require different dynamic pricing and negotiation mechanisms for efficient resource allocation and revenue maximization. Hence analysis and characterization of newly created markets is one of the necessary conditions for designing efficient solution.

The e-service markets can be characterized as “recurring markets using short-term contracts”, because the resources such as computational and network resources are renewable and their allocations to bidders are made for specific time only[15]. Hence, short-term contract is often used in those markets. Such short-term contracts are recurring, because when the allocated renewable resources become free, the auctioneer needs to offer them to the bidders again. Short-term contracts are recurring also from the bidder’s perspective, since each bidder repeatedly enters into them for a specific time interval. This solution provides financial benefits to both sides. Buyers avoid long-term contracts and outsource resources required for service[19,20]. On the other hand, sellers increase resources utilization and increase their revenue via dynamic pricing of such short-term contracts.

In addition to recurring nature, time sensitive perishable property of traded resources (i.e., the fact that unused resources perish) in e-service markets is another important factor. The resources needed for the services cannot be stored in warehouse for future sale, and leaving them unused decreases their utilization[15]. Therefore, the e-service markets need a mechanism optimizing *recurring auction trading perishable resources*.

The previous designs for auction focus on one-time auction for selling physical resources that often can be stored for future sale[2,4,5,6,7,8,10]. Hence, they do not address recurring nature and perishable property of the resources in emerging e-service markets. These two features strongly affect the bidder's bidding behavior and the revenue of the auctioneer. Hence, application of existing basic auctions to e-service markets may result in the following problems.

3.3 Bidder drop problem

Prices bid in an auction reflect willingness of each bidder to pay. This willingness in turn is limited by the bidder's (private) true valuation that is influenced by each bidder's wealth. An uneven wealth distribution can cause starvation of poor bidders in a recurring auction if their true valuations are below winning price. A frequent starvation for the traded resources decreases the bidder's interest in the future auction rounds. In such a situation, if some bidders conclude that it is impossible or unlikely that they will win at the price that they are willing to pay, they will drop from the future auction rounds and find other markets. In a recurring auction, each bidder's drop out of an auction decreases the number of active bidders in the future rounds. Reducing the number of bidders gradually decreases the price competition because the probability of winning increases for the remaining bidders. Hence, their attempts to decrease bidding prices without losing the winning position will be successful causing the overall drop of bid prices. In the long run, when the number of bidders drops close to the number of resources, the revenues of the auctioneer are likely to drop below the acceptable level.

This phenomenon is particularly acute in incentive compatible auctions, such as SPSB auction or UPSB auctions, in which bidder who lost in the previous auction round can easily conclude that his true valuation is not high enough to ever become a winner as all bidders bid their true valuations. Hence, there is no incentive for the loser of the last auction round to participate in the current and future rounds. In fact, continued participations would result in negative expected utility to losers who value their time. Consequently, the losers will immediately drop out of the auction. These dropped bidders decrease the average second highest bid or highest bid of losers. Such decrease results in collapse of auctioneer's revenue. We call this phenomenon '*paradox of incentive compatible mechanism in recurring auction*' because by having the bidders bid their true valuations, this kind of auction motivates low bidding bidders to drop immediately[24]. To the best of our knowledge, the bidder drop problem that is caused by the uneven wealth distribution has been first addressed by our work[15,16,23,24].

3.4 Resource waste problem

In addition to bidder drop problem, the asymmetric balance of negotiation power needs to be considered in auction design. The prices bid in a basic auction are dependent only on the bidder's willingness to pay. This means that intentions of only bidders, but not the auctioneer, are reflected in the auction winning prices. To restore the symmetric balance of negotiating power, the reservation price (RPA) and cancelable (CA) auctions were proposed[10,14]. In RPA, only bids higher than the auctioneer's reservation price are considered during winner selection. On the other hand, in CA, if the resulting revenue of an auction round does not meet the minimum requirement of the auctioneer, the entire auction round is cancelled. By providing reservation price or cancellation option to the auctioneer, the asymmetric negotiation power problem is resolved. However, when the perishable resources are traded, both of these auctions cause resource waste. In RPA, the reservation price restricts the number of winners. Hence, the resources unused because of this restriction are wasted. In CA, the cancellation of an auction round wastes the entire stock of resources that are allocated to this auction round.

4. OPTIMAL RECURRING AUCTION

Based on the additional requirements for designing auctions for e-services markets, we introduce a novel auction called **O**ptimal **R**ecurring **A**uction (ORA). The main idea of this mechanism is based on the demand-supply principle of microeconomics[1].

In Figure 4-1, D1 and D2 denote demand curves for the traded perishable resources while S1 and S2 represent supply levels of the resources. When the overall demand decreases (i.e., the entire demand curve changes from D1 to D2) during a recurring auction, the minimum market clearing price drops from p1 to p2 to maintain the supply at level S1. In such a case, to maintain the minimum market clearing price at p1, an auctioneer must decrease the supply of resources from q1 to q2. Inversely, when the overall demand increases, the auctioneer may increase the supply while keeping the same clearing price.

When the auctioneer decreases the supply of perishable resources for the given time period, the unsold resources are wasted. Thus, to avoid such waste we propose to assign the “unsold” perishable resources (q1–q2 in Figure 4-1) to the bidders who have high probability of dropping out of the forthcoming auction rounds. Such an assignment prevents bidders from dropping out of auction thereby keeping enough bidders in the recurring auction to maintain the competition for resources strong. Simultaneously, using “unsold” perishable resources for bidder drop control resolves the resource waste and increases the number of winners.

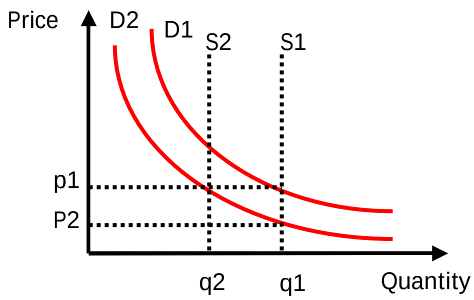


Figure 4-1. Demand and supply principle

To implement this idea, we introduced two types of ORA mechanisms. The first one is the Participation Incentive Optimal Recurring Auction (PI-ORA) that pursues incentive compatible mechanism, and the second one is the Discriminatory Price Optimal Recurring Auction (DP-ORA) that is based on a non-incentive compatible mechanism. From the pricing point of view, PI-ORA uses a variation of a uniform pricing scheme while DP-ORA uses a discriminatory pricing scheme. To describe the proposed auctions, we first define here the basic notions of bidders, bidding prices, and resources.

Players: There are $n+1$ players, denoted by $i=0,...,n$, including n bidders, $i=1,...,n$, and an auctioneer $i=0$. An auctioneer and each bidder enter the bidding price b_0 and $b_1, b_2, ..., b_n$, respectively, in each auction round. We also assume that each bidder is risk neutral and has private true valuation t_i for traded resources.

Resources: There are R units of perishable resources that are assigned for a specific time period in each auction round. We assume that each bidder requires one unit of a resource for the desired quality of e-service. Hence, the maximum number of possible winners in each auction round is R.

4.1 Classification of Bidders in ORA

The first step of the winner selection strategy in ORA is to define bidder's class based on each bidder's bidding price b_i, where $i = 1, ..., n$ and auctioneer's bid price (i.e., reservation price) b_0. The auctioneer classifies the bidders into the Definitely Winner (DW), Possible Winner (PW), and Definitely Loser (DL) classes using the following conditions:

$$\begin{array}{lll} i \in DW & \text{if} \;\; b_i \geq b_0 \;\&\; r_i > n - R, & i = 1, 2, ..., n, \\ i \in DL & \text{if} \;\; b_i \leq 0, \;\; i = 1, 2, ..., n, & \\ i \in PW & \mathit{otherwise}, & \end{array} \qquad (1)$$

where r_i denotes the rank of bidder i in the increasing order of bidding prices of all bidders. The numbers of bidders in the DW, PW and DL classes are denoted as N_{dw}, N_{pw} and N_{dl}, respectively. Figure 4-2 shows the bidder's classes in ORA and compares them with the classes in the traditional auctions where Traditional Losers (TL) and Traditional Winner (TW) classes are defined. WPPW represents the Winning Portion of the PW class, and the number of winners in the PW class is denoted by N_{wppw}. Hence, $N_{wppw} = R - N_{dw}$.

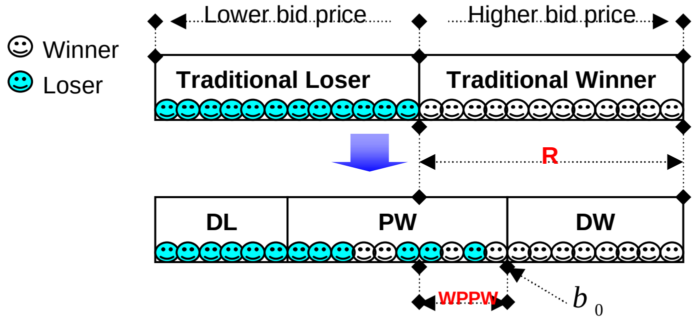


Figure 4-2. Classification of bidders in ORA

In each auction round, the DW class bidders become winners without any additional considerations, since they bid higher than the bid price of the auctioneer and there are enough resources to assign one to all of them. The DL class consists of bidders who already dropped out of the auction. Hence the DL class bidders become losers in each auction round. The bidders who are in the PW class can be winners or losers depending on the bidder drop control algorithm applied, described below (see Sections 4.2.1 and 4.3.1).

The auctioneer's bidding price b_0 in the ORA mechanisms plays the same role as the reservation price does in the Reservation Price Auction. Hence, ORA maintains symmetry of the negotiating power from lack of which the traditional auctions suffer.

4.2 Participation Incentive Optimal Recurring Auction

In PI-ORA, we introduced the following participation incentive bidder drop control algorithm to efficiently select winners in PW class.

4.2.1 Participation Incentive Bidder Drop Control

Enough bidders of PW class must participate in future auction rounds to maintain price competition in the recurring auction. To encourage such participation, the Participation Incentive Bidder Drop Control (PI-BDC) algorithm rewards bidder's participation in each auction round using the following winning score S_i^k for each bidder $i \in PW$:

$$S_i^k = \frac{b_i^k}{\alpha} \cdot B_i - W_i \quad , \qquad (2)$$

where B_i and W_i denote the cumulative weighted number of times that bidder i participated in and won, respectively, in auction rounds up to and including the current one. The outcome of the current auction round is yet unknown and the credit for participation is at most 1. B_i is defined as $B_i = \frac{1}{b_i} \sum_{j=1}^{m} \min(b_{i,j}, b_{i,m})$, where m represents the current auction round and $b_{i,j}$ denotes the bid price of bidder i in auction round j (this price is zero in rounds that the bidder skips). This definition encourages the bidders to bid the same price in each auction round, as this is the only way in which a bidder can receive a full credit of 1 for participation in an auction round.

The term $(b_i^k / \alpha) \cdot B_i$ denotes expected number of wins based on the bidding price and the participation in the past rounds. Thus, the winning score S_i^k of a bidder i in class PW represents the difference between the expected and real number of wins. Hence, the PI-BDC algorithm is based on the insight that higher the winning score of a bidder is, higher the probability of him dropping out of the future rounds is because more below his expectations his winning are. For this reason, the PI-BDC algorithm ranks bidders of PW class in the decreasing order of their winning scores and up to N_{wppw} highest ranked bidders are selected as winners of the current auction round. α in equation (2) is a coefficient that controls the expected number of wins (i.e., win frequency). The optimal value of α depends on seller's strategy and true valuation distributions of the bidders. We set the value of α in such a way that the average value of winning score of all bidders is zero. Since in each auction round all bidders in PW class increase their winning scores cumulatively by $\sum_{j\in PW} b_j^k / \alpha$ (assuming that each bidder uses the same bid as in the previous round) and at the same time their winning scores decrease cumulatively by $R - N_{dw}$ wins, the balancing value is $\alpha = \sum_{j\in PW} b_j^k / (R - N_{dw})$. With this value, the win frequency of each bidder $i \in PW$ with bid price b_i is defined as follows:

$$w_i = \frac{b_i^k \cdot (R - N_{dw})}{\sum_{j\in PW} b_j^k} \tag{3}$$

To differentiate between DW and PW classes, win frequency w_i should be less than 1 for all bidders in PW class, which restricts the feasible values of k and the feasible size of PW class.

As shown in Figure 4-3, in traditional auctions, the win probability of a bidder outside the Traditional Winner class is zero. Hence, there is no incentive for bidders whose true valuations are in the range of bids of member of the Traditional Loser class to participate in the future auction round in incentive compatible auctions. However, in PI-ORA, the win probabilities of bidders in the PW class, including part of the Traditional Loser class, are higher than zero. For this reason, there is an incentive to participate for all bidders in the PW class regardless of their true valuations.

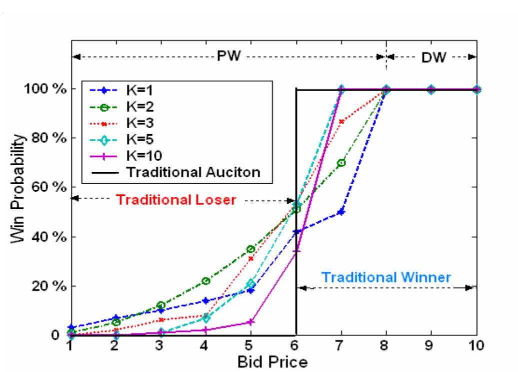


Figure 4-3. Win frequency distribution in PI-ORA

4.2.2 Pricing rules and optimal reservation price

In PI-ORA, winners in the DW and PW classes pay the price $p(b_i) = \rho \cdot \min(b_i, b_0)$, where ρ denotes payment coefficient. The value of the payment coefficient ρ that leads to incentive compatible mechanism and revenue maximization is restricted by the following condition:

$$\rho \leq \frac{k}{k+1+t_{\max PW}^{k} / s} \tag{4}$$

where *maxPW* is the index of the highest bidder in PW class, $s = \sum_{j \neq \max PW, j \in PW} b_j^k$ and, k is a constant used in Eq. (2). Hence, based on bidder's bidding price distribution, the auctioneer selects the optimal payment coefficient ρ, the auctioneer's reservation price b_0 and the constant k that satisfy the payment coefficient condition (4), as well as maximize the revenue. Since $\rho < k/(k+1)$, PI-ORA guarantees that each winner pays less than his bidding price.

4.2.3 Optimal strategies for bidders

The bidder's optimal strategy involve deciding to participate or not in the auction and in participation case, deciding the bidding price. In the reference 24, we proved that under proper selection of parameters k, b_0 and ρ, bidding each bidder's true valuation maximizes his utility in both PW and DW classes. Thus, PI-ORA is an incentive compatible auction. Likewise, participation incentive bidder drop control algorithm makes participation in as many as possible auction rounds a strategy that maximizes the expected utility. In conclusion, the bidder's optimal strategy in PI-ORA is to bid his true valuation (making the mechanism incentive compatible) and to participate in as many as possible auction rounds (see [24]).

4.3 Discriminatory Price Optimal Recurring Auction

In DP-ORA, we introduced the following Valuable Last Loser First Bidder Drop Control algorithm to select winners in PW class efficiently.

4.3.1 Valuable Last Loser First Bidder Drop Control

The purpose of selecting winners in the PW class is to encourage them to stay in the auction. Hence, those winners should include those bidders in the

PW class who are considering dropping out of the auction. This insight is the basis for the Valuable Last Loser First Bidder Drop Control (VLLF-BDC) algorithm. The algorithm consists of two phases. In the first one, bidders who lost in the last auction round but bid in the current round the price higher than in the previous one are marked as potential winners. The marked bidders are ranked according to their bidding prices and up to N_{wppw} highest ranked marked bidders are selected as winners of the current auction round. If the number of the marked bidders is smaller than N_{wppw}, the remaining resources are allocated in the second phase of the algorithm in the decreasing order of their bidding prices.

The winner selection in the first phase is dictated by the bid price and winning record of the previous auction round, so there could be some loss of fairness. To compensate for it, in the second phase, the highest bidding unmarked bidders in the PW class are selected as winners of the remaining resources. By marking only those last losers who bid higher in the current round than in the previous one, the algorithm prevents bidders with low bidding patterns from becoming winners.

5. ORA VERIFICATION VIA SIMULATION

5.1 Simulation Experiments with PI-ORA

In simulations of PI-ORA, we compare the following four different auctions those are all incentive compatible mechanisms. Each one is executed 2000 times recurrently.

- *UPSB auction*: Here, we use the basic uniform price sealed bid auction that has no bidder drop control, so bidders are allowed to drop out of auction at any time.

- *UPSB-NBD auction*: This case uses the basic UPSB auction but with bidders never dropping from the auction, regardless of their results.

- *PI-ORA*: As described above, PI-ORA uses PI-BDC algorithm in winner selection of PW class.

- *PI-ORA-NBD*: Here, we use the PI-ORA mechanism with no bidder dropping out of auction during recurring auction, regardless of possible starvation.

The results of simulating UPSB-NBD and PI-ORA-NBD are used only to obtain upper bounds on the auctioneer's revenue since assuming no bidder drop is unrealistic. The wealth of each bidder limits her willingness to pay defined by the true valuation of a unit of resource. For this reason, we equate wealth distribution with a distribution of bidder true valuations. In the simulations, we consider three types of those distributions, all with the mean of 5: (1) the exponential distribution, (2) the uniform distribution over [0, 10] range, and (3) the Gaussian distribution. Once the true valuations are allocated to bidders, they do not change during recurring auction.

There are 40 bidders in our simulations and 20 units of perishable resources are available for allocation. Hence, there are 20 winners in each auction round. According to the bidder's dominant strategy and risk neutral assumption, each bidder bids his true valuation in each auction round in order to maximize his expected utility. Additionally, bidders participate in auction continuously until they drop out of the auction. Once out of the auction, the bidder never returns to it.

We define Tolerance of Consecutive Loss, abbreviated as TCL, to simulate bidders' drop out of the auction. The bidder's TCL denotes the maximum number of consecutive losses that a bidder can tolerate before dropping out of an auction. TCL of each bidder is uniformly distributed over the range of [2, 10]. If consecutive losses of a bidder exceed his TCL, then the bidder drops out of the auction and never returns to it. The TCL is set to the number larger than the number of auction round simulated for the UPSB-NBD and PI-ORA-NBD cases.

Our simulations collect data on the auctioneer's revenue and mechanism efficiency and stability in response to bidder drops. We use the average payment of winners in each auction round as a measure of auctioneer's revenue. The revenue comparison between original auction and no bidder drop assumption case is used only to measure the mechanism stability. We also measure the total number of wins of each bidder to gauge the efficiency.

As shown in Figure 5-1, the traditional UPSB auction cannot maintain the auctioneer's desired revenue in a recurring auction because the losers of each auction round have no incentive to participate in future rounds so they drop out of the auction. This is the result of phenomena that we termed the 'paradox of an incentive compatible mechanism in a recurring auction'. Since bidders reveal their true valuations in each bid, bidders learn their ability to win and those who cannot win drop out the auction. The decreased price competition for the remaining winners results in a plunge of the auction clearing price (i.e., highest price of losers), which quickly becomes zero). After 10 auction rounds (that is also the upper bound on the TCL value in our simulations), the auction clearing price collapses to 0, since every loser dropped out of the auction. Therefore, in the basic UPSB auction, the bidder drop problem is the sole cause of the seller's revenue collapse.

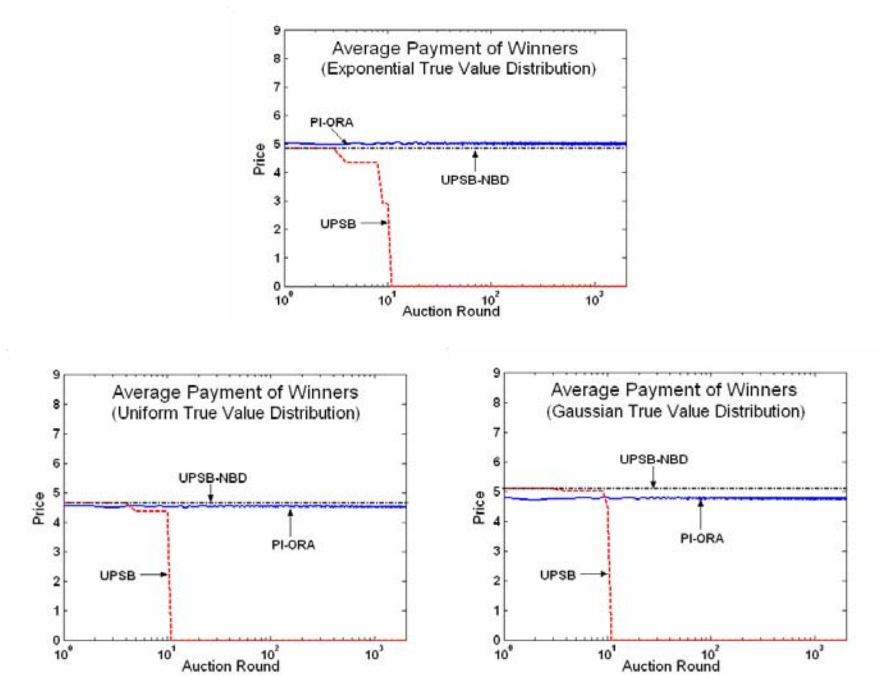
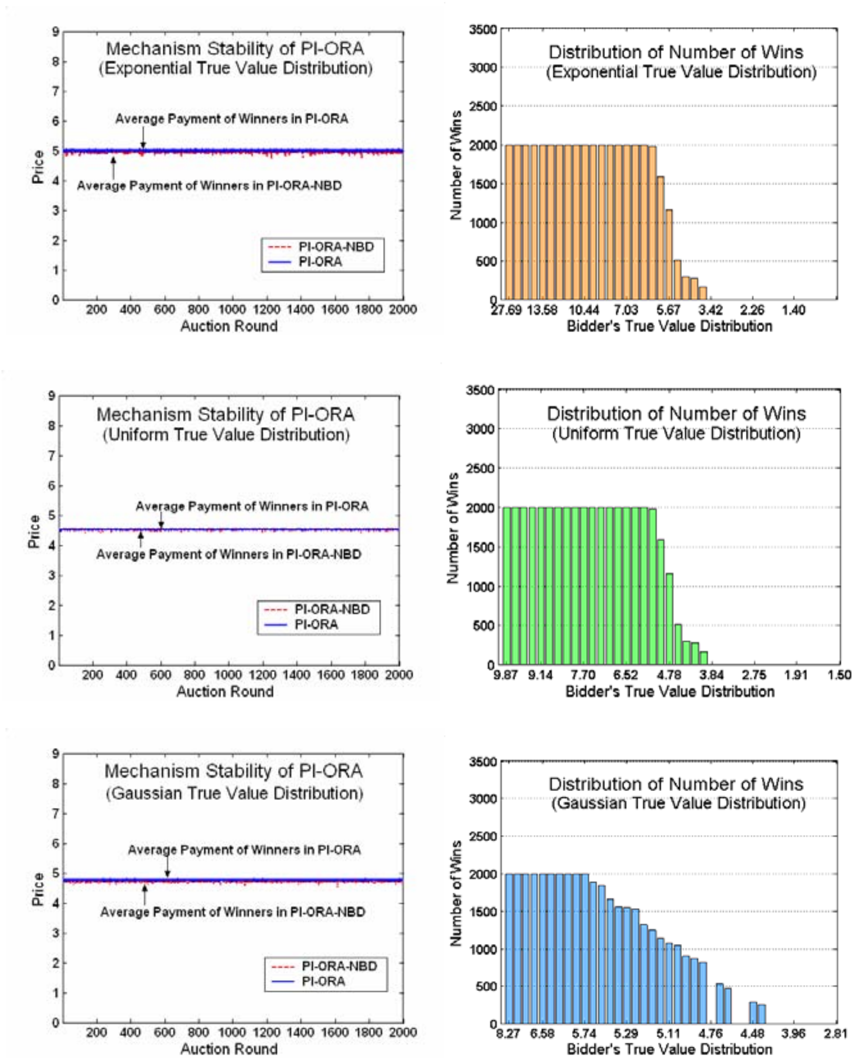


Figure 5-1. Average payment of winners in PI-ORA

An efficient bidder drop control based on PI-BDC algorithm of the PI-ORA supports auction participation of bidders in the PW class and therefore maintains the price competition between bidders in the DW and PW classes permanently. Additionally, by optimally selecting the payment coefficient ρ, the optimal auctioneer's bidding price b_0, and the constant k from Eq. (2), the auctioneer can stabilize and maximize the revenue regardless of the bidder true valuation distribution. The resource waste problem never arises, because the entire stock of available perishable resources is sold in each auction round.

The average payment of winners in PI-ORA and PI-ORA-NBD in each auction round are almost the same, as shown in Figure 5-2 (a) for various true valuation distributions. This indicates that the efficient bidder drop control algorithm makes the PI-ORA stable.



(a) Stability (b) Efficiency

Figure 5-2. Mechanism stability and efficiency

The simulation results also show that PI-ORA is efficient. As shown in Figure 5-2 (b), it distributes the total number of available perishable resources proportionally to each bidder's true valuation. Thus, the bidder who has the higher true valuation and, thus, higher actual payment for the perishable resource, wins more often than the one with the lower true valuation and lower actual payment (under the same participation level). The win distributions of Figure 5-2 (b) also show that the bidders whose bidding prices (i.e., true valuations) are too low are eliminated from the auction automatically by exceeding the number of consecutive losses defined by their TCL. Hence, even though some resources are allocated to the bidders in PW class, the truly low bidders do not impact the revenue of PI-ORA.

5.2 Simulation Experiments with DP-ORA

In simulation of DP-ORA mechanism, we compare the following five auctions based on 2000 round recurrent executions:

- *DPSB auction*: In this case we simulate basic discriminatory price sealed bid auction that has no bidder drop control. Hence, bidders drop out of the recurring auction as a result of starvation for resource allocation.

- *DPSB-NBD*: This case represents an idealized DPSB auction in which bidders never drop during the recurring auction even if they suffer constant consecutive losses.

- *Reservation Price Auction (RPA)*: This is the case of the DPSB auction with reservation price. Hence only the bidders who bid price higher than reservation price can be winners.

- *Cancelable Auction (CA)*: This is another variant of the DPSB auction in which the auctioneer cancels an auction round when the projected revenue does not meet his expectation.

- *DP-ORA*: This case represents DP-ORA with the VLLF-BDC algorithm.

There are 100 bidders in our simulations. The sealed bidding assumption makes each bidder's bidding behavior independent of others. Hence, in a recurring auction, the bidding behavior is influenced only by the results of the previous auction rounds, i.e., the win/loss decision informed to each bidder. Based on the assumption of risk neutral bidders, each bidder will attempt to maximize its expected profit. All the above considerations motivated us to assume the following bidding behavior. If a bidder lost in the last auction round, she increases her bidding price by a factor of $\alpha > 1$ to improve her win probability in the current round. The increase of bidding price is limited by the true valuation. If a bidder won in the last auction round, she, with equal probability of 0.5, either decreases the bidding price by a factor of β or maintains it unchanged. The decrease attempts to maximize the expected profit factor in each bidder's utility. α and β are set in the simulations to 1.2 and 0.8, respectively. The minimum bidding price of each bidder is 0.1. If a bidder drops out of an auction, his bidding price is set to 0. There are 50 units of perishable resources available for allocation in each auction round. Hence, the maximum number of winners in each auction round is 50. If the resulting revenue of an auction round is lower than 250, the auction round is cancelled in CA. All other aspects of simulation scenarios, such as distributions of true valuation or TCL are same as in PI-ORA scenarios. Hence, we set the reservation price for RPA as 5.0.

The simulations of DP-ORA collect data on the auctioneer revenue and resource allocation fairness. The auctioneer's revenue is proportional to the average bidding price of winners in each auction round, so we use the latter as a measure of the former. We also measure the number of wins for each bidder in 2000 rounds of the recurring auction. The resulting distribution is a metric of fairness, because higher bidding bidders should be more frequent winners than the lower bidding ones.

Fairness of DPSB-NBD is optimal, because a bidder with the bid higher than a winner is also a winner. Additionally, by the no bidder drop assumption, DPSB-NBD never looses a bidder with high willingness to pay and low TCL. This means that DPSB-NBD prevents the loss of fairness that may result from the low TCL. Thus, we can measure the loss of fairness of DPSB, RPA, CA and DP-ORA by their degree of deviation from the fairness of DPSB-NBD.

As shown in Figure 5-3, under, various wealth distributions (i.e., true valuation distributions), DPSB cannot maintain the auctioneer's desired revenue. The inevitable bidders' drops decrease the price competition between bidders who remain in the auction. Accordingly, the remaining bidders try to decrease their bidding price in the forthcoming auction rounds to maximize their expected profit. In the long run, the revenue of each auction round plunges to a very low level (i.e., below 1.0), compared to the auctioneer's desired minimum cost (here 5.0). Therefore, in DPSB, an inevitable bidder drop problem is the dominating factor that decreases the auctioneer's revenue, because there are no wasted perishable resources.

In RPA, the revenue of auctioneer is mainly decreased by the resource waste problem. The bidder drop effect is small in this case, because the reservation price prevents the winners from decreasing their bidding price to the very low level. However, RPA does not avoid the resource waste problem. 28.6%, 28.0% and 34.2% of resources are wasted during 2000 recurrent auction rounds in exponential, uniform and Gaussian distributions of true valuation, respectively. As a result, the auctioneer cannot achieve her desired revenue in a recurring auction of this type.

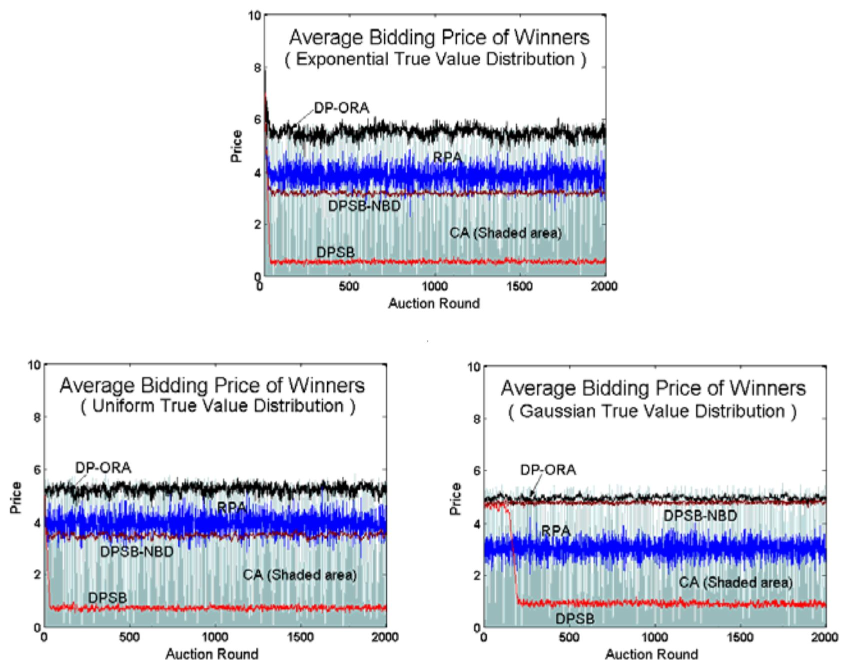


Figure 5-3. Average bidding price of winners in DP-ORA

CA suffers from the same problem as RPA. By canceling auction, CA can prevent remaining bidders from decreasing their bidding price to the very low levels. However, in cancelled auction round, the entire 50 units of perishable resources that are assigned to the auction round are wasted. 23.5%, 32.9% and 34.8% of resources are wasted during 2000 recurrent auction round in exponential, uniform and Gaussian distribution of true valuation, respectively. For this reason, the resources wasted in the cancelled auction rounds prevent the auctioneer from achieving the desired revenue. Figure 5-4 shows amount of the resource waste in exponential true valuation distribution in each auction round of RPA and CA.

DP-ORA is able to maintain price competition permanently in a recurring auction thanks to the VLLF-BDC algorithm. Moreover, in DP-ORA, the resource waste never arises, because the entire stock of perishable resources is sold in each auction round. Therefore, the auctioneer can preserve nearly optimal level of the revenue. Additionally, the bidders whose bid prices are too low are eliminated from the auction automatically based on their TCL. Hence, even though VLLF-BDC algorithm allocates resources to the PW class whose members bid lower than member of the DW class, the low true valuation bidders cannot impact auctioneer's revenue in DP-ORA.

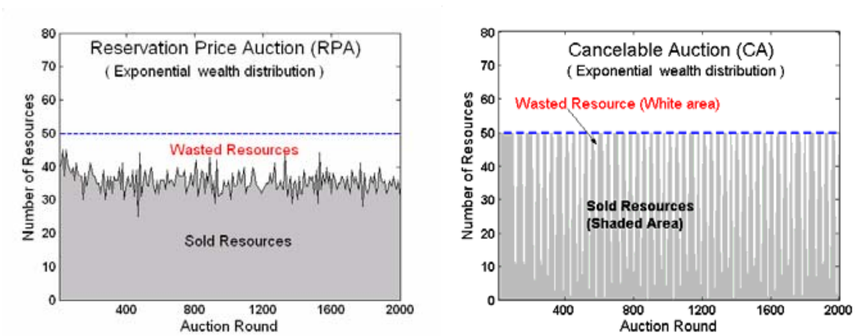


Figure 5-4. Resource waste in RPA and CA

Remarkably, the loss of fairness in DP-ORA is lower than the one observed in DPSB, RPA and CA under all simulated wealth distributions of bidders. This phenomenon results from the fact that DPSB, RPA and CA cannot prevent the loss of fairness caused by high true valuation bidders dropping out of an auction as a result of exceeding their TCLs. In other words, DPSB, RPA and CA cannot prevent a bidder who is willing to pay high prices but has low TCL from dropping out of an auction because he may exceeds his TCL at some auction round. In each auction round, DPSB, RPA and CA have highest possible fairness, because their winners are selected by the current bidding price only. Yet, remarkably, DP-ORA has lower loss of fairness over the entire recurring auction because loss of fairness that results from TCL is the dominating factor in the long run. The specific results measuring the loss of fairness under various bidder wealth distributions are provided in Table 5-1.

Table 5-1. Loss of fairness

Auctions	Exponential	Uniform	Gaussian
DPSB	34.6 %	23.9 %	29.4 %
CA	33.5 %	32.9 %	33.4 %
RPA	30.0 %	28.9 %	41.8 %
DP-ORA	9.4 %	6.0 %	11.9 %

We also simulated the more general case of an auction in which a bidder who dropped out can return when the winning price becomes sufficiently low. For this case, the simulation results show that the revenue of the auctioneer settles somewhere between the revenues of DPSB and DPSB-NBD because those are the border cases of the general one. The revenue of the DPSB case sets the lower bound for the revenues in the general case because there are no bidders returning during the recurring auction. The revenue of DPSB-NBD sets the upper bound because all bidders return immediately to the recurring auction in that case.

In summary, DP-ORA can achieve the increased revenue and the decreased loss of fairness in the recurring auction for perishable resources by resolving the bidder drop problem and the resource waste problem.

6. SUMMARY OF THE CHAPTER

As the current e-market paradigm evolves towards e-service oriented markets, auctions used in such e-services markets are recurring and trade perishable resources. During such auctions, bidders can drop out of an auction at any time. Since an auction relies on a competition based dynamic pricing mechanism, keeping bidders interested in participating in the auction stabilizes the market by preventing a collapse of the price competition. Hence, the bidder drop problem is one of the most important aspects of the designing winner selection strategies for the recurring auction. The resource waste is another problem that needs to be considered in such context.

In this chapter, we introduced two optimal recurring auctions for e-services markets: the Participation Incentive Optima Recurring Auction (PI-ORA) that is incentive compatible, and the Discriminatory Price Optimal Recurring Auction (DP-ORA) that is not. In PI-ORA, each bidder's participation is rewarded by increase in his win frequency. In DP-ORA, the auctioneer allocates a resource to a bidder before he drops out of the auction. Such bidders are identified on the basis of their bid prices and history of wins in the recurring auction. Therefore, the ORA mechanisms using bidder drop control algorithms encourage participation of bidders in the recurring auction and therefore stabilize the e-service markets using short-term contracts and increase auctioneer's revenue in such markets.

REFERENCES

1. R. H. Frank and B.S. Bernanke, "Principle of Economics: 2nd edition", McGraw Hill, New York, 2004.
2. V. Krishna, Auction Theory, Academic Press, San Diego, 2002

3. M. Bichler, “The Future of e-Markets: Multidimensional Market Mechanism”, Cambridge University Press, 2001.
4. R. McAfee and P.J. McMillan, “Auction and Bidding”, Journal of Economic Literature, 25:699 – 738, 1997.
5. W. Vickrey, “Counter speculation, Auction, and Competitive Sealed Tenders”, Journal of Finance, 16(1), March 1961.
6. Agorics, Inc., "Going, Going, Gone! A Survey of Auction Types", available at http://www.agorics.com/Library/auctions.html
7. M.P. Wellman, W.E. Walsh and P.R.Wurman, “Auction Protocols for Decentralized Scheduling”, Game and Economic Behavior, (35), 271-303, 2001.
8. M. Bichler, M. Kaukal, and A. Segev, “Multi-attribute auctions for electronic procurement”, Proc. 1st IBM IAC Workshop on Internet based Negotiation Technologies, Yorktown Heights, NY 1999.
9. T. Sandholm, “Approaches to winner determination in combinatorial auctions”, Decision Support System, 28 (1):165 - 176.
10. J.G. Riely and W.F. Samuelson, “Optimal Auction”, The American Economic Review, 71(3):381 - 392, June 1981.
11. B. Chun and D. Cullar, “Market based proportional resource sharing for cluster”, Technical Report, University of California, Berkeley, September 1999.
12. R. Buyya, D. Abramson, and J. Giddy, “A Case for Economy Grid Architecture for Service-Oriented Grid Computing”, Proc. 15th International Parallel & Distributed Processing Symposium, 2001.
13. D. L. Reiley, “Auctions on the Internet: What's Being Auctioned, and How?”, Journal of Industrial Economics, 48(3): 227-252.
14. A. Fiat, A.V Goldberg, J.D. Hartline , and A.R. Karlin, “Competitive Generalized Auction”, Proc. 34th Annual ACM symposium on Theory of Computing, 2002.
15. J. S. Lee, and B. K. Szymanski, “A Novel Auction Mechanism for Selling Time Sensitive E-Services”, Proc. 7th International IEEE Conference on E-Commerce Technology 2005 (CEC’05), Munich, Germany, 2005.
16. J. S. Lee, and B. K. Szymanski, “Stabilizing Market via A Novel Auction based Pricing Mechanism for Short-Term Contracts for Network Services”, Proc. 9th IFIP/IEEE International Symposium on Integrated Network Management (IM2005), Nice, France, 2005.
17. C.A. Johnson, “Commentary: The boom in online auctions”, article by forester research, 2002, available at http://news.com.com/2009-1069-962530.html
18. H. Varian, “Economic Mechanism Design for Computerized Agents”, Proc. Usenix Workshop on Electronic Commerce, New York, 1995.
19. R.T. Rust and P.K. Kannan, “E-Service: A New Paradigm for Business in the Electronic Environment”, Communication of the ACM, Vol. 46, No. 6, 2003.
20. A. Tiwana and B. Ramesh, “e-Service: Problems, Opportunities, and Digital Platforms”, in proceeding of the 34th Hawaii International Conference on System Science, 2001.
21. M.A. Rappa, “The utility business model and the future of computing services”, IBM System Journal, Vol. 43, No. 1, 2004.
22. L.J. Zhang, H. Li and H. Lam, “Service Computing: Grid Applications for Today”, IEEE IT Pro, July-August 2004, pp 5-7.
23. J. S. Lee and B. K. Szymanski, “An Analysis and Simulation of a Novel Auction-Based Pricing Mechanism for Network Services”, Technical Report TR-05-02, Department of Computer Science, Rensselaer Polytechnic Institute, Jan. 2005.
24. J. S. Lee and B. K. Szymanski, “Network Service Resource Allocation via Participation Incentive Auction for Non-Cooperative Customers”, submitted to *JSAC*, May 2005.