RECURRENT AUCTIONS IN E-COMMERCE

By

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ACKNOWLEDGMENT

"TO MY LOVELY WIFE HAESOO, MY PRINCESS EUNICE AND MY MOTHER"

I would first like to thank my advisor, Claire and Roland Schmitt Distinguished Professor Boleslaw K. Szymanski, who has encouraged and mentored me throughout my doctoral study. Additionally I also thank all of my committee members: Prof. Christopher Carothers, Prof. Mukkai Krishnamoorthy and Prof. T. Ravichandran. Finally, I would like to thank my mother for her supports and her belief in me. I would also like to thank my lovely wife Haesoo for her dedication to me and my daughter Eunice who is a constant source of my happiness.

ABSTRACT

Recent developments of information technologies are causing shift from fixed pricing to dynamic pricing mechanisms in electronic marketplaces. The latter can improve revenue and resource utilization. However, the dynamism makes seller's price decision and buyer's budget planning difficult. Auction based dynamic pricing and negotiation mechanism can resolve such difficulties because price emerges from buyer's (i.e., bidder's) willingness to pay. Thanks to these advantages and inherent negotiation nature, the application domain of auction as dynamic pricing and negotiation mechanism covers service oriented electronic short-term contract marketplaces. Auctions in such markets are recurring since the contracts must be offered repeatedly for specific time intervals. In such recurring auction, uneven wealth distribution of bidders causes the least wealthy bidders to persistently lose auction rounds that motivate them to drop out of recurring auction. This bidder drop problem arises also in the traditional combinatorial winner selection strategy that only focuses on revenue maximization. The bidders dropping out of an auction decrease price competition and may cause a collapse of market price. At the same time, all available resources for fulfillment of electronic services must be sold in each auction round to avoid waste of resources. For these reasons, the previously designed traditional basic auction mechanisms may not be efficient in such service oriented electronic marketplaces.

To overcome these problems, this thesis proposes and evaluates novel auction mechanisms for selling short-term contracts in service oriented electronic marketplaces. For homogeneous market structure in which bidders' requirements are homogeneous, we propose a Participation Incentive Optimal Recurring Auction (PI-ORA) mechanism that is incentive compatible and a Discriminatory Price Optimal Recurring Auction mechanism that is not incentive compatible. Compared to the traditional basic auction mechanisms, the proposed mechanisms (i.e., PI-ORA and DP-ORA) stabilize the market prices and increase the auctioneer's revenue by preventing the bidder drop problem and avoiding the resource waste problem. Additionally, the proposed mechanisms achieve better long-term fairness of resource allocations. For markets in which bidders'

requirements are heterogeneous, we propose and evaluate a Participation Incentive Generalized Vickery Auction (PI-GVA) mechanism. Compared to the traditional Generalized Vickery Auction mechanism, the proposed PI-GVA mechanism prevents market price collapse and stabilizes the market by a novel combinatorial winner selection strategy in which bidder’s participation is directly rewarded.

The three proposed mechanisms also achieve other desirable properties for auction mechanism such as light communication overhead needed to reach agreement between auctioneer and bidders, the simple bidder’s optimal strategy that is desirable for implementing an auction in electronic environments, and the distributed resources allocation.

1. INTRODUCTION

1.1 An Auction as a Dynamic Pricing Mechanism

In recent years, with the development of information technologies and expansion of electronic marketplaces, the role and importance of efficient pricing mechanism has been constantly increasing. In many existing electronic marketplaces, fixed pricing or static time-differential pricing mechanisms are widely used because of their simplicity. However, there is a natural variation in buyer’s demand over time. For this reason, those pricing mechanisms are inefficient. They lead to under-utilization of resources when demand is low and under-pricing when demand is high. In a static time differential pricing mechanism two or more tiers of on/off peak rates 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 [54].

A continuously adjustable dynamic pricing mechanism that adapts to changing market conditions constantly is more efficient. It can maximize resource utilization and the seller’s revenue in variety of market conditions. During low utilization period, low price invoked by the adaptive pricing can increase competition. During the high demand period, high prices increase the seller’s revenues. Moreover, with such a mechanism, the price itself becomes an important signal of controlling fair resource allocation. Hence, by ensuring that prices match current market conditions, fully adjustable dynamic pricing mechanisms create a favorable outcome for both buyers and sellers. However, this very dynamism of those pricing mechanism makes seller’s pricing decision and buyer’s budget planning difficult. An auction mechanism mitigates those difficulties since the price emerges from the bidder’s (buyer’s) willingness to pay. Hence, auctions eliminate the need for defining a dynamic pricing structure from the seller’s point of view and prices are decided by buyer’s side from the buyer’s point of view.

Auctions that have been used from ancient times are one of the most popular market mechanisms used to match supply with demand today. They achieve this goal by allowing buyers and sellers to establish a mutual agreement on the product or service price, and the corresponding allocation of resources to participants is governed by the well established rules and procedures.

Additionally, using auction as a basic dynamic pricing mechanism in electronic market environments yields the following benefits:

- *A simplified pricing mechanism:*

  An auction based pricing mechanism is easily understood by market participants - both the buyers (bidders) and the sellers (auctioneer).

- *A decentralized pricing:*

  Prices emerge from the buyer's valuation of resources and are determined by the market on the basis of the demand and supply.

- *Compatibility with automated negotiations:*

  Negotiations are an important part of commercial activities in physical and electronic market environments based on dynamic pricing mechanism [3]. Well defined rules and procedures of an auction mechanism ease the difficulty and cost of the implementation of the automated negotiations in electronic environments.

1.2 Challenges of Auction Mechanisms

Accompanying the recent expansion of electronic environments, including the Internet, is the growth in use of various auction mechanisms as tools for dynamic pricing and automated negotiations in electronic commerce markets. The fraction of electronic commerce marketplaces that use auction mechanism is rapidly increasing. Additionally, thanks to the auction's inherent negotiation nature[1], application domain of auction mechanisms have been extended to newly arising markets. Of particular interests to this thesis are service oriented electronic marketplaces such as the ones for network services, grid computing services (including utility computing services), and so on. An auction in such markets is in fact a recurring auction, because allocation of service oriented resources is made for a specific time only, and once the allocated resources become free, the seller (i.e., auctioneer) needs to offer them to the buyers (i.e., bidders) again. Moreover, the resources are perishable, that is the unused resources cannot be stored for future use and are lost if unused. The computational power and the network bandwidth are examples of such resources, as are the airplane seats or concert tickets.

We have observed that applying traditional auction mechanisms to such newly created service oriented electronic marketplaces may result in an inevitable starvation for resources for certain bidders based on their valuation of the resources because of recurring nature of the marketplaces. Frequent starvation may decrease bidder's interests in participating in an auction. As a result, the affected bidders may decide to drop out of the future auction rounds, thereby decreasing the long-term demand for the traded resources. Since an auction is non-cooperative competition based dynamic pricing and negotiation mechanism, the lowered demand will lead to the collapse of the value of bids that win an auction round and the resulting auctioneer revenue. The conclusion is that to stabilize revenues in a recurring auction for perishable resources, the auctioneer must prevent price collapse that requires controlling the supply of resources and solving the *bidder drop problem*. This thesis identified this problem and also attempts to resolve it by introducing novel auction based dynamic pricing and negotiation mechanisms.

1.3 Scope of the Thesis

The scope of this thesis is defined in terms of the market structure and properties of the traded resources of the newly arising service oriented electronic marketplaces. As

[1] The various aspects of an inherent negotiation nature of auction mechanisms are discussed in several references. see for example [2, 8, 10, 26].

shown in Table 1.1, a market structure can be classified based on the number of participants, the number of traded resources and the kinds of these resources [3]. This thesis focuses on markets in which there are one-to-many participants (i.e., one seller and many buyers) and multiple units of homogeneous or heterogeneous resources. In markets trading homogenous resources, buyers' requests are homogeneous (for example, bidders request the same number of resource units). On the other hand, in markets for heterogeneous resources, the buyers make heterogeneous requests (for example, each bidder requests the different number of resource units).

From the traded resource perspective, this thesis focuses on developing auctions for multiple units of perishable resources that are sold recurrently for a specific time interval. Hence, multiple winners are selected for a specific time period, an auction round, but the resources that are not sold can not be stored for future sale, and perish for the corresponding round.

Number of Participants	**Traded Resources**			
	Single Unit		Multiple Units	
	Homogeneous	Heterogeneous	Homogeneous	Heterogeneous
1 to 1				
1 to N			√	√
M to N				

Table 1.1: The market structure classification

1.4 The Approach

This thesis focuses on developing novel auction mechanisms that can resolve challenges described in the previous section for newly created service oriented homogenous and heterogeneous electronic marketplaces. The auction mechanisms proposed in the thesis prevent potential revenue collapse by resolving bidder drop problem in the recurring auction. For homogeneous market structure, we propose the Participation Incentive Optimal Recurring Auction (PI-ORA) that is incentive compatible and the Discriminatory Price Optimal Recurring Auction (DP-ORA) that is not. We also propose the Participation Incentive Generalized Vickery Auction (PI-GVA) for heterogeneous markets.

The common idea underlying these three auction mechanisms is to providing rewards for bidder's participation in an auction round to maintain price competitions and prevent bidder drop. In PI-ORA mechanism, when a bidder participates in auction, its win probability in future auction rounds increases as its winning score grows. At the same time, the resources are allocated proportionally to the bidders' bids made during recurring auction. Hence, least wealthy bidders can be selected winners during recurring auction with win frequency proportional to their bids. In DP-ORA mechanism, the auctioneer allocates the traded resources into bidders likely to drop out of the auction based on their bids and track record of wins. In PI-GVA mechanism for markets with heterogeneous resources, auctioneer selects a combination of bidders' requests that maximizes the sum of winning scores of the selected bidders. Bidder's participation is rewarded by increasing its winning score in the forthcoming auction rounds and such increased winning score also increases the probability that the bidder will be included in the winning combination of bidders.

In additional to resolving bidder drop problem, our approach to designing novel auction mechanisms also attempts to minimize the overhead of communication needed to reach an agreement between the auctioneer and the bidders as well as to simplify the bidder's optimal strategy, so it could be implemented easily in agent based electronic environments.

1.5 Thesis Outline

This thesis focuses on providing efficient auction-based dynamic pricing and negotiation mechanisms for emerging service oriented electronic marketplaces. The reminder of the thesis is organized as follows.

In chapter 2, we define basic terms that are used in this document and we survey the existing basic types of auction mechanisms and their extended forms that are currently used in practice or were proposed in the literatures. We also define a general procedure common to all auction mechanisms, and analyze the bidders' bid behavior in terms of their risk management patterns. The guidelines for designing optimal auction mechanisms that aim at maximizing seller's revenue are also described in this chapter.

In chapter 3, we survey various newly arising service-oriented electronic marketplaces in which auctions can be used as a dynamic pricing and negotiation mechanism. We also analyze and define those properties of such marketplaces that affect the bid behavior of bidders and the revenue of an auctioneer.

In chapter 4, we discuss an observation underpinning the research that problems arise when traditional auction mechanisms are applied to newly arising service oriented electronic marketplaces. We define these problems for both homogeneous and heterogeneous markets. We also verify their existence by using a theoretical analysis and simulations of auctions in such environments.

In chapter 5, we propose two novel auction mechanisms that focus on resolving the discovered problems for markets for homogeneous resources: the **P**articipation **I**ncentive **O**ptimal **R**ecurring **A**uction (PI-ORA) that is incentive compatible and the **D**iscriminatory **P**rice **O**ptimal **R**ecurring **A**uction (DP-ORA) that is not. Various simulations and their analyses verify the observed desired properties of the proposed novel auction mechanisms.

In chapter 6, we define and analyze a potential market collapse problem that arises when the traditional combinatorial winner selection strategy is used in heterogeneous market with recurrent auction and perishable resources. To resolve this problem, we propose the **P**articipation **I**ncentive **G**eneralized **V**ickery **A**uction (PI-GVA) that rewards bidder's participation in the auction and stabilizes market prices by maintaining price competitions. We also verify the proposed auction mechanism by various simulations and analyses.

Finally, in chapter 7, we summarize the thesis and enumerate its contributions. We also define possible future research work.

2. BACKGROUND

2.1 Introduction

An auction is an efficient negotiation and dynamic pricing mechanism that resolves the , resource allocation problems in one-to-many and many-to-many market structures. For this reason, auction mechanisms are widely used in various electronic marketplaces. The technical infrastructure required to support an auction in an electronic environment is currently available and well accepted [54]. Additionally, the well defined rules and procedures of auction mechanism are easy to implement. To design optimal auction mechanisms for electronic marketplaces of interest to this thesis, appropriate basic auction mechanisms should be surveyed and analyzed first, what is done in this chapter.

In the next section, the basic definitions that are used in this thesis are provided. In section 2.3, basic auction mechanisms, widely used in various markets, are described. A general procedure of auction mechanisms is explained in section 2.4, and section 2.5 describes the requirements of optimal auction mechanisms that maximize the revenue of an auctioneer. The bid behavior of bidders is described in section 2.6. Finally, section 2.7 summarizes the chapter.

2.2 Basic Definitions

By the definition given by McAfee and McMillan, an auction is a market institution with an explicit set of rules matching supplies with demands for the traded resources[2], and determining prices on the basis of bids from the market participants [4]. There are two types of players in auction mechanism. One is a bidder and the other is an auctioneer.

- **Bidder:** Bidder makes their bids to the auctioneer to buy or occupy traded resources in an auction market. The bid may consist of a price alone or a price in combination

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[2] Traded objects are called resources, goods or products. In this paper, we uniformly use the term 'resources' in order to denote them.

with other attributes, such as quantity, delivery time, etc. Hence, we refer to a valuation of the entire bid that could be a combination of a price and other attributes as a ‘bid value’ in this document.

- **Auctioneer:** An auctioneer creates an auction, selects winners for traded resources and closes the auction by collecting the prices from and distributing resources to the winners.

From the market types perspective, various buyers (or customers) and sellers become bidders and auctioneers, respectively, in a general auction mechanism. In contrast, a buyer becomes an auctioneer and many sellers become bidders in a reverse auction mechanism. A person, a computerized agent, or a company such as a service provider can be bidders or auctioneers in an auction mechanism. The third parties, such as various types of brokers can also be auctioneer or bidders. Hence, in this document, we use the term ‘bidder’ to denote the buyer or bidders in general auction mechanism, and use the term ‘auctioneer’ to represent seller, or service provider in such a mechanism.

The bid of each bidder is dependent on the bidder’s valuation of the traded resource. Additionally, each bidder has the limit on her bids which is her valuation of the traded resources. This upper bound of a valuation of each bidder is called as the bidder’s ‘true valuation’ of the traded resource.

2.3 Types of Basic Auction Mechanisms

The commonly used basic auction mechanisms can be classified into the following two main categories based on the number of bidding sides: a single auction and a double auction [2,3,6]. In a single auction, participants can take part only in one side of an auction (i.e., be either an auctioneer or a bidder). In a double auction, participants are free to take part in both side of an auction. Figure 2.1 shows the classification of basic types of auction mechanism.

2.3.1 Single Auction Mechanisms

This type of auction can be divided into an open-outcry auction and a sealed bid auction based on bidding methods. In an open-outcry auction, the bids are open to public and bidders can adjust their bids in the full knowledge of other bids. In a sealed bid auction, only a bidder and the auctioneer can communicate with each other, and bidder to bidder communication is forbidden. The basic single auction sub-types with open-cry bid are English and Dutch auctions:

1) English auction

In an English auction, an auctioneer creates an auction market and proceeds to solicit in open successively higher bids from the bidders until no one raises the bid. The highest bidder is the winner and pays the price he/she bid.

2) Dutch auction

An auctioneer announces the bids to all bidders. The auctioneer starts the bidding at an extremely high price and then progressively lowers it until a buyer claims an item by calling "mine", or by pressing a button that stops an automatic clock. The winner pays the price bid at the stop time.

The English auction is widely used in offline and online environments to sell various resources such as art, collectables, electronic devices, and so on. The Dutch auction is used for selling traditional perishable resources such as flowers and fish. On the other hand, the basic single auction types with sealed bids include the First Price Sealed Bid (FPSB) auction and the Second Price Sealed Bid (SPSB) auction:

3) First Price Sealed Bid (FPSB) auction

In an FPSB auction, when a single unit of a resource is traded, each bidder submits one sealed bid in ignorance of all other bids to the auctioneer. The bidder with the highest bid is the winner of the auction and pays its bid for the single resource traded. When multiple units of resources are traded, sealed bids are sorted from the highest to the lowest, and items are allocated to the bidders in the decreasing order of the bids until all available resource items are allocated. The winners pay their bids, hence different prices for each item. This auction mechanism is known as '***Discriminatory Price Sealed Bid (DPSB)'*** auction [6].

4) Second Price Sealed Bid (SPSB) auction

An SPSB auction is similar to the FPSB auction, since each bidder submits one sealed bid and the highest bidder becomes the winner. However, the selected winner pays the price that is equal to the second-highest bid. This auction mechanism is also called the Vickrey Auction [5]. When multiple units of resources are traded, sealed bids are sorted from the highest to the lowest, and units of resources are allocated to bidders in the order of their bids until their supply is exhausted. The winners pay the highest bid among the losers. Hence, this type of auction mechanism is called a '***Uniform Price Sealed Bid (UPSB)***' auction mechanism [6].

Vickrey proved theoretically that the optimal bid that maximizes each bidder's expected utility in the SPSB auction is her true valuation [5]. This property is known as '*incentive compatibility*' which is very desirable for an auction mechanism that aims at maximizing the seller's revenue. The specific explanation of incentive compatibility is included in section 2.4 of this thesis. Vickrey also showed that the average expected revenue of the English auction, the FPSB auction and the SPSB auction are same in an IPV (Independent Private Value) model with risk neutral bidders [5]. This is also known as the 'revenue equivalence theorem'. The detail explanation of risk neutrality is given in section 2.4. The FPSB and SPSB auction mechanisms are widely used in procurement environments.

2.3.2 Double Auction Mechanisms

A double auction admits multiple buyers and multiple sellers concurrently into the market. Thus, the double auction must match bids of the both sides in the market. The double auction can be divided into two main classes based on the auction clearing time: Call Market and Continuous Double Auction (CDA). In a Call Market, bids are collected over 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, an 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 a stock exchange.

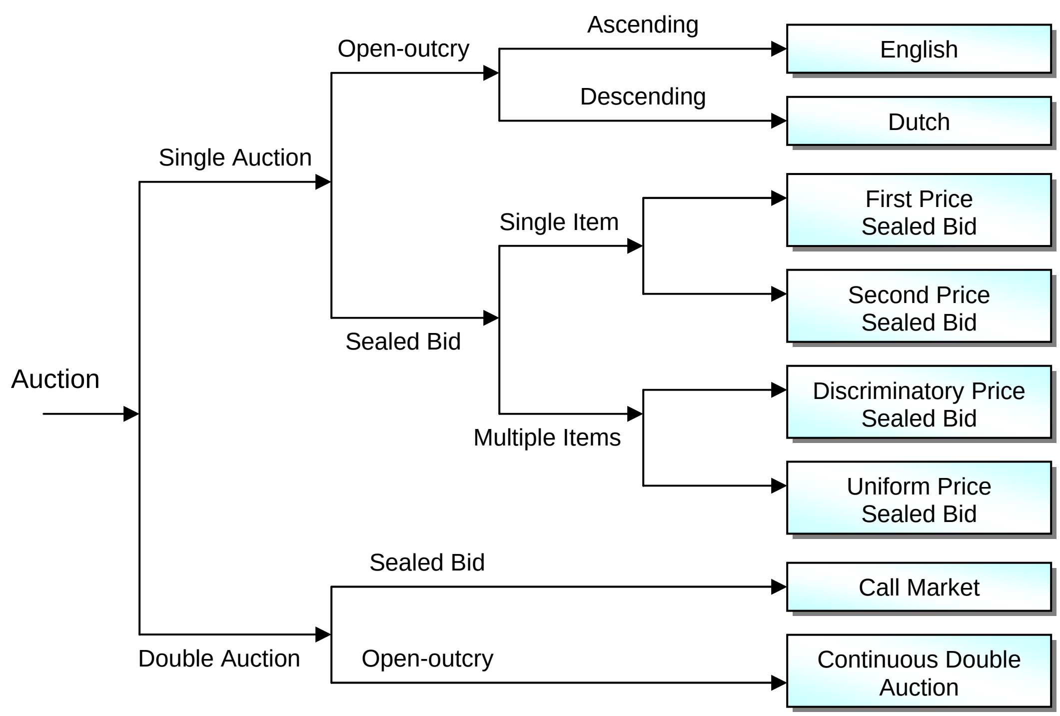

Figure 2.1: A classification of basic auction type

2.3.3 Extended Types of Auction Mechanisms

Beyond the described above classification of the traditional basic auction types, the following extensions to the basic auction have been proposed.

1) Multi-attribute Auction (MA)

A Multi-attribute Auction allows bidders to bid on various attributes beyond the price. In this type of an auction, the auctioneer selects winners based on the price as well as on those various attributes. Thus, the overall utility of a deal for the buyer must consider not only the price of the auctioning item, but also a combination of the different attributes. This difference is a major change from the traditional basic auction mechanisms which negotiate only on price. Bichler, et al describe generic procedures of a Multi-attribute Auction in electronic procurement environments [3, 8]. A buyer first has to define her preference for certain goods in terms of various attributes in a form of a utility function. The buyer has to reveal her utility function to suppliers. A supplier should bid based on this utility function. The mechanism selects the supplier who produces the highest overall utility for the buyer (i.e., the bidder who best fulfills the buyer's preferences). The utility function of a Multi-attribute Auction is based on the Multi-Attribute Utility Theory (MAUT) [26]. The most widely used multi-attribute utility function in a Multi-attribute Auction is an additive utility function that is defined as follows:

$$U(x_j) = \sum_{i=1}^{n} U_i(x_j^i) \ , \qquad (2\text{-}1)$$

where, x_j^i denotes the bid for attribute $i = 1..n$, made by the bidder j, $U(x_j)$ represents the buyer's evaluation of the bid x_j, and $U_i(x_j^i)$ denotes the overall utility of each bid attribute x_j^i assigned by the bidder j. The Multi-attribute Auction is also called a 'multidimensional auction'.

2) Combinatorial Auction

In a Combinatorial Auction, each bidder offers a bid for a collection of resources (of the bidder's choosing) rather than placing a bid on each item separately. This enables the bidder to express dependencies and complementarities between various resources. The auctioneer selects such set of these combinatorial bids that result in the highest revenue without assigning any item to more than one bidder**.** Snadholm showed that the number of possible allocations in a combinatorial auction is $O(m^m)$, where m is the number of items traded in the auction. He also proved that selecting the auction winners in such a way that the revenue is maximized is NP-complete [10]. Several researchers have tried to solve this problem. Rothkof, at al. use a dynamic programming approach which takes $O(3^m)$ steps to find an approximate solution [22]. Sandholm proposes a search algorithm for winner determination in polynomial time under the severe restrictions such as number of bids [10]. He also describes the Internet based e-commerce server, called eMediator, which implements several relevant procedures and protocols, including an auction house with a generalized combinatorial auction [23].

3) Generalized Vickrey Auction (GVA)

Another mechanism for determining prices for an allocation of multiple units of resources is the Generalized Vickrey Auction [26]. In GVA, the price of a bidder k in the efficient allocation is computed by deducting the sum of payments of all other bidders in an allocation from the sum of the payments that would be obtained from those bidders in the optimum allocation where the bidder k removed from the allocation. The GVA mechanism is an incentive compatible direct mechanism in which the true valuation bidding is a dominant strategy (i.e., such bidding maximizes each bidder's expected utility).

2.4 General Procedure of an Auction Mechanism

In the current state of art, all auction mechanisms can be describes by the six-step process described below and shown in Figure 2.2 [56].

1) Bid Collection and Validation

The bid collection and validation procedure collects the bids from the players participating in the markets. Bids may be 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.

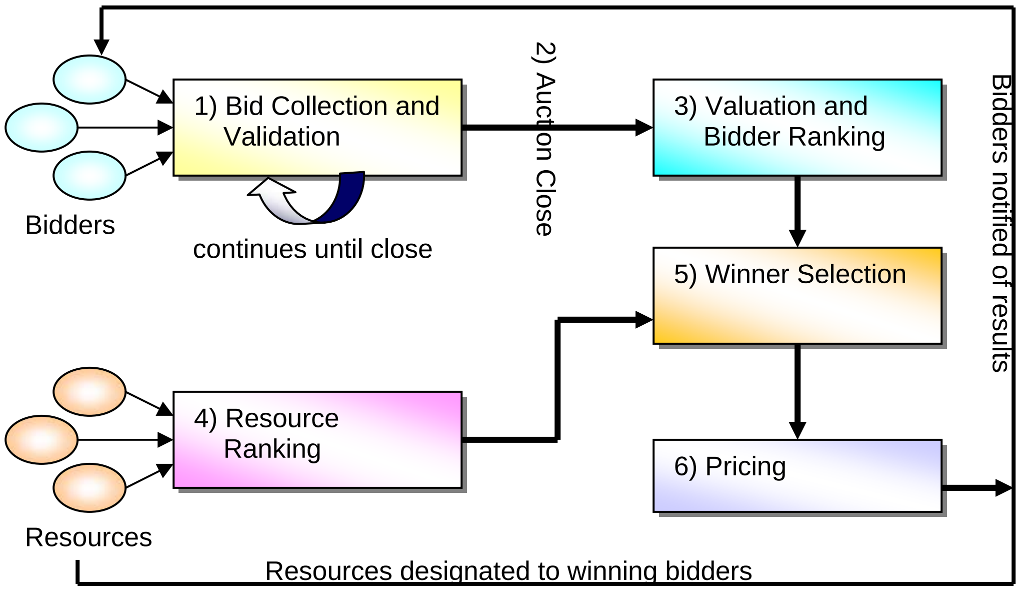

Figure 2.2: General procedures of an auction

2) Auction Close

The auction close can occur once a specific set of circumstances are met, as defined by the auction organizer. These could include time elapsed, receipt of sufficient bids, availability of resources, or any other conditions relevant to the specific application. Once an auction closes, bids would not be changeable.

3) Valuation and Bid Ranking

This procedure 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 auction mechanisms equate the bid value with the price of the bid. A lot of innovation went into providing more suitable bid valuation methods, reflecting additional features. In multi-attribute auctions, multiple attributes of the bids are combined into a single bid utility value [3, 8]. Other potential methods for assigning a value to a bid by the given bidder include additional information about the bid and the bidders, such as the time of the bid, the history of the bidder's activities, etc. The final result of this procedure is the list of bidders ranked according to the values assigned to their bids.

4) Resource Ranking

In the resource ranking procedure, all resources available for allocation in the given round are ranked according to their intrinsic value, which may be identical or different for each item. Any resource can be placed in any arbitrary order with respect to other items from which its intrinsic value cannot be differentiated. Any relevant factors can be used to assign intrinsic value rank order to the resources based on the specific application. Generally, the ranking reflects differences in intrinsic value of each individual unit of the resources. An example is the set of seats at the theater, where the distance from the stage and the visibility of the stage impacts the intrinsic value of a seat.

5) Winner Selection

The winner selection procedure defines the way of allocating or mapping ranked resources offered in the market with specific bidders based on predefined rules. The universally used winner selection procedure is to allocate available resources starting with the bidder with the highest bid value and then following in a decreasing order of bid values until all resources are allocated.

6) Pricing

After the winners are selected in the winner selection procedure, pricing procedure compute the payments that are charged to the winners for the allocated resources. The two main variants of pricing method in the current state of art are to pay the price equal to the bid (also known as the first price rule) or equal to the bid of the next highest bidder (also known as the second price rule).

2.5 Requirements for the Optimal Auction Mechanism

One of the important design requirements for the traditional basic auction is to maximize seller's revenue. An auction mechanism that satisfies this requirement is called the '*optimal auction*' mechanism. Additional design requirements for designing the auction mechanism for electronic market environments are described in [3] as follows.

- **Incentive compatibility**: An auction mechanism is incentive compatible if an honest bidding true valuation of each bidder is the dominant strategy (i.e., the strategy that maximizes the expected utility for the bidder). This property is useful for agent-based automated negotiations since it simplifies the bidder's strategy implementation.

- **Efficiency**: In an efficient auction, the resources should be allocated to the bidders who value them highest.

- **Individual rationality**: The expected payoff of a bidder who behaves according to the dominant strategy[3] is always nonnegative.

- **Minimization of the cost of negotiations and convergence to the agreement**: In an electronic auction mechanism, the communication overhead of conducting optimal negotiations and arriving at the agreement should be minimized. Often, the direct mechanism in which a bidder can communicate with the auctioneer directly (i.e., via the sealed bids) minimizes the communication overhead.

Riley and Samuelson introduce the reservation price in order to design optimal auction mechanism [11]. Such an auction mechanism requires that the auctioneer sets the reservation price, and the bidders who bid higher than the reservation price are qualified to become winners. Hence, the seller will not allocate the resources below the reservation price.

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[3] Dominant strategy is strategy of bidder that maximizes his expected utility.

Based on the guidelines for the optimal auction design, the Second Price Sealed Bid (SPSB) auction, known also as Vickrey auction, with reservation price (abbreviated as SPSB-R) has been regarded as optimal auction mechanism for traditional markets [2]. This is because SPSB auction not only provides incentive compatibility, efficiency, and individual rationality but also its sealed bidding minimizes the communication overhead and the reservation price maximizes the expected revenue of allocating the resources that can be stored in warehouse for the future use if the bid dose not meet the auctioneer's reservation price.

2.6 Analysis of Bidding Behavior

Bidding behavior of each bidder can be classified based on the auction mechanism used and the risk management characteristics of the bidder. Each bidder estimates[4] its gain from engaging in an auction according to the following utility function $U_i(b_i)$

$$U_i(b_i) = [t_i - c_i(b_i)] \cdot q_i(b_i), \tag{2-2}$$

where t_i and b_i denote the true valuation and the bid of bidder i. $c_i(b_i)$ and $q_i(b_i)$ represent the expected payment and the estimated winning probability of bidder i with bid b_i respectively. Based on this utility function and risk management characteristics of the bidders, a bidder's bidding behavior can be classified into following one of the three types:

1) Risk neutral bidding behavior

Risk neutral bidders always try to maximize the expected utility (i.e., gain or payoff). Hence, risk neutral bidders consider the trade-off between the profit factor (i.e., $t_i - c_i(b_i)$) and the winning probability factor $q_i(b_i)$. If the bidder increases its bid, the

[4] In a sealed bid auction that we are considering here, the bidder knows only his own bid and therefore can only estimate his gain. Only auctioneer knowing all bids is able to determine the winners and compute the prices that they will pay.

winning probability rises, but the resulting profit factor decreases. Conversely, if the bidder decreases the bid, the profit factor increases at the expense of the winning probability.

Based on this goal, if a bidder lost in the last auction round using a non-incentive compatible mechanism with perfectly sealed bid, such as FPSB auction, she may increase her bid in the current round to increase the winning probability in the future round. Reversely, if a bidder won in the last round, he may maintain the bid or decrease it in the current round to increase the profit factor. We refer to this behavior as an '*adaptive bid behavior of risk neutral bidder*'. In an incentive compatible mechanism, such as the SPSB auction, the bid behavior of risk neutral bidders is simple because reporting the true valuation by each bidder maximizes the expected utility. Hence, during a recurring auction, risk neutral bidders bid their true valuations in an auction with incentive compatible mechanism.

2) Risk aversion bidding behavior

Risk aversion bidders always try to maximize the winning probability. For this reason, we can assume that they bid their true valuations. This behavior is also expected in recurring auction environments.

3) Risk preference bidding behavior

Risk preference bidders try to maximize the gain given a win. For this reason, we can assume that they either bid the minimum possible price. Such a behavior is also expected in recurring auction environments.

Most of the previous auction related studies assume a risk neutral bidding behavior [4,5,7,8,9,11], and we also make this assumption here.

2.7 Summary of the Chapter

An auction is a market institution with an explicit set of rules matching supplies with demands for the traded resources, and determining prices on the basis of bids received from the market participants. The bidders and auctioneers are two main market participants. The basic auction mechanisms can be classified into single auction mechanisms and double auction mechanisms. English and Dutch auctions are open-outcry single auctions, and the First Price Sealed Bid auction and the Second Price Sealed Bid auction are sealed bid single auctions. A Continuous Double Auction and a Call Market are examples of a double auction. In a Multi-attribute Auction, bidders bid on various attributes beyond price and the auctioneer selects winners based on the price as well as on those attributes.

Such various auction mechanisms can be described by the six-step process consisting of Bid Collection and Validation, Auction Close, Valuation and Bid Ranking, Resource Ranking, Winner Selection and Pricing. The optimal auction mechanism maximizes the seller's revenue. Incentive compatibility, efficiency, individual rationality, and minimization of negotiation cost are basic requirements in designing optimal auction mechanisms.

From the risk management perspective, the bidding behavior can be classified as a risk neutral, risk aversion or risk preference behavior. A risk neutral bidding behavior tries to maximize the expected utility. On the other hand, a risk aversion behavior aims at maximizing the win probability, while a risk preference behavior attempts to maximize the profit factor of the utility.

3. E-MARKETPLACES FOR AUCTION MECHANISMS

3.1 Introduction

With the expansion of electronic environments, increasing dominance of a service oriented paradigm and the auction's inherent dynamic pricing and negotiation nature, many researchers have tried to extend the application areas of auction mechanisms into newly created markets, such as the network services and resource allocation, the grid computing services (including utility computing services), the Internet search engine marketing, and so on. In this section, we describe various electronic markets in which an auction can be used as a dynamic pricing and negotiation mechanism. They range from existing e-commerce markets for physical resources to newly created service oriented electronic markets. In this chapter, we also analyze and characterize the common properties of newly created service oriented electronic markets in terms of market structures and properties of the traded resources. The reminder of this chapter is organized as follows. In section 3.2, existing and newly created markets which can use an auction as a basic dynamic pricing and negotiation mechanism are described. Section 3.3 characterizes common properties of newly created markets from the point of view of auction mechanisms. Finally, section 3.4 summarizes the chapter.

3.2 Auction Mechanisms in E-Commerce

During the past few years, there have been a tremendous number of auctions conducted over the Internet. The Forester Research forecasts that the auction in e-commerce markets will grow from $13 billions in 2002 to $54 billions in 2007 [30]. Various types of auction mechanisms are widely used in B2C (Business to Customer), C2C (Customer to Customer), B2G (Business to Government), and B2B (Business to Business) markets. In B2C and C2C markets, the English auction is the most popular auction type since it is relatively easy to understand, allows bidder interaction and competition, and is particularly well suited to periods longer than a few minutes. Additionally, bidders enjoy placing multiple bids in competition with other bidders, and this entertainment value of the online English auction is an important feature in B2C and C2C markets [3]. uBid (www.ubid.com) and eBay (www.ebay.com) are the most prominent examples of applying auctions to B2C and C2C markets, respectively. eBay also uses auctions for B2C markets. In B2G and B2B markets, sealed bid auction types (i.e., FPSB or SPSB auctions) are widely used. Those markets rely on a procurement process that requires a 'Reverse Auction' mechanism in which one buyer (i.e., a manufacturer) is an auctioneer that collects the bids from many sellers (i.e., the suppliers) who supply the resources.

The traditional types of resources that are traded in the current e-commerce markets through various types of auction mechanisms are: (i) physical goods such as collectibles including antiques, stamp and coins, (ii) electronic equipment, (iii) real estate and (iv) used equipment. With the recent expansion of electronic environments, the application domains of auction mechanisms are also extended to the service oriented markets such as various electronic services (abbreviated as e-services here).

3.3 Auction Mechanisms in Markets for Network Services

Recently, several dynamic pricing mechanisms have been studied as a method for an efficient management of the continuously changing network resources. In Quality of Service (QoS) enabled networks, appropriate pricing mechanisms encourage bidders to choose services adequate to their needs and such choices result in the efficient network resource allocation. Hence, the network can be regarded as a market in which various QoS enabled network services are traded. If a fully dynamic pricing mechanism is applied to a network, price may become a signal for the congestion control, admission control, and fair allocation of network resources. However, this very dynamism of pricing makes both the seller's (e.g. ISP, Network Providers, etc) pricing decisions and the buyer's budget planning difficult. An auction can avoid these difficulties because price emerges from willingness of bidders (i.e. buyers) to pay. Additionally, its simplicity can lower complexity of the fully dynamic pricing mechanism. Therefore, several auction based mechanisms have been studied for pricing the network services, for congestion control and for the efficient resource allocation in dynamically changing networks.

One of the first attempts to use an auction as a mechanism for the resource allocation in a congested network was ‘smart market’ proposed by Varian and Mackie-Mason [12]. In a ‘smart market’ approach, the network can be viewed as an auction market in which the router is an auctioneer and the bidder is a packet owner who wants to send this packet through the router. Each packet has a bid value that is assigned by the packet owner based on his/her willingness to pay for the transfer through the router. For this purpose, the ‘smart market’ introduces a new packet header to express willingness to pay of each packet owner. Each router has a threshold value that is dynamically changed based on the network capacity and congestion. The router admits only those packets that have values higher than the predetermined threshold that is set by each router. The auction winners (packets that pass through the router) pay this threshold price. Hence, the smart market has pricing behavior similar to the SPSB-R auction. However, this mechanism has been determined to be unsuitable for large networks in which packets make many hops on a route from the source to the destination. The reason is that a bidder needs to bid new (higher) values to the routers encountered after the congested ones to prevent the loss of money already spent at the congested routers. This is hardly scalable and may increase the traffic overhead in the already congested network [15].

Lazar and Sermet propose the Progressive Second Price (PSP) auction mechanism for the network resource (i.e., bandwidth) sharing [13]. In PSP auction, bidders submit two-dimensional bids: value in one dimension is the price and the value in the other is the desired quantity of network resources. The bidders can modify their bids iteratively in a response to the current strategy of their opponents to reach the best response. These iterations lead to an equilibrium state in which no bidder want to change the current state. The pricing mechanism of PSP auction is similar to that of the Generalized Vickrey Auction (GVA). For this reason, the main advantage of the PSP auction mechanism is that it is incentive compatible. However, the PSP auction mechanism can increase the communication overhead between the seller and the bidders while both sides try to reach an equilibrium state, since the bidders are allowed to bid iteratively in each auction round.

Shu, at al. proposed an auction based network service pricing mechanism that is called the SPAC (Smart Pay Admission Control) [14]. The SPAC mechanism has been designed for the DiffServ network architectures. It is inspired by the ‘smart market’ auction idea of assigning to each packet a price determined by the packet sender based on the sender budget and this particular packet value. Based on the bids of all packet senders, the SPAC mechanism decides to which color (QoS level) each sender is entitled. Those color marked packets are treated differently by receiving different quantities of bandwidth according to the assigned QoS level in the network interior. In there, different quantities of bandwidth are assigned to the packets based on the marked color. When congestion arises, the router charges a congestion fee to the passing packets by raising the price of acquiring the higher QoS. As a result, users with low service valuations cannot win the higher QoS in an auction, and will voluntarily back down when the congestion occurs. Thus, the SPAC mechanism provides the congestion control economically. The prices charged to packet senders are calculated based on a variant of generalized Vickrey auction. Thus theoretically, the SPAC mechanism supports incentive compatibility and individual rationality.

3.4 Auction Mechanism in Markets for Computing Services

In recent years, interest in and demands for Grid Computing Services (GCS), including Utility Computing Services and Distributed Computing Services, have been growing rapidly. Fully implemented grid computing services provide a transparent access to a wide variety of large scale geographically distributed computational resources (i.e., CPU, memory, storage, etc.). With the current trend of the high performance computing moving into the service-oriented computing, grid computing can be organized into a market in which the GCS buyers demand computing services needed by tier desired applications, and the GCS providers allocate such computing services that enable them to return the desired computing results to the buyers [25]. This market provides following benefits to the GCS buyers and GCS providers. From the GCS buyer point of view, outsourcing computing services minimizes the cost of desired computing compared to owning application software and hardware. On the other hand, such outsourcing improves the grid resource utilization from the GCS provider's point of view and accordingly increases the provider's revenue. For efficient contracting in such a market, the GCS providers need tools for expressing their pricing policies and mechanisms that can maximize their profits and the resource utilization. For this purpose, various economic models, including various auction models, for computational resource trading and for establishing efficient pricing strategies have been proposed [16, 17]. Among the various economic models, the following two models denote basic scenarios that use the auction mechanism: the Tender/Contract Net model and the general auction model [16].

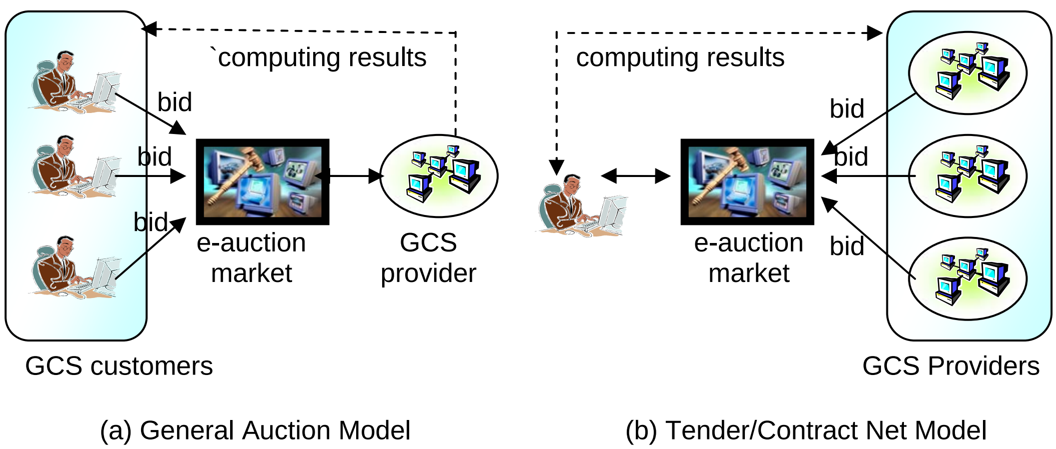

Figure 3.1: Auction based economic model for computing service markets

As shown in Figure 3.1, in a general auction model, the GCS provider invites bids from many GCS buyers (i.e., bidders) for each application computing service. Based on the auction mechanism used and on the current conditions of distributed computational resources, the GCS provider selects the winners and clears the auction. Auction mechanisms 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 [17, 18].

In the Tender/Contract Net model, a reverse auction mechanism is used. Hence, a GCS buyer (i.e., an auctioneer) invites sealed (or open-outcry) bids from several GCS providers by advertising his desired application computing service and the time constraints such as the deadlines for receiving the results. The buyer selects the bid that offers lowest service cost with the acceptable time deadline for the delivery of the results. The selected winner makes a contract with the buyer, provides the computing service and then returns the computed result to the buyer at the price of the provider bid. This is the same model as the one used in the reverse auctions in procurement environments, where the buyer is a GCS buyer and the suppliers are the several GCS providers.

3.5 Auction Mechanisms in the Internet Search Engine Marketing

Next to e-Bay, sponsored search advertisement auctions are one of the most common and widespread examples of an electronic auction system in use today with enormous economic impact on advertising and computer industries. The revenues from the sponsored search advertisement auctions have been increasing continuously and have already exceeded billions of dollars annually. They are projected to reach $4.9 billion in the U.S. market alone in 2009 [41]. An important reason for so fast and wide-spread adoption of the sponsored search advertisement is its high return on investment (ROI) for advertisers, compared to other marketing methods. The search engine customers already pre-select themselves by initiating a search for keywords relevant to the advertisement and then show further interest in the advertised products by clicking on the link to the specific advertisement. Hence, as shown in Figure 3.2, the average cost per leading purchase is lower in the sponsored search advertisement than in other marketing channels.

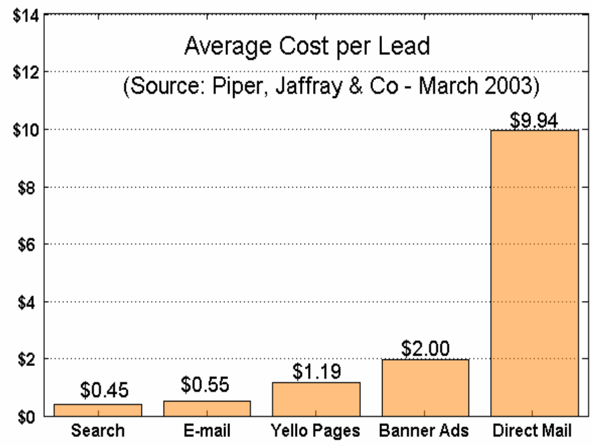

Figure 3.2: A comparison of the average cost per lead to purchase

The idea behind the sponsored search advertisement is simple. The search engine produces the search result pages with positions for sponsored search advertisements associated with a particular keyword used in the search query entered by the customer. These sponsored positions contain paid advertisements with embedded links pointing to the advertiser's web pages. Advertisers pay the search engine for their advertising whenever the search engine customer clicks on the link embedded in a sponsored position. Accordingly, this form of advertising is called 'Pay-Per-Click' (PPC) advertisement.

From the auction structure point of view, a search engine company is an auctioneer and advertisers are auction participants who bid for the sponsored positions. Hence, this is one-to-many market structure. The resources traded in the sponsored search advertisement auction are ranked advertising positions in a web page produced in response to a user query. It is well known that different positions yield different numbers of user clicks per time period, even when they display the same advertisement. Generalized Second Price (GSP) auction are widely used in the most of the current sponsored search auctions. In a GSP auction, each bidder's payment is equal to the bid of the bidder who occupies a position with a rank one below the payer's position.

3.6 Analysis and Characterization of New Auction Markets

Different market structures require different dynamic pricing and negotiation mechanisms for efficient resource allocation and revenue maximization [4]. Hence, an analysis and characterization of newly created markets from the auction mechanism point of view is one of the necessary steps in designing an efficient auction based dynamic pricing and negotiation mechanism for these markets.

We can characterize discussed above newly created markets as '*short-term contract markets*', because the resources traded in them are renewable and their allocations to bidders are made for a specific time only. Additionally, the short-term contract markets have recurring nature, because, once the allocated renewable resources become free, the seller (or the auctioneer) needs to offer them to the bidders again, recurrently. From the bidder's perspective, the short-term contract market is recurring, since each bidder requests the traded resources repeatedly for a specific time interval. The example resources for newly created markets are various electronic services that are operated over the Internet. Examples are video conferencing, music on demand service, video on demand service, and so on.

In addition to their recurring nature, these markets trade resources that are time sensitive and perishable (i.e., the fact that unused resources perish) which is another important factor. The traded network or computing services and resource for the services cannot be stored in a warehouse for future sale and leaving them unused decreases utilization of the resources. Therefore, the new markets from the point of view of auction mechanisms can be characterized as '***Recurring Short-Term Contract Markets for Selling Perishable Resources***'. Hence, from the auction point of view, bidders participate in an auction recurrently acquiring resources for a specific time interval based on their needs and the auctioneer opens and clears the auction recurrently allocating or reallocating resources for the same time interval.

Other recurring short-term contract markets for selling perishable resources in which auctions can be used as a basic dynamic pricing and negotiation mechanism include car parking services, various e-services that require system resources to fulfill their tasks, airline ticket reservations, hotel room reservations and so on.

3.7 Summary of the Chapter

Auction mechanisms have been widely used as trading tools that support dynamic pricing and negotiations in various electronic markets. In addition to the current e-commerce markets, the application domains of auction mechanisms are extended to the service oriented electronic markets such as the network services, the computing services and the Internet search engine marketing services. In the current electronic commerce domain, an open-outcry English auction is widely used in B2C and C2C markets while the reverse sealed bid auctions are used in B2B and B2G markets. In network service markets, an auction can be used for the optimal resource allocation in dynamically changing QoS enabled networks. The grid computing service markets attempt to allocate the computational resources, that are located in distributed locations, fairly and to maximize the resource utilization by an auction based economic model. The Internet search engine marketing also uses an auction for allocating sponsored advertisement slots in the search result page for each search key word. In such an auction, the generalized second price auction is widely used. The newly created service oriented auction markets are recurring short-term contract markets in which perishable time sensitive resources are traded recurrently for a specific time period.

4. AN OBSERVATION UNDERPINNING THE RESEARCH

4.1 Introduction

The previous design approaches to auction mechanisms focus on a one-time (i.e., one shot) auction for selling physical resources that can be stored in the warehouse for future sales [4,5,6,7,9]. Hence, they did not consider a recurring nature of the auctions and the perishable property of the resources in the newly created service oriented short-term contract markets. These two features strongly affect the bidding behavior of bidders and the revenue of the auctioneer. Additionally, we observed that applying existing basic auction mechanisms to newly created service oriented short-term contract markets can cause various problems that motivated our research. For this reason, in this chapter, we analyze, define and verify the problems that should be considered and resolved in designing optimal auction mechanisms for the newly created markets. The reminder of this chapter is organized as follows. In section 4.2, various problems, some of them discovered in the course of our research, are analyzed and defined. The newly discovered problems are verified theoretically and experimentally in section 4.3. The summary of the chapter is given in section 4.4.

4.2 Analysis of Newly Discovered Problems

In most of the traditional basic auction mechanisms, the prices bid in an auction are dependent only on the bidder's willingness to pay for the traded resources. 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 Auction (RPA) and the Cancelable Auction (CA) mechanisms were proposed [11, 31]. In RPA, only bids higher than the auctioneer's reservation price are considered during winner selection. Hence, the auctioneer can select potential winners and losers based also on the auctioneer's intention (i.e., the reservation price). On the other hand, in CA, if the resulting revenue does not meet the minimum requirement of the auctioneer, the entire auction is cancelled. By providing the auctioneer with the ability to set the reservation price or to cancel an auction, the asymmetric negotiation power problem is resolved. However, when the perishable resources, such as short-term contracts are traded, both of these auction mechanisms waste resources. In RPA, the reservation price restricts the number of winners. Resources unused because of this restriction are wasted. In CA, a cancellation of an auction round wastes all resources allocated to this auction round.

In addition to the resource waste problem, the recurring nature of newly created markets results in the following problem whose discovery provided an underpinning of our research. Prices bid in an auction reflect willingness of each bidder to pay. This willingness to pay is limited by the bidder’s (private) true valuation that is influenced by each bidder’s wealth. An uneven wealth distribution causes starvation of those bidders in a recurring auction whose true valuations are below the winning price. Frequent starvation for resources decreases the bidder’s interest in the future auction rounds. Additionally, each bidder learns if her true valuation is sufficient to ever become a winner. If a bidder concludes that it is impossible or unlikely that he will win at the price that he is willing to pay, he will drop out of the future auction rounds. Such a drop decreases the number of bidders in future rounds. Moreover, although such a drop is the fastest in the case when all customers participate in each auction round, it will happen also when the pattern of customer’s participation in auction rounds is periodic as long as the demand exceeds the supply of the traded goods in each round. Indeed, regardless of the participation scheme, the lowest bidding customer loses each auction in round in which he participates.. This bidder will experience starvation for resources and will drop out of the auction in the long run.

In a recurring auction, each bidder’s drop out of an auction decreases the number of active bidders. Reducing the number of bidders gradually decreases the price competition. Hence, the probability of winning increases for the remaining bidders so their attempts to decrease bids without losing the winning position will be successful and the winning bids will decline in such a scenario. In the long run, when the number of bidders decreases close to the number of resources, the auctioneer revenue is likely to drop below the acceptable level. This is because the remaining bidders constantly win and as a result they may decrease their bids to the very low level.

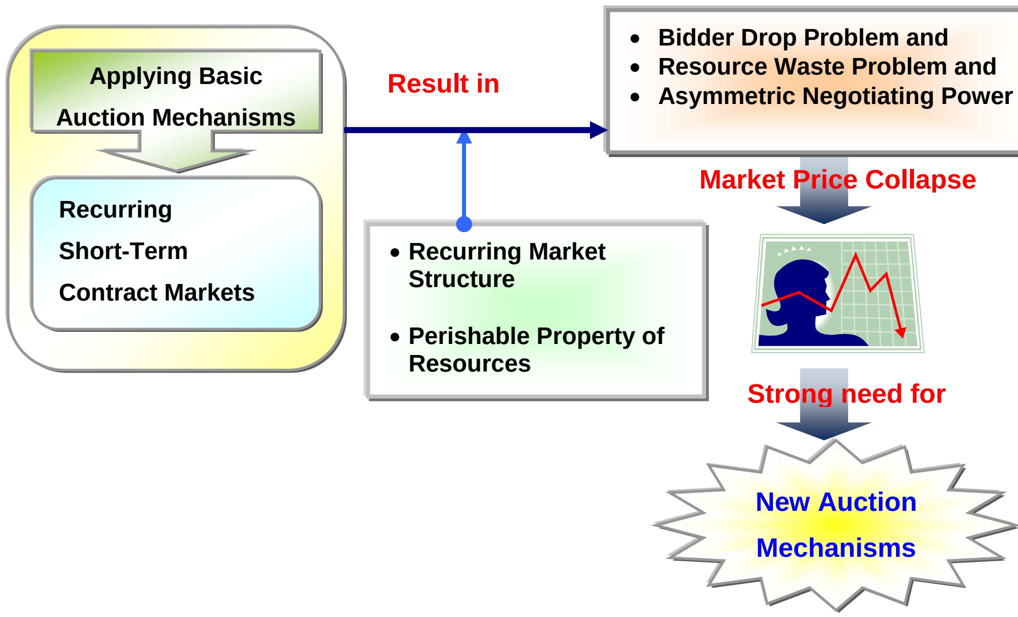

Figure 4.1: The problems resulting from application of traditional auction mechanism to markets of a recurring nature for perishable resources

This phenomenon is exacerbated in incentive compatible auctions, such as the Second Price Sealed Bid (SPSB) auction or the Uniform Price Sealed Bid (UPSB) auction, in which all bidders bid their true valuations to maximize their expected utilities. A bidder who lost in such an auction can easily conclude that his true valuation is not large enough to ever become a winner. Hence, there is no incentive for losers of the auction to participate in the future rounds. Consequently, they may drop out of the auction and such drops decrease the auction clearing price and the auctioneer's revenue. We call this phenomenon the '***paradox of incentive compatible mechanism in recurring auction***' because by achieving the goal of motivating the bidders to bid their true valuations, the mechanism, when applied to a recurring auction, leads to the market collapse after a few rounds. The collapse may be delayed if the bidders return to the market when the winning prices drop, a phenomenon that is likely to occur when highly desirable resources are traded. However, even in the latter case, periodic fluctuations of the auctioneer's revenue may lead to its demise anyway and are certainly disadvantageous. To the best of our knowledge, the bidder drop problem in a recurring auction market has not been addressed in the previous research. The Figure 4.1 summarizes the problems arising when traditional auction mechanisms are applied to markets of a recurring nature for perishable resources.

4.3 Verification of the Discovered Problem

In the First Price Sealed Bid (FPSB) auction with single resource traded and under the assumption of (i) a uniform distribution of bidders' true valuations, and (ii) the risk neutral bidders, the optimal bid b_i^* that maximizes the bidder's expected utility (i.e., profit or payoff) of bidder i is

$$b_i^* = \left(\frac{n-1}{n}\right) \cdot t_i \ , \tag{4-1}$$

where t_i represents the true valuation of bidder i , and n denotes the number of active bidders (i.e., participants in the auction) [4]. To maximize an auctioneer's revenue from an FPSB auction, the optimal bid of each bidder should be a fraction of his true valuation. Additionally, to avoid wasting of perishable resources, the single resource should be allocated to a single winner in each auction round. Hence, to keep the optimal bid given by Eq. (4-1) close to the true valuation, the number of bidders should be high during each recurring auction round. In other words, the auctioneer should keep the sufficient number of bidders participating in each round to maximize the revenue. Figure 4.2 shows the change of a coefficient $(n-1)/n$ of the optimal bid as a function of the number of bidders.

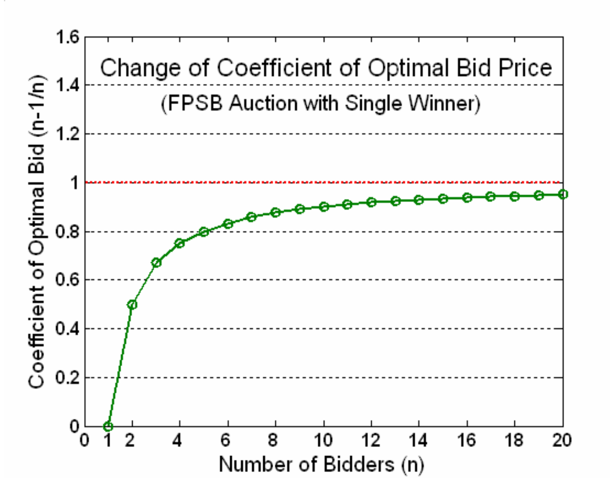

Figure 4.2: A coefficient of the Optimal Bid (OBP)

The bidder drop problem is also an important factor for the auctioneer's revenue also in the Discriminatory Price Sealed Bid auction.

Lemma 4-1: The optimal bid b_m that maximizes the expected utility of a bidder is an increasing function of the difference between the total number of bidders and the number of winners in the Discriminatory (First) Price Sealed Bid auction for the risk neutral bidders with the uniform distribution of their private true valuations.

Proof: First, we show that the probability of win in such an auction increases when the bid of a bidder increases. Second, we prove that the bid that optimizes the bidder expected utility decreases when the difference between the number of bidders and the winners decreases. This is an extension of the well-known case of a single winner. The utility with bid b and the true valuation t for n bidder auction with R winners is

$$U(b,R)=(t-b)\cdot\left(\sum_{s=1}^{R}\binom{n-1}{s-1}\left(\frac{b}{t}\right)^{n-s}\left(\frac{t-b}{t}\right)^{s-1}\right) \qquad (4\text{-}2)$$

The first factor, $(t-b)$ monotonically decreases with the growth of b. It is easy to show by induction on R that the next factor, the probability $p(b,R)=\sum_{s=1}^{R}\binom{n-1}{s-1}\frac{b^{n-s}(t-b)^{s-1}}{t^{n-1}}$, has the following derivative with regard to b

$$p'(b,R)=\binom{n-1}{R-1}\frac{(n-R)b^{n-R-1}(t-b)^{R-1}}{t^{n-1}}. \tag{4-3}$$

Since the derivative is always non-negative for feasible bids, the probability of a win is a non-decreasing function of *b.* Hence, there is only one maximum of the bidder's utility. Let denote the bid at this maximum utility as b_m, $0<b_m<t$. Hence,
$U'(b_m,R)=0=-p(b_m,R)+(t-b_m)\,p'(b_m,R)$, so

$$b_m=t-\frac{p(b_m,R)}{p'(b_m,R)}. \tag{4-4}$$

To prove that the optimal bid decreases when $n-R$ decreases, we need to show that the second term in Eq. (4-4) increases when R increases while n is kept constant or in other words that $p(b_m,R+1)p'(b_m,R)>p'(b_m,R+1)p(b_m,R)$. Let $m(b,s)$ denote $\binom{n-1}{s-1}\left(\frac{b}{t}\right)^{n-s}\left(\frac{t-b}{t}\right)^{s-1}$ so, $p(b,R)=\sum_{s=1}^{R}m(b,s)$ and $p(b,R+1)=p(b,R)+m(b,R+1)$. Denoting $dm(b,s)/db=m'(b,s)$, we need to prove the following inequality: $m'(b_m,R+1)p(b_m,R)<m(b_m,R+1)\,p'(b_m,R)$ which is equivalent to

$$\frac{m'(b_m,R+1)}{m(b_m,R+1)}<\frac{p'(b_m,R)}{p(b_m,R)}. \tag{4-5}$$

We also get

$$\frac{m'(b,s)}{m(b,s)}=\frac{(n-s)(t-b)-b(s-1)}{b(t-b)}=\left(\frac{n-s}{b}-\frac{s-1}{t-b}\right)=v(b,s). \tag{4-6}$$

It follows from Eq. (4-6) that $v(b,s) - v(b,s+1) = 1/b + 1/(t-b) > 0$, so that $v(b,s) > v(b,s+1)$. From that, by induction, we get that $v(b,s) > v(b,R)$ for all $s < R$ and, finally, the following inequality becomes apparent, proving Ineq. (4-5) and the Lemma:

$$\frac{p'(b,R)}{p(b,R)} = \frac{\sum_{s=1}^{R} m'(b,s)}{p(b,R)} = \frac{\sum_{s=1}^{R} v(b,s)m(b,s)}{p(b,R)} > \frac{v(b,R)\sum_{s=1}^{R} m(b,s)}{\sum_{s=1}^{R} m(b,s)} > v(b,R) = \frac{m'(b,R)}{m(b,R)}.$$

□

In conclusion, the dropping bidders decrease the optimal bids of the remaining bidders. On the other hand, controlling number of winners by decreasing the number of resources can cause resource waste when perishable resources (i.e., if the resources that perish when unused) are used. Hence, regardless of the auctioneer’s attempt to maintain the price, the auctioneer’s revenue decreases.

To strengthen our argument, we simulated recurring UPSB and DPSB auctions under simulation scenarios described in sections 4.4.1 and 4.6.1, respectively. The simulation results, shown in Figure 4.3, demonstrate that the bidder drop problem causes a collapse of the auctioneer’s revenue. The additional simulations with results presented in Figure 4.4 show the extent of the resource waste in RPA and CA mechanisms based on simulation scenario of Section 4.6.1. As shown, 28.6 % of resources in RPA and 23.5 % of resources in CA are wasted during recurring auction in which bidders have the exponential true valuation distribution. The corresponding loss for the uniform and the Gaussian distributions of true valuations were 28.0 % and 34.2 % in RPA and 32.9 % and 34.8 % in CA, respectively.

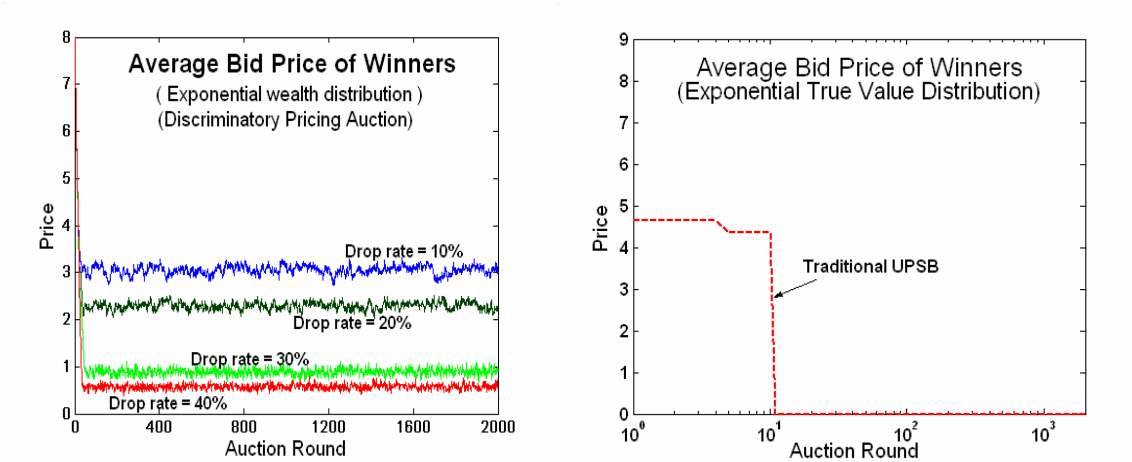

Figure 4.3: The bidder drop problem in the DPSB and UPSB auctions

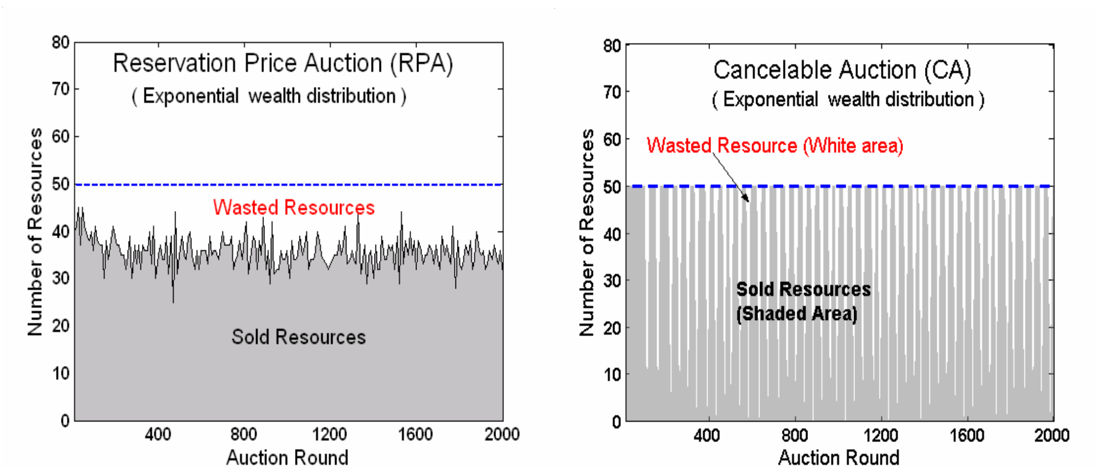

Figure 4.4: The resource waste problem in the DPSB auction

4.4 Summary of the Chapter

Applying the traditional basic auction mechanisms to the newly created service oriented short-term contract marketplaces causes an inevitable starvation for resources among least wealthy bidders because of recurring nature of auctions in those marketplaces. The starvation may decrease the bidders' interests in the future auction round. Finally, the bidders may drop out of the auction (and some of them may find other markets). Such dropped bidders decrease the price competition and decrease the auction market price.

The bidder drop problem is exacerbated in the incentive compatible auctions because of the paradox of an incentive compatible mechanism in recurring auctions. The unbalanced negotiation power and the resource waste problem caused by perishable property of the short-term contracts should be considered in designing optimal auction mechanisms for the newly created service oriented short-term contract marketplaces.

This chapter also verified theoretically the potential market collapse by the bidder drop problem. The optimal bids are an increasing function of the difference between the number of bidders and the number of resources in the First Price Sealed Bid auction and the Discriminatory Price Sealed Bid auctions. Hence, decreasing number of bidders also decreases the optimal bid of each bidder and thereby decreases the revenue of auctioneer.

5. NOVEL AUCTIONS FOR HOMOGENEOUS MARKETPLACE

5.1 Introduction

To prevent the discovered scenario for market collapse from happening, we introduce in this chapter two auction mechanisms of a novel type of auctions that termed the **O**ptimal **R**ecurring **A**uction (abbreviated as ORA). ORA mechanisms are applicable to marketplaces for trading homogeneous resources. The first one is the Participation Incentive Optimal Recurring Auction (PI-ORA) that is incentive compatible and the second one is the Discriminatory Price Optimal Recurring Auction (DP-ORA) that is not. From the pricing point of view, PI-ORA uses a variation of the uniform pricing scheme while DP-ORA uses the discriminatory pricing scheme. To describe the introduced auction mechanisms, we first define here the basic notions of bidders, bids, and resources.

Players: There are $n+1$ players, numbered consecutively starting from 0, that denotes the single auctioneer and n bidders numbered uniquely from 1 to n. An auctioneer and each bidder enter their bids b_0 and $b_1, b_2, ..., b_n$, respectively in each auction round. We also assume that all n bidders are risk neutral and that each bidder has the private true valuation t_i for each unit of the traded resource.

Resources: There are R units of a homogeneous perishable resource that are allocated for a specific time period in each auction round. We assume that each bidder requires one unit of this resource in each auction round, since each bidder's requirement is homogeneous in this market. Hence the maximum number of possible winners in each auction round is R.

We also define the fairness of an auction mechanism from two perspectives: An auction is entirely fair if a bidder with a bid higher than any winner is a winner as well. This condition is often referred to as price fairness. We call this type of fairness horizontal since this fairness considers only a single auction round. The other type is vertical fairness in the recurring auction, where a bidder with the higher willingness to pay should be the winner more times than a bidder with the lower willingness to pay.

The reminder of this chapter is organized as follows. In section 5.2, the main idea of introduced auction mechanisms is described. Section 5.3 introduces the incentive compatible Participation Incentive Optimal Recurring Auction (PI-ORA). The verification of the PI-ORA mechanism by various simulation experiments is described in Section 5.4. Section 5.5 introduces the Discriminatory Price Optimal Recurring Auction (DP-ORA) that is not incentive compatible. The verification of the DP-ORA mechanism by various simulations is described in section 5.6. Finally, the chapter is summarized in section 5.7.

5.2 Illustration of the Main Idea

The main idea of the introduced here Optimal Recurring Auction (i.e., PI-ORA and DP-ORA) is based on the demand-supply principle of microeconomics [1]. In Figure 5.1, D1 and D2 denote the demand curve for the traded perishable resources while S1 and S2 represent the supply curve of the resources. When the overall bid 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. In such a case, to maintain the minimum market-clearing price at p1, the auctioneer should decrease the supply of resources from q1 to q2 (i.e., the entire supply curve needs to change from S1 to S2). Inversely, when the overall bid increases, the auctioneer may increase the supply. However, when the auctioneer decreases the supply of perishable resources for the given time period, the unsold resources are wasted. Thus, in the proposed auction mechanisms, the “unsold” perishable resources (q1–q2 in Figure 5.1) are assigned to the bidders who have high probability of dropping out of the forthcoming auction round. This assignment prevents such a bidder from dropping out of the auction and keeps enough bidders in the future rounds to maintain the competition for resources strong. Simultaneously, using “unsold” perishable resources for the bidder drop control resolves the resource waste problem and increases the number of winners in the recurring auction. Additionally, the reservation price prevents the asymmetric balance of negotiation power.

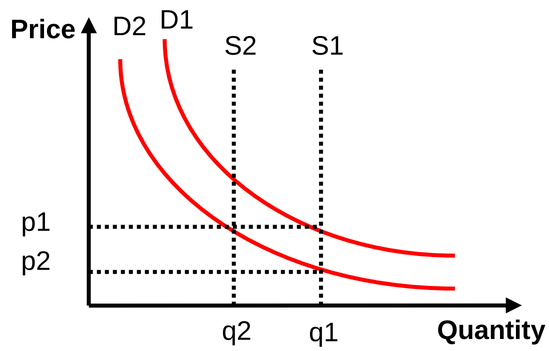

Figure 5.1: The demand and supply principle

5.3 Participation Incentive Optimal Recurring Auction

In this section, we describe the novel Participation Incentive Optimal Recurring Auction (PI-ORA) mechanism in terms of the winner selection strategy, the pricing rule, and the bidder's strategy.

5.3.1 Novel Winner Selection Strategy

The first step of the winner selection strategy of PI-ORA mechanism is to define bidder's class based on each bidder's bid 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:

$$\begin{aligned} &i \in DW \quad \text{if} \quad b_i \geq b_0 \ \& \ r_i > n - R, \quad i = 1, 2, ..., n, \\ &i \in DL \quad \text{if} \quad b_i \leq 0, \ i = 1, 2, ..., n, \\ &i \in PW \quad otherwise, \end{aligned} \tag{5-1}$$

where r_i denotes the rank of bidder i in the increasing order of bids 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 5.2 shows the bidder's classes in PI-ORA and compares them with the classes in the traditional auction mechanisms. The traditional losers and winner classes are defined according to the traditional auction mechanisms. WPPW represents the Winning Portion of the PW class, and the number of winners in the PW class is denoted by N_{wppw}. Hence, $N_{wppw} = R - N_{dw}$.

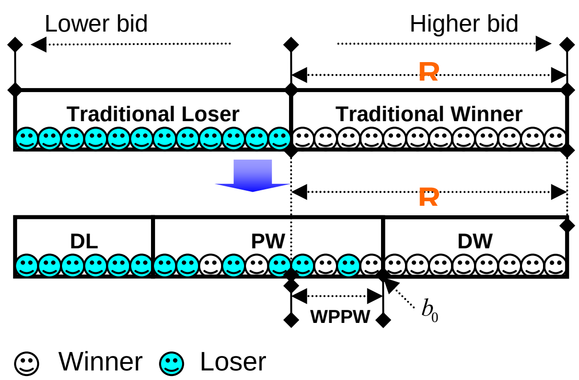

Figure 5.2: The classes of bidders in PI-ORA

In each auction round, the DW class bidders become the 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. In PI-ORA mechanism, we propose the Participation Incentive Bidder Drop Control for winner selection in PW class.

The auctioneer's bid price b_0 in the PI-ORA mechanism plays the same role as the reservation price does in the Reservation Price Auction. By introducing the reservation price, the proposed PI-ORA mechanism creates symmetry in the negotiating power from lack of which the traditional auction mechanisms suffer.

5.3.2 Participation Incentive Bidder Drop Control (PI-BDC)

Enough bidders of PW class should participate in the future auction rounds to maintain price competition in the recurring auction. To encourage participation of bidders in future auction rounds, the Participation Incentive Bidder Drop Control (PI-BDC) uses the following winning score S_i^k for each bidder $i \in PW$ to decide the winners in PW class:

$$S_i^k = \frac{b_i^k \cdot B_i}{\alpha} - W_i \ , \tag{5-2}$$

where W_i is the number of wins by bidder *i*, up to the current auction round, B_i denotes the weighted number of participations of bidder i until the current auction round m :

$$B_i = \frac{\sum_{j=1}^{m} \min(b_{i,j}, b_{i,m})}{b_i} \ , \tag{5-3}$$

where $b_{i,j}$ denotes the bid of bidder *i* in auction round *j* (we assume that this price is zero for rounds in which bidder *i* did not participate). The term $b_i^k B_i \ / \alpha$ denotes the expected number of wins based on the average cumulative bid and the number of participations. α in Eq. (5-2) is a coefficient that controls the expected number of wins (i.e., win frequency) during a recurring auction. Such definition of B_i encourages 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 for participation in an auction round. Thus, the winning score S_i^k of bidder $i \in PW$ represents the difference between the expected and real numbers of wins during the recurring auction. Hence, 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 winnings are. For this reason, the PI-BDC algorithm ranks bidders of PW class in decreasing order of their winning scores and up to N_{wppw} highest ranked bidders are selected as winners of the current auction round.

By Eq. (5-2), the participation of a loser in the last auction round is rewarded directly by increasing her winning score in the current and future auction rounds. Therefore, the PI-BDC algorithm controls the bidder drop problem by encouraging bidders' participation in the future auction rounds. If the coefficient α is increased, the effect of the bid on the winning score is diminished. Thus, the total number of wins achieved by the low bidding bidder's increases and the range of winners broadens across the PW class. Reversely, if α is decreased, the win distribution narrows and concentrates on the high bidding bidders in the PW class. The optimal value of α depends on the auctioneer's strategy and the distribution of true valuations of the bidders. In our simulation experiments, described later, we set α in such a way that the average value of the 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 they bid the same price as previously) 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 $p_i(b_i)$ of each bidder $i \in PW$ with bid b_i is defined as $\frac{b_i^k \cdot (R - N_{dw})}{\sum_{j \in PW} b_j^k}$ and the following inequality must be satisfied:

$$\sum_{j \in PW} \left(\frac{b_j}{b_{\max PW}} \right)^k > R - N_{DW} \quad , \tag{5-4}$$

where b_{maxPW} is the largest bid in PW class. In contrast, as shown in Figure 5.3, in the traditional auction mechanisms, the win probability of a bidder outside the Traditional Winner class is zero. Hence, there is no incentive for the bidders whose true valuations are in the range of the Traditional Loser class to participate in the future auction round in incentive compatible auctions. However, in the PI-ORA mechanism, the win probabilities of bidders in the PW class, including the Traditional Loser class, are higher than zero. For this reason, there is an incentive to participate for all bidders regardless of their true valuations. If k of the winning score in Eq. (5-2) tends to infinity, the PI-ORA mechanism converges to a traditional auction mechanism. If k is small, the distribution of wins in the PW class is broad. Hence, the auctioneer can choose the win frequency distribution of the PI-ORA mechanism by selecting a proper value of k. In this selection, the auctioneer is restricted to those values of k and N_{dw} which satisfy the Ineq. (5-4).

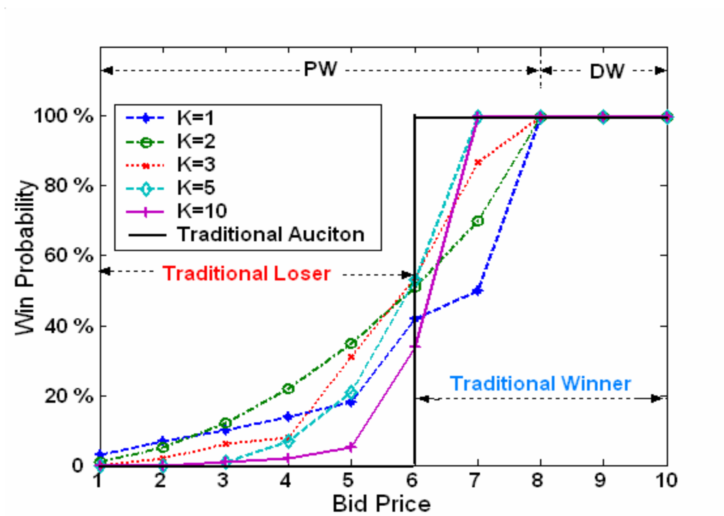

Figure 5.3: The win probability distribution in PI-ORA

From the fairness perspective, the participation incentive bidder drop control achieves the long-term fairness of resources allocation in the recurring auction. Figure 5.4 shows the example of resources allocation during the recurring auction in the proposed participation incentive bidder drop control. In Figure 5.4, we assume that bidders B1, B2, B3 and B4 bid \$4, \$3, \$2, and \$1, respectively, in each auction round, and that there are two units of a resource allocated to the PW class (this means that $R-N_{dw}=2$). As seen in Figure 5.4 (a), in traditional auctions, the win distributions are concentrated on the highest two bid bidders (B1 and B2). However, in the proposed PI-BDC, the win distribution is proportionally allocated to all bidders based on their bids computed according to the winning score of Eq. (5-2).

W: Winner of the auction round

	B1	B2	B3	B4
Round 1	**W**	**W**		
Round 2	**W**	**W**		
Round 3	**W**	**W**		
Round 4	**W**	**W**		
Round 5	**W**	**W**		

(a) Traditional Auction

	B1	B2	B3	B4
Round 1	**W**	**W**		
Round 2	**W**		**W**	
Round 3		**W**		**W**
Round 4	**W**		**W**	
Round 5	**W**	**W**		

(b) PI-BDC

Figure 5.4: Resources allocation fairness in PI-BDC

5.3.3 The Pricing Rule and the Optimal Auctioneer's Bid Price

The PI-ORA mechanism uses the following pricing rule for winners. Winners in the DW class pay $\rho \cdot b_0$ while winners in the PW class pay $\rho \cdot b_i$, where b_0 denotes the seller's bid (i.e., the minimum price needed to become a member of the DW class), b_i denotes the bid of a winner in the PW class and ρ represents payment coefficient. Hence the price $p(b_i)$ that the bidder i pays for a win is

$$p(b_i) = \begin{cases} \rho \cdot b_0 & \text{for } \forall i \in DW \\ \rho \cdot b_i & \text{for } \forall i \in PW \end{cases} \qquad (5\text{-}5)$$

The payment coefficient ρ should be selected based on the following conditions:

$$\rho \le \frac{k}{k+1+t_i^k / s} \qquad \text{for } \forall i \in PW \text{ and} \qquad (5\text{-}6)$$

$$\rho \le \frac{k}{k+1+b_0/s} \cdot \frac{t_i}{b_0} \quad \text{for } \forall i \in DW, \tag{5-7}$$

where $s = \sum_{j \in PW} b_j^k$ and, k is a constant used in Equation (5-2). Based on the bidder's bid distribution, the auctioneer selects the optimal payment coefficient ρ, the auctioneer's bid price b_0 and the constant k that satisfy the both payment coefficient condition (5-6) and (5-7), as well as maximize the revenue. Thus, thanks to the payment coefficient conditions (5-6) and (5-7), the PI-ORA mechanism guarantees that the payments of winners are lower than their bids. Like other incentive compatible mechanism, such as the Vickery auction and the Generalized Vickrey auction, this price is uncertain until the auction closes. All what is guaranteed is that the price will not exceed the bid. In PI-ORA, the auctioneer may decide to guarantee the minimum value of ρ, thereby assuring certain minimum of Return on Investment (ROI) to the bidders.

5.3.4 The Optimal Strategies for Bidders

The bidder's optimal strategy can be approached from two perspectives: the bid and the participation level. We show below that based on the pricing rule of the PI-ORA mechanism, reporting each bidder's true valuation maximizes his expected utility (i.e., it is a dominant strategy) in the PW and DW classes. Additionally, the bidder in the DW class (i.e., the bidder whose true valuation is larger than auctioneer's bid price) would draw no benefits from so decreasing his bid that he would move to the PW class.

Lemma 5-1: For a bidder i, if $t_i < b_0$, then bidding his true valuation in each auction round maximizes his expected utility.

Proof: Let's assume that the bid of bidder i is $I \cdot t_i < b_0$, where $0 \le I \le 1$. Then, this bidder win probability is proportional to $b_i^k/(s+b_i^k)$ and the ratio of the expected utility with bids $I \cdot t_i$ and t_i is:

$$\frac{(t_i - \rho I t_i) I^k t_i^k (s + t_i^k)}{(t_i - \rho t_i) t_i^k (s + I^k t_i^k)} = \frac{(1-\rho I) I^k (u+1)}{(1-\rho)(u + I^k)}, \text{ where } u = \frac{s}{t_i^k}. \tag{5-8}$$

To show that this ratio is always smaller than or equal to 1, we need to show that

$$\frac{(1-\rho I) I^k}{u + I^k} \leq \frac{1-\rho}{1+u}. \tag{5-9}$$

We assume that $\rho < 1$, hence this inequality holds at $I = 0$ and becomes equality for $I = 1$. The left hand side of Ineq. (5-9) reaches the maximum for I satisfying the following equation, resulting from equating the derivative of the left hand side to zero:

$$I^{k+1} + u(k+1)I = uk / \rho \tag{5-10}$$

The left hand side of the Eq. (5-10) is monotonically growing for $I \geq 1$, so Ineq. (5-9) is satisfied if and only if $I_{\max} \geq 1$ or equivalently when $1 + uk + u \leq uk / \rho$, hence

$$\rho \leq \frac{k}{k + 1 + t_i^k / s} \tag{5-11}$$

To maximize the auctioneer revenue, we want value of ρ as close to 1 as possible. By increasing k, we increase numerator on the right hand side of Ineq. (5-11) but at the same time we increase term t_i^k / s in the denominator, so k and then ρ should be selected by computing ρ for *k=1,2,…*until the maximum is found. For k and ρ selected in this way the Lemma 1 holds. □

Lemma 5-2: For bidder i, if $t_i \geq b_0$, then bidding his true valuation in each auction round maximizes the expected utility of this bidder.

Proof: The DW class members pay $\rho \cdot b_0$, so as long as the bidder is in the DW class, his bid impacts neither the price he pays for the win nor his utility. Hence, any bid higher than the reservation price, including true valuation, brings the same utility. Moreover reservation price is not known and bidding the true valuation gives the bidder the highest chance of winning while in the DW class. Therefore, to prove Lemma 5-2, we just need to show that bidder i gains no advantage by bidding below reservation price (and by doing so, moving to the PW class). Comparing bidder's utility in the DW class with bid t_i and in the PW class with bid Jb_0, where $0 \le J < 1$, we need to show that

$$(t_i - \rho b_0) > (t_i - \rho J b_0) J^k b_0^k / (s + J^k b_0^k) . \tag{5-12}$$

Putting this inequality in a form similar to Ineq. (5-11) we get:

$$\frac{(p - \rho \cdot J) \cdot J^k}{u + J^k} < P - \rho, \text{ where } u = s / b_0^k, P = t_i / b_0 > 1. \tag{5-13}$$

By analyzing the derivative of the left hand side of the above inequality, we conclude that it is satisfied if and only if the maximum is reached for $J \ge 1$ which is equivalent to inequality $ukP / \rho \ge uk + u + 1$. Hence

$$\rho \le \frac{k}{k + 1 + b_0 / s} \cdot \frac{t_i}{b_0} \tag{5-14}$$

The condition (5-14) is likely to be more stringent than (5-11), because $b_0 > t_i$ for bidders in PW class analyzed in Lemma 1, but it still must be satisfied for Lemma 2 to hold, so selecting values of k and ρ, b_0 we need to satisfy both of them. □

Therefore, by selecting the optimal payment coefficient ρ, the auctioneer's bid price b_0 and the constant k that satisfy conditions (5-11) and (5-14), the auctioneer makes bidding true valuation the dominant strategy in PI-ORA. Also, participating in as many as possible auction rounds maximizes the cumulative utility of every bidder because the level of participation directly increases the wining score of the current auction round and the expected number of wins.

In conclusion, the bidder's optimal strategy in PI-ORA mechanism is to bid his true valuation (making the mechanism incentive compatible) and to participate in as many as possible auction rounds.

5.4 Simulations Experiments and Results

5.4.1 Simulation Scenarios

In the simulations, we compared four different auction mechanisms that are based on the Uniform Price Sealed Bid (UPSB) auction. Each auction mechanism is executed 2000 rounds.

- 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 the auction at any time. In UPSB, all winners pay the price equal to the highest bid of losers.

- 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, this case involves selection of the payment coefficient ρ, the optimal auctioneer's bid price b_0, and the constant k in the winning score equation (5-2) that satisfy the conditions Ineq. (5-11) and Ineq. (5-14). The PI-BDC algorithm is applied during the winner selection process in the PW class.

- PI-ORA-NBD

  Here, we use the PI-ORA mechanism with no bidder dropping out of the recurring auction, regardless whether the starvation arises or not.

In the UPSB and PI-ORA scenarios, a bidder may drop out of the auction at any time as a result of starvation for resources. The results of simulating UPSB-NBD are used only to obtain the upper bounds on the auctioneer's revenue since assuming no bidder drop is unrealistic. The PI-ORA-NBD scenario is used to observe the stability of the PI-ORA mechanism in response to the bidder drops.

The wealth of each bidder limits her willingness to pay and is defined by the true valuation of a unit of a resource in the auction. For this reason, we can equate the wealth distribution with a distribution of the 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, such true valuations do not change during the recurring auction.

There are 40 bidders in our simulations and 20 units of perishable resources available for allocation in each auction round. Thus, there are 20 winners in each auction round. Since all of the compared auction mechanisms are incentive compatible, each bidder bids his true valuation in each auction round under the risk neutral bidding behavior. Additionally, bidders participate in an auction continuously until they drop out of it. Once out of the auction, the bidder never returns to it.

The bidder's tolerance of consecutive losses, abbreviated as 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 rounds simulated for the UPSB-NBD and PI-ORA-NBD cases.

5.4.2 Analysis of Simulation Results

Our simulations focus on the auctioneer's revenue, fairness of resource allocation and stability of each auction mechanisms in response to bidder drops. In our simulations, the average payment of winners in each auction round is used as a measure of auctioneer's revenue. The revenue comparison between original auction mechanism 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 in the recurring auction in order to gauge the long-term fairness.

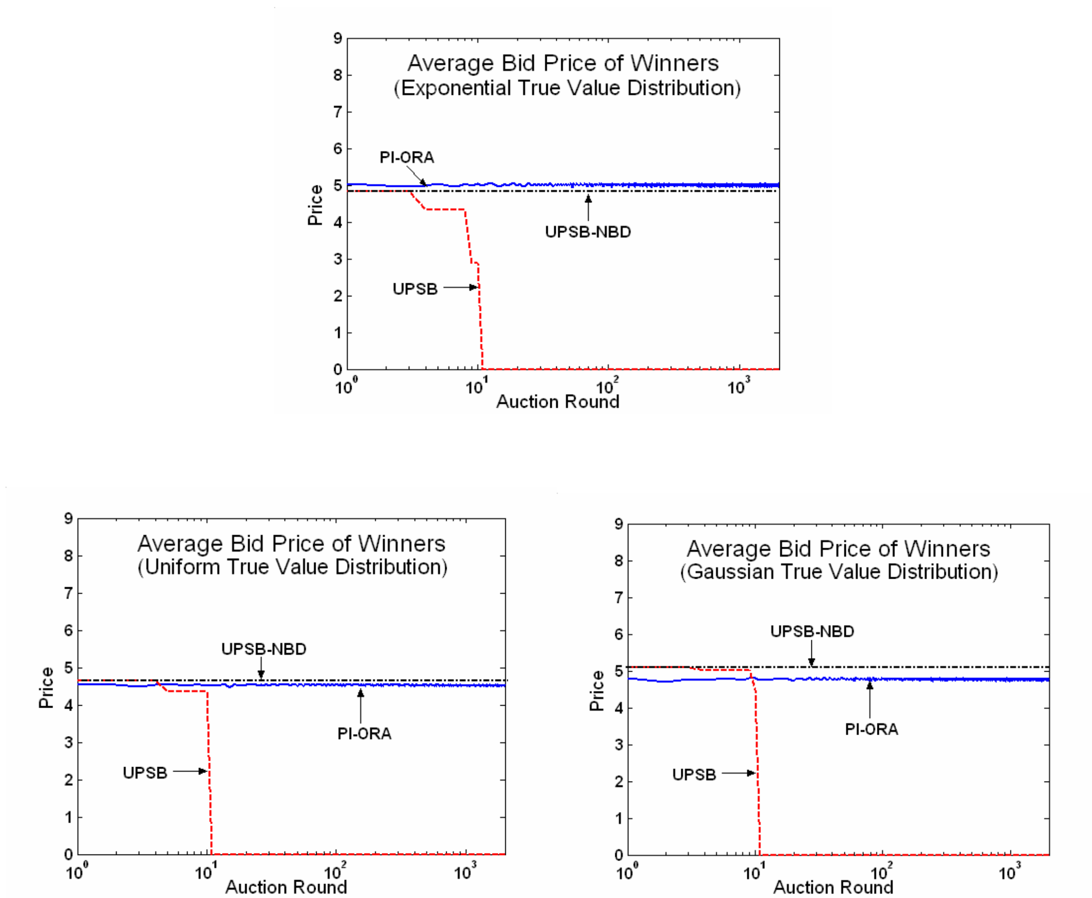

Figure 5.5: The Average Auction Clearing Price

As shown in Figure 5.5, the traditional UPSB auction cannot maintain the seller's desired revenue in a recurring auction because the losers of each auction round have no incentive to participate in future auction rounds and 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., the highest bid 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 traditional basic UPSB auction, the bidder drop problem is the sole cause of the seller’s revenue collapse.

An efficient bidder drop control based on the PI-BDC algorithm of the PI-ORA mechanism 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 bid price b_0, and the constant k from Eq. (5-2), 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. Therefore, the proposed PI-ORA mechanism addresses all the problems that motivated our research.

In a more general case, the dropped bidder can rejoin the auction, once the auction-clearing price becomes sufficiently low, so the revenue of the UPSB auction mechanism settles somewhere between the revenues of the basic UPSB and the UPSB-NBD. The revenue of the basic UPSB auction sets the lower bound since there are no bidders returning in this case. The revenue of the UPSB-NBD auction sets the upper bound, because all bidders return immediately to the recurring auction in that case. Therefore, in a general case of dropped bidders being able to rejoin the auction, the revenue may oscillate between the revenues of the basic UPSB and the UPSB-NBD depending on how quickly bidders drop and rejoin the auction. However, in such an auction, even if dropped losers of previous auction round rejoin the auction again, they cannot become winners permanently when the existing winners never exit the auction. Such property is one of the reasons why without decrease of bids, the dropped bidders are unlikely to rejoin the recurring auction.

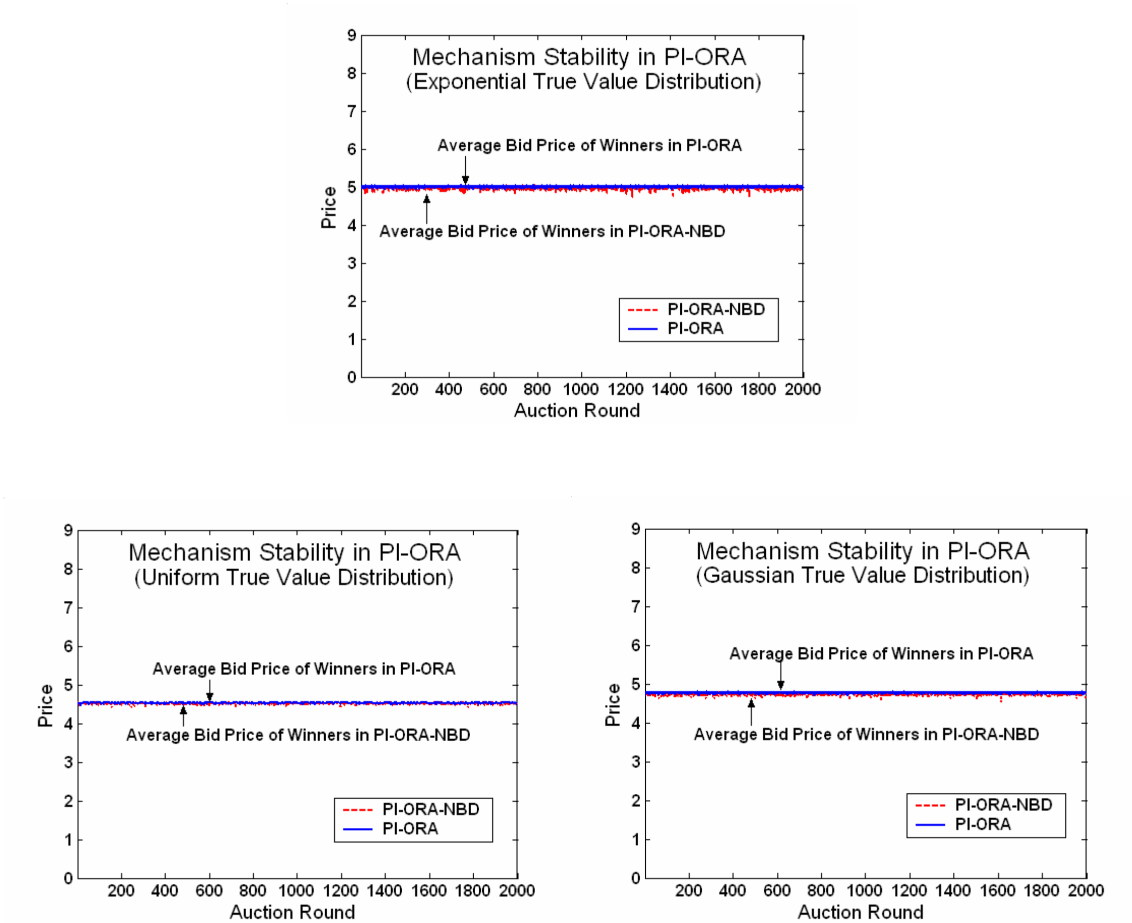

Figure 5.6: The Mechanism Stability in PI-ORA

The average auction clearing prices of PI-ORA and PI-ORA-NBD in each auction round are almost the same in each auction round, as shown in Figure 5.6 for various true valuation distributions. This indicates that the efficient bidder drop control algorithm makes the PI-ORA mechanism stable.

Our simulation results show also that the proposed PI-ORA mechanism achieves the long-term fairness. As shown in Figure 5.7, this mechanism distributes the total number of available perishable resources proportionally to each bidder's true valuation during recurring auction. 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 5.7 also show that the bidders whose bids (i.e., true valuations) are 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 cannot hurt the revenue of PI-ORA.

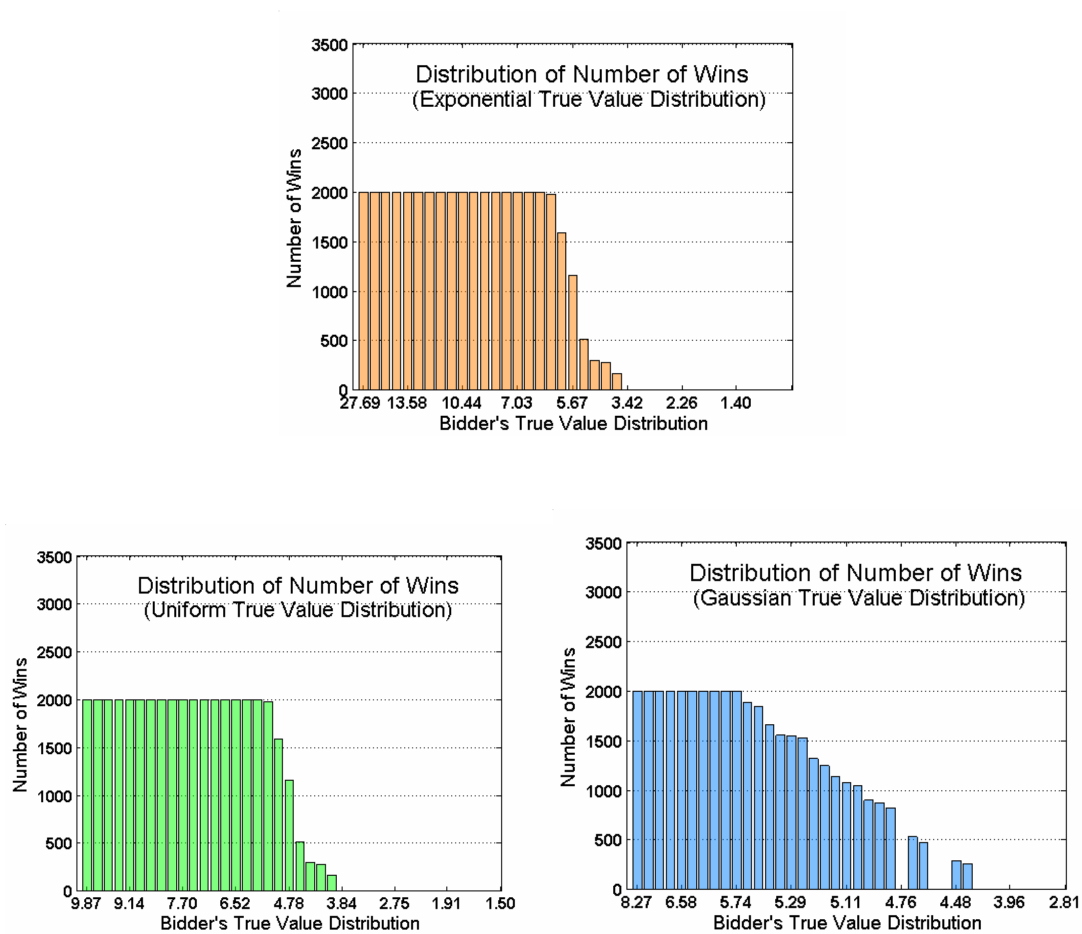

Figure 5.7: The number of win distributions

5.5 Discriminatory Price Optimal Recurring Auction

In this section, we describe the proposed Discriminatory Price Optimal Recurring Auction (DP-ORA) mechanism in which multiple winners are selected and each winner pays his bid. Hence, the DP-ORA mechanism is not incentive compatible.

5.5.1 Winner Selection Strategies

The first step of DP-ORA mechanism is the same as the first step of DP-ORA mechanism. Hence, as shown in Figure 5.2, in each auction rounds, an auctioneer classifies the bidders into one of the three classes: Definite Winner (DW), Possible Winner (PW) and Definite Loser (DL) based on the bids made by the bidders and the auctioneer. As we already explained, the DW class bidders become winners and the DL class bidders become losers without any additional considerations. The bidders in the PW class can be winners or losers based on the described below Valuable Last Loser First (VLLF) bidder drop control algorithm.

5.5.2 VLLF Bidder Drop Control Algorithm

By selecting winners in the PW class, the DP-ORA mechanism encourages them to stay in the auction, so the winners should include those bidders in the PW class who are considering dropping out of the auction. For this purpose, we propose the Valuable Last Loser First Bidder Drop Control (VLLF-BDC) algorithm. The main idea behind this algorithm is to allocate the desired resources to a bidder before he drops out of an auction. The algorithm consists of two phases. In the first phase, the bidders who lost in the last auction round but bid higher in the current round than in the previous one are marked as potential winners. The marked bidders are ranked according to their bids 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.

The winner selection in the first phase is influenced by the bid and the 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.

5.5.3 Optimal Distribution of Resources

By using the VLLF bidder drop control algorithm, the proposed DP-ORA mechanism attempts to maintain the price competition and therefore to stabilize the auctioneer revenue. To be successful, it requires that some resources be reserved for the bidder drop control (allocating all resources to the DW class would reduce the DP-ORA mechanism to the traditional DPSB auction with all its disadvantages in the recurring auction environments). Since the reservation price of the auctioneer defines the membership in the DW class, there is a need to find an optimal value for this price.

Throughout this thesis, we denote the minimum cost of a unit of traded resources as C_m. The auctioneer should set this cost after considering internal and external expenses. This cost can also be interpreted as the auctioneer's desired minimum price for the unit of perishable resources. The specific method for deciding C_m is beyond the scope of this thesis.

The minimum revenue of an auction round with the bidder drop control should be larger than the auctioneer's profitability revenue. A sufficient condition to ensure this constraint is

$$b_0 \cdot N_{dw} + P_{pwmp} \cdot (R - N_{dw}) > C_m \cdot R, \qquad (5\text{-}15)$$

where P_{pwmp} represents the average bid of winners in the PW class. By definition, $P_{pwmp} < b_0$. Based on inequality (5-15),

$$b_0 > C_m \tag{5-16}$$

because $C_m \cdot R < b_0 \cdot N_{dw} + P_{pwmp}(R - N_{dw}) < b_0 \cdot N_{dw} + b_0 \cdot R - b_0 \cdot N_{dw} = b_0 \cdot R$. Therefore, the auctioneer should bid a higher than the minimum cost of a unit of perishable resources to ensure profitability of each auction round.

The upper bound of the optimal reservation price is constrained by the interrelationship between three types of bidder's classes and the auction fairness. As shown in Table 5.1, an increase in the reservation price decreases the number of bidders in the DW class (i.e., N_{dw} decreases). This change results in an increase in the number of resource units reserved for the bidder drop control. Thus, in this case, the size of the DL class decreases (i.e., N_{dl} decreases). Since decreasing N_{dl} means increasing the price competition, the resulting total revenue of the auctioneer usually increases. However, increasing the number of resource units reserved for the bidder drop control decreases fairness of the resource allocation. This is because the winners in the first phase of the VLLF bidder drop control algorithm are selected based not only on their current bids but also on their past bids and the status in the previous auction rounds.

Our simulation results, as shown in Figure 5.8, also show inter-relationships between the members of the DW, PW and DW classes and the revenue in the DP-ORA mechanism. Accordingly, in deciding the upper bound of the reservation price, the auctioneer should balance an increase in the total revenues with the loss of fairness induced by the selected reservation price.

↑: Increase ↓: Decrease ~: Close to

Reservation Price	N_{dw}	N_{wppw}	N_{dl}	Revenue	Fairness
↑	↓	↑	↓	↑ for N_{dw} **~R**	↓
↓	↑	↓	↑	↓ for N_{dw} **~R**	↑

Table 5.1: The interrelationship of bidder's classes

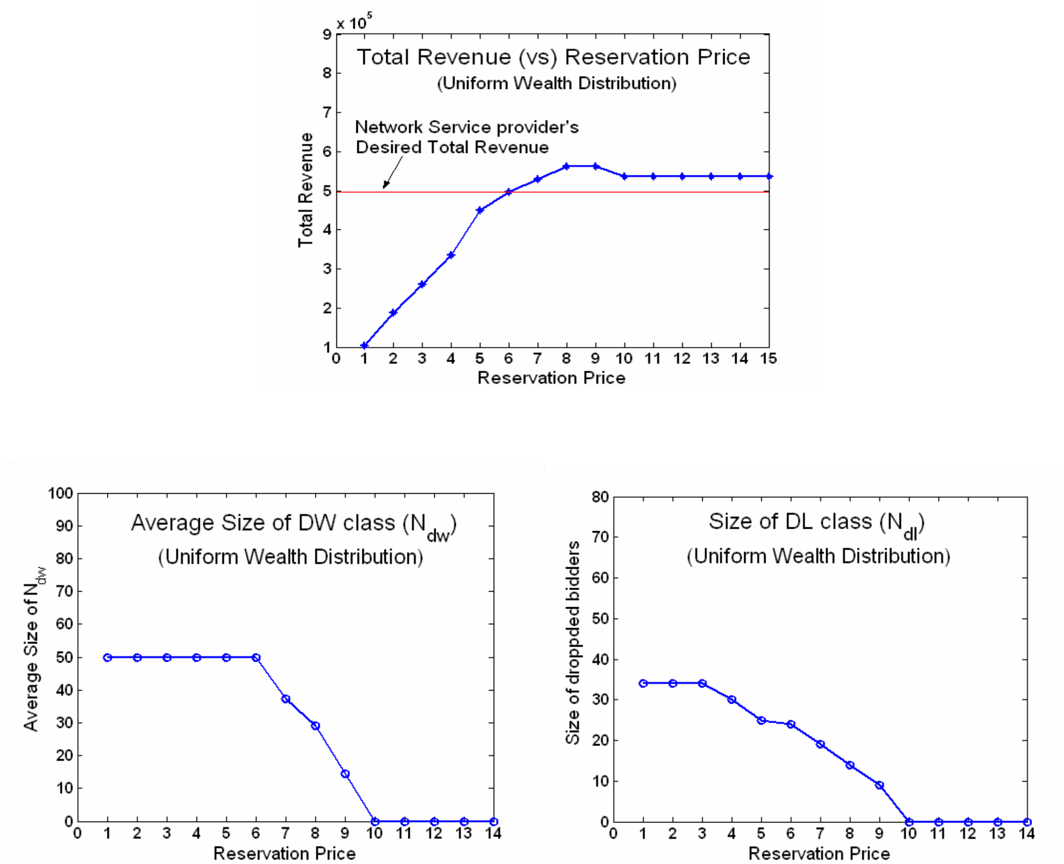

Figure 5.8: Impact of the selection of the reservation price

5.6 Simulation Experiments and Results

As previously, simulations execute 2000 auction rounds in each run. The following scenarios are simulated.

5.6.1 Simulation Scenarios

We compare the following five auction mechanisms that are based on the Discriminatory Price Sealed Bid (DPSB) auction for short-term contract markets in which single item homogeneous perishable resources are sold recurrently for a specific time interval.

- **Traditional Auction (TA)**: In this case we simulate an auction mechanism that has no bidder drop control. Hence, bidders drop out of the recurring auction as a result of starvation for resources.

- **Traditional Auction with No Bidder Drop (TA-NBD)**: This case represents an idealized traditional auction mechanism 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 TA mechanism with a reservation price. Hence only the bidders who bid higher than the reservation price can be selected winners.

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

- **Discriminatory Price Optimal Recurring Auction (DP-ORA)**: This case represents our newly designed DP-ORA auction mechanism with the VLLF bidder drop control algorithm.

The simulation results of TA-NBD are impossible to achieve in the real recurring auction because no bidder drop assumption is unrealistic. In the real world, starvation, triggered by the uneven wealth distribution, will cause bidders to drop out of the auction. Thus, the TA-NBD scenario is only used for a theoretical comparison.

The wealth of each bidder limits her willingness to pay and dictates her true valuation of a unit of resource in the auction. For this reason, we equate the wealth distribution with the distribution of the bidder true valuations. We set the auctioneer‘s minimum cost of a unit of the resource at 5. Accordingly, we set the reservation price of RPA as 5, too. We consider three types of the standard distributions of the bidder true valuations, all with the mean of 5: (1) the exponential distribution, (2) the uniform distribution over [0, 10] range, and (3) the Gaussian distribution.

There are 100 bidders in our simulations. Initially, all are active. We assume that the initial bids are randomly selected from the range $[t_i / 2, t_i]$, where t_i represents the true valuation of bidder i. 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 decisions informed to each bidder by the auctioneer. Based on the assumption of the 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 bid by a factor of $\alpha > 1$ to improve her win probability in the current round. This increase of a bid stops at the true valuation. If a bidder won in the last auction round, she, with equal probability of 0.5, either decreases the bid 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 bid of each bidder is 0.1. If a bidder drops out of an auction, his bid is set to 0. There are 50 units of perishable resources available for allocation in each auction round. Hence, if the resulting expected revenue of each auction round is not higher than or equal to 250, this auction round is cancelled in CA.

The bidder's tolerance of consecutive losses, abbreviated as 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 the consecutive losses of a bidder exceed his TCL, then the bidder drops out of the auction and never returns to it.

5.6.2 Analysis of Simulation Results

Our simulations focus on the auctioneer revenue and the resource allocation fairness. The auctioneer's revenue is proportional to the average bid 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 TA-NBD is optimal, because a bidder with the bid higher than a winner is also a winner. Additionally, by the no bidder drop assumption, TA-NBD never loses a bidder with the high willingness to pay and the low TCL. This means that TA-NBD prevents the loss of fairness that may result from the low TCL. Thus, we can measure the loss of fairness of TA, RPA, CA and DP-ORA by their degree of deviation from the fairness of TA-NBD. We measure the loss of fairness LF_k of the auction mechanism k by the distribution of wins between the bidders:

$$LF_k = \frac{\sum_{i=1}^{n} \left| NW_{TANBDA}(i) - NW_k(i) \right|}{R \cdot N_{Total\_Auction}} \cdot 100, \tag{5-17}$$

where n denotes the total number of bidders in the recurring auction, $NW_{TANBDA}(i)$ and $NW_k(i)$ represent the total number of wins by bidder i during $N_{Total\_Auction}$ of auction rounds in TA-NBD and auction mechanism k, respectively.

As shown in Figure 5.9, under, various wealth distributions, TA 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 bids 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 TA, 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 bids to the very low level. However, RPA does not avoid the resource waste problem. As a result, the auctioneer cannot achieve her desired revenue in a recurring auction of this type.

CA suffers from the same problem as RPA. By canceling auction, CA prevents the remaining bidders from decreasing their bids to the very low levels. However, in a cancelled auction round, the entire 50 units of perishable resources that are assigned to the auction round are wasted. For this reason, the resources wasted in the cancelled auction will prevent the auctioneer from achieving the desired revenue.

DP-ORA is able to maintain the price competition permanently in a recurring auction thanks to the efficient VLLF bidder drop control algorithm. Moreover, in DP-ORA, the resource waste problem 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 bids are very low are eliminated from the auction automatically based on their TCL. Hence, even if the VLLF bidder drop control algorithm allocates resources to the PW class whose members bid lower than members of the Definite Winner class, the low true valuation bidders cannot hurt the auctioneer’s revenues under the DP-ORA mechanism.

As shown in Figure 5.9, the bidder drop and resource waste problems arise under all simulated wealth distributions in our simulation scenarios for the traditional auction mechanisms.

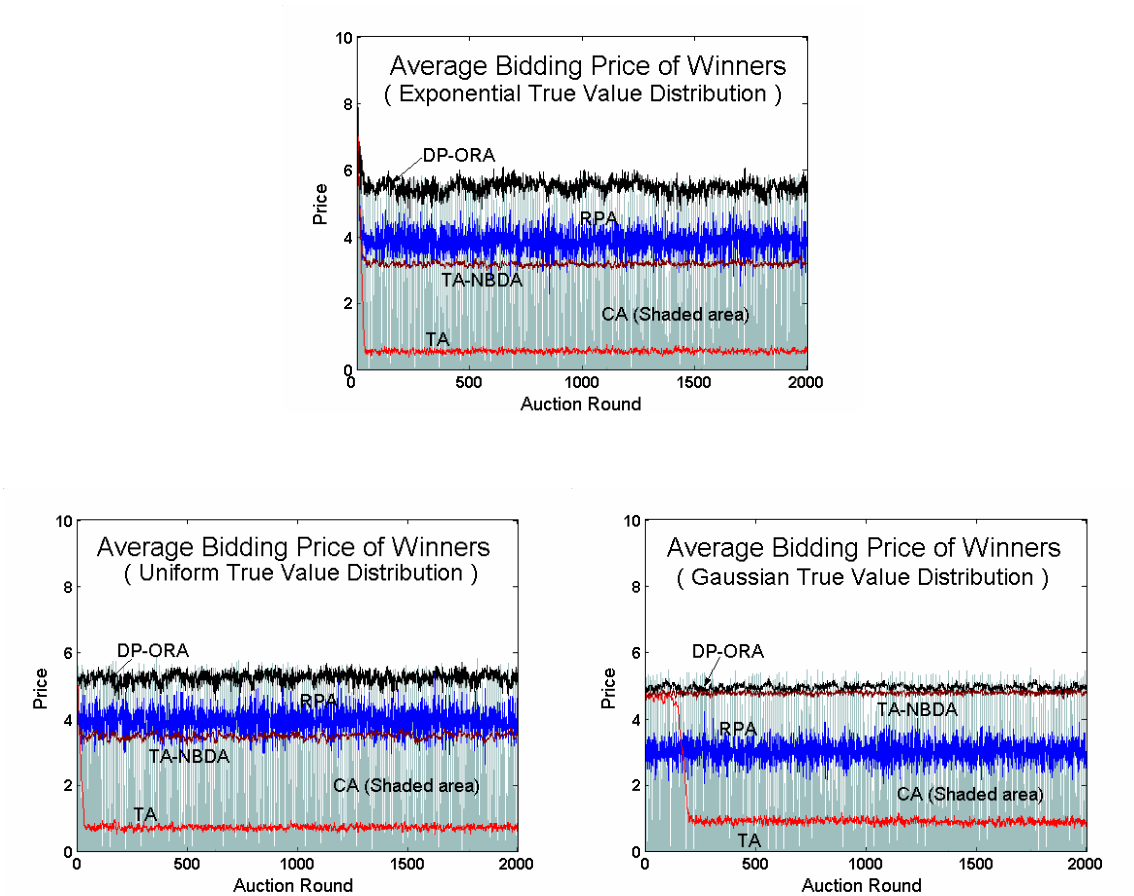

Figure 5.9: The average winning price of winners

The loss of fairness of DP-ORA is remarkably lower than the one observed in TA, RPA and CA under all simulated bidders wealth distributions. This phenomenon arises because TA, RPA and CA cannot prevent the loss of fairness caused by the high true valuation bidders dropping out of an auction as a result of exceeding their TCLs. In other words, TA, RPA and CA cannot prevent a bidder who is willing to pay high prices but has low TCL from dropping out of an auction after exceeding his TCL at some auction round. In each auction round, TA, RPA and CA have the highest possible fairness, because their winners are selected by the current bid only. Yet, remarkably, compared with them, DP-ORA has lower loss of fairness over the life-time of recurring auction because loss of fairness that results from TCL is the dominant factor in the long run. The specific results measuring the loss of fairness under various bidder wealth distributions are provided in Table 5.2.

	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 %

Table 5.2: Loss of fairness

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 TA and TA-NBD because those are the border cases of the general one. The revenue of the TA 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 TA-NBD sets the upper bound because all bidders return immediately to the recurring auction in that case. In summary, DP-ORA achieves 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.

5.7 Summary of the Chapter

In designing auction based dynamic pricing and negotiation mechanisms for markets trading homogeneous multiple unit resources, the bidder drop problem is one of the most fundamental aspects of the environment that need to be considered. Another such aspect is the resource waste possibility.

We have introduced and evaluated two types of the optimal recurring auctions. One is the PI-ORA mechanism that supports incentive compatibility. The other is the DP-ORA mechanism that does not.

In the PI-ORA mechanism, each bidder’s participation in an auction round is rewarded by increasing his winning score for the forthcoming auction rounds. Hence, larger number of bidders can be winners than in a traditional acution. Such incentive keeps bidder interested in the future auction round and maintains the price competition in the recurring auction. Hence, the introduced PI-ORA mechanism prevents the potential market price collapse and stabilizes the markets in the recurring auction. The winning score enables the PI-ORA mechanism to achieve vertical long term fairness because the win distributions are proportional to each bidder’s average bid. Additionally, incentive compatibility of the PI-ORA mechanism simplifies the bidder’s optimal strategy since bidding the true valuation is the optimal strategy for each bidder.

The DP-ORA mechanism prevents the bidder drop problem and the resource waste in the recurring auction thanks to use of the VLLF bidder drop control algorithm that enables less wealthy bidders to become the winners. This in turn prevents a continuous decrease of the bids through the adaptive bidding strategy. It also maintains the price competitions over the recurring auction. Hence, the DP-ORA mechanism stabilizes the market revenue. This mechanism also decreases loss of fairness by preventing the drop of bidders who have the high willingness to pay in the recurring auction.

6. NOVEL AUCTION FOR HETEROGENEOUS MARKETPLACES

6.1 Introduction

In this chapter, we consider markets in which each bidder requests the different number of resource units for his desired level of quality of service. Hence, the combinatorial winner selection strategy is optimal in a single auction round because it probes all possible combinations of bidders' requests and selects the combination of winners that maximizes the auctioneer's revenue. In such environments, use of the Generalized Vickery Auction (GVA) with the combinatorial winner selection is often recommended. To describe the GVA mechanism in such a setting, we enumerate all possible combinations of bidders as C_k, where $k = 1, ..., 2^n - 1$, since $2^n - 1$ bidders' combinations are possible. We will also denote the set of indexes of all feasible combinations as F, where a combination C_k is feasible if the allocation of resources requested collectively by the bidders in C_k does not violate the restriction on the number of available resources at the time t of the auction round close. In other words, the following inequality, called the resources constraint at time t, must be satisfied:

$$\sum_{j \in C_k} r_j \le R^t \quad , \tag{6-1}$$

where r_j denotes the number of resource units requested by bidder j and R^t represents the number total number of resource units available at time unit t. Based on this resource constraint, the auctioneer selects the combination C_k that maximizes the sum of products of the bids and the requested number of the corresponding resources (i.e., maximizes the resulting revenue) among all feasible combinations of bidders. Hence, the winner selection strategy of the GVA mechanism can be defined as

$$\underset{k \in F}{MAX} \sum_{i \in C_k} b_i \cdot r_i \tag{6-2}$$

To define the payment (i.e., the pricing rule) for selected winners, we denote by x_i^* the membership vector of the optimal combination of bidders that maximizes the revenue (i.e., if bidder i is included in the optimal combination, $x_i^* = 1$, otherwise $x_i^* = 0$), and $x_i^{*\neg k}$ is the membership vector of the optimal combination with the bidder k removed from the auction. The payment price of winner k is computed by deducting the sum of products of the bids and the requested number of the corresponding resource units for all bidders, except bidder k, in x_k^* from the sum of products of the bids and the requested resource units for all bidders in $x_i^{*\neg k}$ [5, 7]. Hence, the payment $G_k(b_k)$ for a selected winner k with the bid b_k can be expressed as

$$G_k(b_k) = \sum_{\substack{i=1 \\ i \neq k}}^{n} b_i \cdot r_i \cdot x_i^{*\neg k} - \sum_{\substack{i=1 \\ i \neq k}}^{n} b_i \cdot r_i \cdot x_i^* \tag{6-3}$$

Example 6-1: There are four bidders denoted as B1, B2, B3 and B4, and an auctioneer. Three resource units are available in each auction round. B1, B2, B3 and B4 request 1, 2, 1 and 2 resource units with bids (i.e., their true valuations) \$3, \$5, \$6 and \$8 for a unit, respectively. In the GVA mechanism, bidders B3 and B4 are selected as winners according to the winner selection strategy. According to the pricing rule defined by Eq. (6-3), the payment for a resource unit of bidder B3 is (\$19 - \$16) / 1 = \$3 and the payment for a resource unit for bidder B4 is (\$16 - \$6) / 2 = \$5.

Based on its pricing rule and the winner selection strategy, the GVA mechanism is incentive compatible since the truthful bid (i.e., bidding the true valuation) by each bidder maximizes its expected utility [5, 7].

However in a recurring auction, the combinatorial winner selection strategy that focuses on revenue maximization rewards only the bidders with the highest wealth. Hence, this strategy causes starvation for the traded resources among the least wealthy bidders. The incentive compatibility of GVA mechanism exacerbates this phenomenon. A bidder who lost in such an auction can easily conclude that its true valuation is not large enough to ever become a winner. There is no incentive, therefore, for losers of the current auction round to participate in the future auction rounds. Specifically, in the GVA mechanism, the bidders who do not belong to the optimal combination x_i^* may quickly drop out of the future auction rounds. In the long run, only bidders who belong to the optimal combination are left. In this situation

$$\sum_{\substack{i=1 \\ i \neq k}}^{n} b_i \cdot r_i \cdot x_i^{*\neg k} = \sum_{\substack{i=1 \\ i \neq k}}^{n} b_i \cdot r_i \cdot x_i^{*} \text{, for all } i \text{ with } x_i^* = 1 \qquad (6\text{-}4)$$

Hence, based on the pricing rule of the GVA mechanism defined by Eq. (6-3), the resulting payment of each selected winner i becomes zero, thereby reducing the auctioneer's revenue to zero. The following example shows the revenue collapse of the traditional GVA mechanism with the combinatorial winner selection in a recurring auction.

Example 6-2: In Example 6-1, bidders B3 and B4 are selected as winners with the payment of \$3 and \$5 for a resource unit, respectively. After one auction round, bidders B1 and B2 have no incentive to participate in the future auction rounds and drop out of the auction. In the next auction round, bidders B3 and B4 are selected as winners again. However, this time, the payment for bidder B3 is \$16 – \$16 = \$0, and for bidder B4 is (\$6 – \$6) / 2 = \$0, according to the pricing rule of Eq. (6-3). Therefore, the revenue of the auctioneer collapses to zero.

To resolve a potential revenue collapse problem in the traditional GVA mechanism, we introduced the Participation Incentive Generalized Vickrey Auction (PI-GVA). The reminder of this chapter is organized as follows. Section 6.2 introduces a novel auction mechanism based on the Generalized Vickrey Auction that provides incentives for bidders' participation. In section 6.3, the verification of the proposed auction mechanism by various simulation experiments is described. Section 6.4 summarizes the chapter.

6.2 Participation Incentive Generalized Vickrey Auction

To prevent bidder drop problem arising in a traditional combinatorial winner selection strategy applied to the recurring GVA mechanism, we introduce here the **P**articipation **I**ncentive **G**eneralized **V**ickrey **A**uction (PI-GVA) mechanism that is incentive compatible [5].

6.2.1 A Novel Winner Selection Strategy

The introduced auction mechanism rewards each bidder's participation in a round of the recurring auction by using the similar winning score $S_i(b_i)$ of Eq. (5-2) that is used in PI-ORA mechanism.

$$S_i(b_i) = \frac{b_i}{\mu} \cdot p_i - w_i \ , \tag{6-5}$$

As described in Chapter 5, the winning score $S_i(b_i)$ of bidder i represents the difference between the expected and real numbers of wins during the recurring auction. Hence, higher the winning score of a bidder, higher the probability of him dropping out of the future rounds, because more below his expectations his winnings are. Based on this property of the winning score $S_i(b_i)$, the proposed PI-GVA selects the optimal combination of bidders that maximizes the sum of each bidder's winning score in each auction round based on the available number of resource units. Hence, the novel winner selection strategy of the proposed PI-GVA mechanism can be defined as

$$\underset{k \in F}{MAX} \sum_{i \in C_k} S_i(b_i) = \underset{k \in F}{MAX} \sum_{i \in C_k} \left(\frac{b_i}{\mu} \cdot p_i - w_i \right) \tag{6-6}$$

Such winner selection strategy is restricted by the resource constraints and the winning score constraints in each auction round (i.e., in each time unit):

$$\sum_{i \in C_k} r_i \le R^t \text{ and } S_i(b_i) > 1 - \frac{b_i}{\mu} \text{ for } \forall i \in C_k \qquad (6\text{-}7)$$

The winning score constraint $S_i(b_i) > 1 - (b_i / \mu)$ ensures that the winning score of each bidder is always higher than zero. This constraint can be easily satisfied by assigning each bidder the initial winning score credit and selecting the proper value of μ, so the sum of all winning scores in each auction round increases.

Because of the property of winning score, the participation of a loser in the last auction round is rewarded directly by increasing its winning score that increases its win probability in the future auction rounds. Since the cumulative average bid b_i is used in the winning score, decreasing the bid in a recurring auction will decrease the expected number of wins under the same participation record. Hence, the PI-GVA mechanism encourages even bidding in all auction rounds. The coefficient μ controls the effect of the average bid. If μ is increased, the effect of the bid is diminished, therefore the chance of winning with the low bid increases. Reverse is true when μ is decreased. The optimal value of coefficient μ depends on the GCS provider's policy. We propose setting μ to the average bid of all bidders, based on various experimentation results.

6.2.2 The pricing Rule of PI-GVA

To describe the pricing rule of the PI-GVA mechanism, we denote by $x_i^{\oplus}$ the variables of an optimal combination according to Eq. (6-2). $x_i^{\oplus \neg k}$ denotes the variables of optimal combinations with bidder k skipped. The pricing rule of PI-GVA mechanism is analogous to the pricing rule of the traditional GVA. It consists of a two-step procedure. The first step is to compute the payment winning score $I_k(b_k)$ of the selected bidder k (i.e., the winner with $x_k^{\oplus} = 1$) with its average bid b_k, according to the following equation:

$$I_k(b_k) = \sum_{\substack{i=1 \\ i \neq k}}^{n} S_i(b_i) \cdot r_i \cdot x_i^{\oplus \neg k} - \sum_{\substack{i=1 \\ i \neq k}}^{n} S_i(b_i) \cdot r_i \cdot x_i^{\oplus} \qquad (6\text{-}8)$$

From the payment winning score of the selected bidder k in Eq. (6-8) and the winning score function in Eq. (6-5), the payment price $G_k(b_k)$ for a resource unit by bidder k is computed as follows

$$G_k(b_k) = \frac{I_k(b_k) \cdot b_k}{r_k \cdot S_k(b_k)} \qquad (6\text{-}9)$$

Based on this pricing rule, the PI-GVA mechanism guarantees that each winner pays the price lower than its bid.

6.2.3 The Optimal Strategy for Bidders in PI-GVA

The bidder's optimal strategy under the PI-GVA mechanism is defined for two aspects: the bid value and the participation level. We show below that the optimal strategy of each bidder is to bid its true valuation, making the PI-GVA mechanism incentive compatible. Indeed, from the utility function in Eq. (2-2) it follows that bidding the true valuation by bidder k maximizes its utility U_k:

$$U_k = (t_k - G_k(b_k)) \cdot q(b_k) = \left(t_k - \frac{I_k(b_k) \cdot b_k}{r_k \cdot S_k(b_k)} \right) \cdot q(b_k) \quad , \qquad (6\text{-}10)$$

where $q(b_k)$ represents win probability with bid b_k.

Lemma 6-1: Increasing bid also increases the profit factor $(t_k - G_k(b_k))$ of utility function, or in other words, the profit factor is an increasing function of bid b_k.

Proof: The profit factor $(t_k - G_k(b_k))$ can be rewritten as $\left(t_k - \frac{I_k(b_k)\cdot b_k}{r_k \cdot S_k(b_k)}\right)$. Note that the computed payment winning score $I_k(b_k)$ of bidder k is not dependent on bid b_k (see Eq. (6-8)) and the required number of resource units r_k and the true valuation t_k can be regarded as constants. Hence, the profit factor can be influenced only by a fraction $(b_k / S_k(b_k))$. To prove lemma 6-1, we show that increasing the bid decreases this fraction. Indeed, we have:

$$\frac{\frac{b_k}{S_k(b_k)}}{\frac{b_k+\alpha}{S_k(b_k+\alpha)}} = \frac{b_k S_k(b_k+\alpha)}{(b_k+\alpha)S_k(b_k)} = \frac{b_k\left(\frac{(b_k+\alpha)}{\mu}p_k - w_k\right)}{(b_k+\alpha)\left(\frac{b_k}{\mu}p_k - w_k\right)} =$$

$$\frac{(b_k+\alpha)\left(\frac{b_k}{\mu}p_k - w_k\right) + \frac{b_k \alpha p_k}{\mu} - \alpha\left(\frac{b_k}{\mu}p_k - w_k\right)}{(b_k+\alpha)\left(\frac{b_k}{\mu}p_k - w_k\right)} = 1 + \frac{\alpha w_k}{(b_k+\alpha)\left(\frac{b_k}{\mu}p_k - w_k\right)} \geq 1. \qquad ,(6\text{-}11)$$

where $\alpha > 0$. The Ineq. (6-11) is always true because b_k, α, μ and w_k are always greater than zero, and the current winning score $\left(\frac{b_k}{\mu}p_k - w_k\right)$ is always positive according to the winning score constraint expressed by Ineq. (6-7).□

Lemma 6-2: Increasing a bid of bidder k increases or maintains the winning probability $q(b_k)$ of its utility function, or in other words, the win probability $q(b_k)$ is a non-decreasing function of bid b_k.

Proof: In a specific auction round (i.e., a time unit), the winning score coefficient μ, the cumulative number of win w_k, and the number of participations p_k can be regarded as constants. Hence, increasing the bid b_k increases the winning score. In the PI-GVA mechanism, the ranks of bidders are decided by the winning score, so increasing winning score may increase or maintain the ranks of bidders. Since the combinatorial winner selection strategy of Eq. (6-6) in the PI-GVA mechanism focuses on maximizing the sum of winning scores, the following three cases are possible in terms of the winning probability when a bidder increase his bid.

Case 1) Rank of bidder is increased, so the win probability also increases.
Case 2) Rank of bidder is increased but there is no change in the win probability.
Case 3) Rank of bidder is not changed, and there is no change in the win probability.

In all of three cases, the win probability does not decrease whenever bidder's bid increase. Since the winning score is cumulative, the increased winning score will increase the winning probability in the long run. □

Based on Lemmas 6-1 and 6-2, we conclude that increasing bid increases the expected utility U_k. Each bidder's bid is limited by its true valuation. Hence, bidding each bidder's true valuation maximizes the expected utility in the PI-GVA mechanism.

From the participation point of view, increasing the number of times that the bidder k participated in an auction decreases the fraction $(b_k / S_k(b_k))$ of the profit factor $(t_k - G_k(b_k))$. Hence, it increases the resulting profit factor. Additionally, increasing the number of participations increases the winning score. By Lemma 6-2, increasing the winning score increases or maintains the bidder's wining probability. Hence, the winning probability $q(b_k)$ of bidder k is a non-decreasing function of the number of participations p_k. Hence, increasing the number of participations increases the expected utility U_k.□

In conclusion, the bidder's optimal strategy under the PI-GVA mechanism is to bid its true valuation and to participate in as many auction rounds as possible.

6.3 Simulation Experiments and Results

6.3.1 Simulation Scenarios

In our experiments, we compare the following two auction mechanisms that are based on one time sealed bids for short-term contracts for e-services.

- **Traditional Generalized Vickrey Auction (TGVA)** described in section 6.1. Its combinatorial winner selection focuses on revenue maximization.

- **Participation Incentive Generalized Vickrey Auction (PI-GVA)** introduced in section 6.2.

There are 15 bidders (i.e., customers) and a service provider (i.e., the auctioneer). In each auction round (i.e., time unit), 10 resource units are traded for short-term contracts for customers requesting the desired e-services. Each bidder specifies individual e-service level and a time limit for fulfilling the request. We assume that the bidding time is the desired computing service start time. The desired number of resource units and the deadlines are randomly distributed in the range of [1, 4] and [1, 6] respectively.

We suppose that the desired application e-services are fully parallelized. Hence, if a bidder cannot be selected as winner at current time unit, it participates in the next auction round with the same bid, as long as its deadline can be met. If a bidder cannot be selected as winner before the deadline, this failure is counted as a loss in the recurring auction. The auction round is executed for each time unit for which there are resources available. After the deadline, each bidder re-enters the auction with a request for a new e-services.

In addition to the perceived intrinsic value of the traded resources, the wealth of each bidder limits its willingness to pay for e-services and defines its true valuation of the traded units of resources. For simplicity, we consider only the distribution of the customer's true valuation here. For this purpose, we consider three distributions, all with mean of 5, of the customers true valuations: (i) the exponential distribution, (ii) the uniform distribution over the range [0, 10], and (iii) the Gaussian distribution. All distributions have the same average cost of a grid resource unit set at 5. Because of incentive compatibility of TGVA and PI-GVA, each bidder bids its true valuation in each auction round to maximize his expected utility.

The customer's tolerance of consecutive losses, abbreviated as TCL, denotes the maximum number of consecutive losses that a customer can tolerate before exiting the auction. If the consecutive losses exceed the bidder's TCL, the bidder exits the auction. We assume, that the bidders who exited never returns to the auction. TCL of each customer is uniformly distributed over the range of [2, 6]. Based on these scenarios, the simulation is executed over 2000 time unit.

6.3.2 Analysis of Simulation Results

In our experiments, we focus on the revenue of service provider (i.e., the auctioneer). We use the average price of a resource unit at the end of every 50 time units to measure the revenue of service provider over the entire recurring auction.

TGVA cannot prevent the market price collapse because bidders exit from the auction. The traditional combinatorial winner selection of TGVA mechanism causes the starvation for resources among the least wealthy bidders during the recurring auction. Hence, in the simulations, the least wealthy bidders drop out of the auction after their numbers of consecutive losses exceed their TCL. As a result, only the bidders who can be allocated the resource units remain in the auction and the resulting prices of the resource unit for each of the remaining bidders becomes zero based on the pricing rule of TGVA. This illustrates the paradox of incentive compatible mechanism in a recurring auction. Because of the incentive compatible property of TGVA, the dropped bidders never want to return to the auction market since there is no chance for them to win if the current winners never drop out of the auction. Therefore, the bidder drop is the sole cause of revenue collapse in the recurring TGBA.

In contrast, the combinatorial winner selection based on the winning score in the PI-GVA mechanism allocates resources efficiently to the whole range of bidders and prevents bidders from dropping out of the auction. Hence, the novel winner selection strategy maintains the price competition and stabilizes the markets with recurring auctions for heterogeneous resources. Figure 6.1 shows the average price pattern for a resource unit under the compared TGVA and PI-GVA mechanisms.

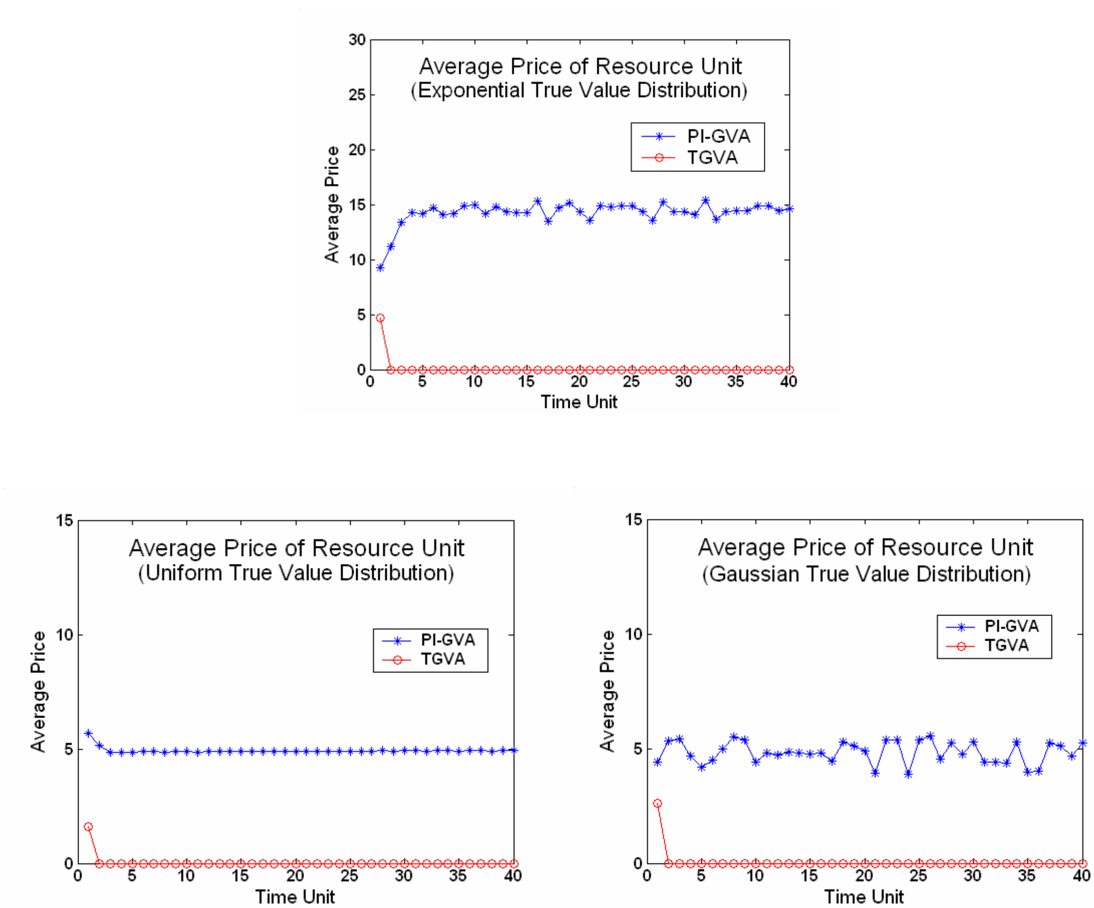

Figure 6.1: Revenue comparison of TGVA and PI-GVA

6.4 Summary of the Chapter

The combinatorial winner selection strategy of the traditional GVA mechanism yields the optimal resource allocation in a single round auction because all of possible combinations of bidders' requirements for resources are probed and the combination of bidders that maximizes the auctioneer's revenue is selected. However, applying the combinatorial winner selection strategy of the traditional GVA mechanism to heterogeneous service oriented short-term contract marketplaces may results in a market price collapse resulting from the bidder drop problem. We have introduced the Participation Incentive Generalized Vickery Auction for such environments. The main idea of the PI-GVA mechanism is to reward bidder's participation in auction rounds by using the proper winning score. Hence, in the PI-GVA mechanism, the auctioneer selects the optimal combination of bidders that maximizes the sum of the winning scores of the selected bidders. With this approach, the proposed mechanism can maintain the price competitions by resolving the bidder drop problem and therefore it prevents the market price collapse and stabilizes the auctioneer's revenue. Additionally, PI-GVA satisfies other desirable auction design requirements such as incentive compatibility and low cost of negotiations.

7. SUMMARY AND FUTURE WORK

7.1 Thesis Summary

With the expansion of electronic environments, increasing dominance of service-oriented paradigm, and the auction's inherent dynamic pricing and negotiation nature many researchers have attempted to extend application domain of auction mechanisms to the newly emerging marketplaces. Examples of such markets include network services, application computing services (including grid computing services and utility computing services), Internet advertising services, and so on. These markets can be characterized as recurring short-term contract marketplaces selling perishable resources. Hence, auctions designed for these markets also must be recurring auctions with perishable resources traded.

During a recurring auction for short-term contracts, bidders can drop out of an auction at any time because of the starvation for resources. Additionally, such bidder drop problem is exacerbated in any incentive compatible auction mechanism, such as the Second Price Sealed Bid Auction or the Uniform Price Sealed Bid Auction, because of the paradox of an incentive compatible mechanism in a recurring auction.

A combinatorial winner selection strategy of the Generalized Vickery Auction yields optimal resource allocation in a single round and is used in markets where bidders may request different numbers of resource units. However, applying the combinatorial winner selection to the recurring heterogeneous marketplace causes the bidder drop problem because some bidders will suffer starvation for resources. Hence, the paradox of an incentive compatible mechanism in a recurring auction is a cause of the bidder drop problem also in the Generalized Vickery Auction.

Since an auction relies on a non-cooperative competition-based dynamic pricing mechanism, the bidder drop problem decreases price competition in the recurring auction, and thereby decreases the auctioneer revenue. Hence, 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 design of a recurring auction mechanism. The resource waste is another problem that needs to be considered in this context when the traded resources are perishable.

We have proposed two novel recurring auction mechanisms for markets with the homogenous resources traded and one novel recurring auction mechanism for markets fir the heterogeneous and perishable resources. In the first case, the Participation Incentive Optima Recurring Auction (PI-ORA) that is incentive compatible, and the Discriminatory Price Optimal Recurring Auction (DP-ORA) that is not have been proposed. In the second case, we have proposed the Participation Incentive Generalized Vickery Auction (PI-GVA) that is incentive compatible. The common idea that is shared by these three proposed auction mechanisms is providing rewards for bidder's participation in auction rounds in the form of increased probability of winning resource allocation in the future auction rounds.

In the PI-ORA mechanism, each bidder's participation is rewarded by increasing its win probability through the increased winning score. Hence, even not wealthy bidders can become winners in the recurring auction. Such a bidder drop control algorithm in PI-ORA stabilizes market prices by preventing the bidder drop and also increases the expected revenue by avoiding the resource waste. Additionally, the incentive compatible property of the PI-ORA mechanism simplifies implementation of a bidder agent for an electronic auction as a tool for automated negotiations. In the recurrent auction, the PI-ORA mechanism achieves the long-term fairness since bidders with high true valuations win more frequently than the ones with low true valuations. Moreover, the PI-ORA mechanism satisfies the other desirable properties of the optimal auction mechanism, such as the individual rationality and a short time to negotiation convergence by using the sealed bid direct mechanism.

In the DP-ORA mechanism, the auctioneer allocates the traded resources to bidders that are about to drop out of the auction. Those are identified by their bids and history of wins. The DP-ORA mechanism stabilizes the auctioneer's revenue by maintaining the price competition and decreases the loss of resource allocation fairness by preventing the bidders who are willing to bid high prices from dropping out of the auction. Additionally, the pattern of the winning price distributions shows that DP-ORA, when compared to the traditional auctions, supports larger active bidder base by occasionally allocating resources to the bidders with the low resource valuation.

In the PI-GVA mechanism, the auctioneer selects that combination of bidder's requests that maximizes the sum of winning scores of the selected bidders. Hence, the bidder's participation is rewarded by increasing its winning score in the forthcoming auction rounds that in turn increases the probability that the bidder is included in the winning combination of bidders. The least wealthy bidders win proportionally to their bids. The mechanism also simplifies the bidder strategy and minimizes the negotiation cost because PI-GVA is an incentive compatible direct mechanism.

7.2 Contributions

This thesis contributes to our understanding of the basic trading mechanisms for the newly arising or future service-oriented electronic marketplaces, such as various e-services, network services, grid computing services (including on-demand computing services), car parking services, procurement, Internet based services, Internet advertising, etc. The followings bullets described more specifically the contributions of the thesis:

- Surveyed and analyzed basic auction mechanisms, bid behavior and requirements for the design of the optimal auction mechanisms (Chapter 2).

- Surveyed and analyzed the newly arising service-oriented electronic marketplaces in which auctions can be used as dynamic pricing and negotiation mechanisms (Chapter 3).

- Recognized and analyzed the recurring nature of auctions for the newly arising service-oriented marketplaces for short-term contracts and perishable resources (Chapter 3).

- Discovered, analyzed and verified the ‘bidder drop problem’ in recurring auctions for homogeneous resources, both analytically and by simulations (Chapter 4).

- Discovered, analyzed and verified the ‘bidder drop problem’ in the recurring Generalized Vickrey Auction with the combinatorial winner selection for trading heterogeneous resources, both analytically and by simulations (Chapter 6).

- Defined, analyzed and verified the ‘resource waste problem’ in recurring auctions for perishable resources, such as short-term contracts for electronic services (Chapter 4).

- Developed two novel auction mechanisms for trading homogenous resources in recurring markets, PI-ORA and DP-ORA. They are based on two bidder drop control algorithms, PI-BDC and VLLF-BDC, respectively (Chapter 5).

- Verified the design of the PI-ORA and DP-ORA mechanisms analytically and by simulations (Chapter 5).

- Developed a novel auction mechanism for trading heterogeneous resources in recurrent markets, termed PI-GVA, that is based on a novel combinatorial winner selection strategy that rewards the bidders’ participation in the recurring auction (Chapter 6).

- Verified the design of PI-GVA mechanism analytically and by simulation (Chapter 6).

7.3 Future Research

A list of possible future research based on the proposed three novel auction mechanisms includes:

- In the Participation Incentive Optimal Recurring Auction mechanism:
    - Searching for more efficient ways of deciding the auctioneer's optimal bid that defines the DW and PW classes.
    - Seeking a better way to find the optimal winning score coefficient for the winner selection strategy of the PI-ORA mechanism.
    - Attempting to identify more efficient and simpler pricing rules that preserve incentive compatibility but achieve higher auctioneer's revenue.

- In the Discriminatory Price Sealed Bid Auction mechanism:
    - Searching for more efficient ways of deciding the auctioneer's optimal bid price that yields the optimal distribution of resources between the DW and PW classes.
    - Seeking more efficient bidder drop control algorithms.

- In the Participation Incentive Generalized Vickery Auction mechanism:
    - Searching for more efficient bidder drop control algorithms for the combinatorial winner selection strategy.
    - Seeking a better way to find the optimal winning score coefficient for the winner selection strategy of the PI-GVA mechanism.
    - Attempting to identify more efficient pricing rules that preserve incentive compatibility.

We also intend to extend our research into developing the novel auction mechanisms for other emerging or already established marketplaces such as sponsored advertisement auctions employed by the Internet search engines, car parking services, and so on.

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