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EGALITARIAN BEHAVIOUR IN MULTI UNIT COMBINATORIAL AUCTIONS

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Egalitarian Behaviour in Multi Unit Combinatorial Auctions

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy (Major subject: computer science) at the University of Girona

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Abstract

In environments where resources are perishable and the allocation of resources is repeated over time with the same set or a very similar set of agents, recurrent auctions come up. A recurrent auction is a sequence of auctions where the result of one auction can influence the following ones. These kinds of auctions have particular problems, however, when the wealth of the agents is unevenly distributed and resources are perishable. The bidder drop problem appears when many bidder agents decide to leave the market (because they are participating in many auctions and they are always losing); this lowering of the demand produces a decrease in the prices and, consequently, the auctioneer gets less profit and the auction could even collapse. The resource waste problem turns up when not all the resources are sold (which could be a solution to the previous problem) and they lose their value because perishable resources cannot be stored for future sales. Finally, the asymmetric balance of negotiation power occurs when the richest agents gain enough power to set the prices and they set it at the minimum price possible, causing the collapse of the market. The revenue of the auctioneer is then being affected by all these problems.

In this thesis some fair mechanisms are proposed to deal with these problems, so that the revenue of the auctioneer is improved in the long term. In a recurrent auction a fair solution means that at long term, all participants accomplish their goals in the same degree or in the most equal possible degree, independently of their wealth. Concretely this thesis tackles the recurrent multi-unit auctions (Recurrent MUA) and recurrent multi-unit combinatorial auctions (Recurrent MUCA). In a MUA the auctioneer sells several units of a unique resource and the bidders bid for only a unit while in a MUCA the auctioneer sells several resources and several units of each resource and bidders can bid for packages of resources and different quantities for each resource.

We have experimentally shown how the inclusion of fairness incentives to bidders stay in the auction reducing the effect of the bidder drop problem and reducing the effects of resource waste. We have also experimentally shown how the use of reservation prices can be mixed with priorities in order to obtain mechanisms able to maintain the negotiation power of the auctioneer. However there are some dynamic situations where the fair mechanism needs also a method to avoid that rich bidders obtain the resources at a cheaper price. We have called this mechanism control of fair resources. The combination of these three components: priorities, reservation prices and control of rich bidders bring two of the proposed mechanisms to obtain the best performance under all simulated situations.

Finally, the possible manipulations performed by bidders and equilibriums reached by the fair mechanisms have been studied concluding that fair mechanisms work well in domains where bidders are honest. However, in other situations bidders can manipulate in some way the priorities and reservation prices obtaining non desirable equilibriums for the auctioneer.

Resumen

En entornos donde los recursos son precederos y la asignación de recursos se repite en el tiempo con el mismo conjunto o un conjunto muy similar de agentes, las subastas recurrentes pueden ser utilizadas. Una subasta recurrente es una secuencia de subastas donde el resultado de una subasta puede influenciar en las siguientes. De todas formas, este tipo de subastas tienen problemas particulares cuando la riqueza de los agentes esta desequilibrada y los recursos son precederos. El problema de la marcha de *bidders* aparece cuando algunos *bidders* deciden dejar el mercado (ya que están participando en distintas subastas y están perdiendo continuamente); esta bajada en la demanda produce un decrecimiento en los precios y consecuentemente, el subastador obtiene menos beneficio y la subasta puede incluso llegar a colapsarse. El problema del desperdicio de recursos aparece cuando no todos los recursos son vendidos (lo cual puede ser una solución al anterior problema) y estos pierden su valor ya que los recursos precederos no pueden ser guardados para ser subastados en el futuro. Finalmente, el balance asimétrico del poder de la negociación ocurre cuando los *bidders* más ricos consiguen suficiente poder para fijar los precios y ellos lo fijan al mnimo posible, causando el colapso del mercado. El beneficio del subastador es afectado por todos estos problemas.

En esta tesis se proponen algunos mecanismos justos o equitativos para minimizar los efectos de estos problemas, es decir para mejorar el beneficio del subastador a largo plazo. En una subasta recurrente una solución justa significa que todos los participantes consiguen a largo plazo sus objetivos en el mismo grado o en el grado más parecido posible, independientemente de su riqueza. Concretamente esta tesis trata con las subastas recurrentes multi unidad (MUA recurrente) y con las subastas combinatorias recurrentes muti unidad (MUCA recurrente). En una MUA el subastador vende diversas unidades de un único recurso y los *bidders* envían un *bid* por una única unidad mientras que en una MUCA el subastador vende diversos recursos y diversas unidades de cada recurso y el *bidder* puede enviar *bids* por conjuntos de recursos y pedir diferentes cantidades de cada recurso.

Hemos demostrado experimentalmente que la inclusión de justicia incentiva a los *bidders* en permanecer en la subasta reduciendo el efecto del problema de la marcha de los *bidders* y reduciendo los efectos del desperdicio de recursos. También hemos demostrado experimentalmente como el uso de precios de reserva se puede mezclar con prioridades con el objetivo de obtener mecanismos capaces de mantener el poder de la negociación. De todas formas existen algunas situaciones dinámicas donde los mecanismos justos necesitan también un método para evitar que los *bidders* más ricos obtengan los recursos a precios demasiado baratos. Hemos llamado a este mecanismo control de los recursos justos. La combinación de estos tres componentes: prioridades, precios de reserva y control de los recursos justos llevan a dos de los mecanismos propuestos a obtener el mejor rendimiento bajo todas las circunstancias simuladas.

Finalmente, las posibles manipulaciones que pueden llevar a cabo los *bidders* y el equilibrio alcanzado por los mecanismso justos ha sido estudiado concluyendo que los mecanismos justos funcionan bien en dominios donde los *bidders* son honestos. De otro modo los

bidders pueden manipular las prioridades y los precios de reserva obteniendo equilibrios no deseables para el subastador.

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Chapter 1 Introduction

This chapter introduces an overview about this dissertation and presents the main hypothesis addressed in this thesis and the methodology used in order to achieve the objectives. Finally an outline of the contents of each chapter is described.

1.1 Overview

Auctions have been widely used in electronic markets because they are a mechanism that buyers and sellers find easy to understand, and also because it eliminates the necessity to set an exact price for products [49]. This is the case of service-oriented marketplaces [41] where the seller offers electronic services or resources over the Internet. In an auction, the resource supply and the existing demand determine the prices of products at every moment and, therefore, auctions seem appropriate for these markets. Examples of e-services are the Grid Computing Services (GCS). In last years the interest in GCS has been growing. The GCS buyers demand computing services and the GCS provider, that is the owner of the resources, temporarily allocates the necessary computer hardware and software resources to the buyer's application to produce the desired Quality Of Service (QoS) [78]. The main reason to use an auction-based mechanism in this domain is that the GCS provider needs a tool for expressing its pricing policies and needs to maximize the resource utilization [42].

Our work concerns the use of auctions in domains such as service oriented marketplaces. These markets are recurrent in nature since the same goods are periodically sold. In this scenario, the owner of the resources sells units of resources that agents need. In each run, the owner of resources assigns the units of resources to the agents by means of an auction. The latter send bids to buy an electronic service that needs different units of resources and the auctioneer clears the auction by determining the best assignment according to his objectives. Agents compete for limited resources and it is assumed that the agents may have different wealth. Another feature of these domains is that resources are perishable, that is, if they are not allocated they can not be stored for future sales; they lose their value.

The target of study in this dissertation are Recurrent Multi-Unit Auctions (RMUA) and Recurrent Multi-Unit Combinatorial Auctions (RMUCA). This latter case has special importance. A variety of industries have employed combinatorial auctions. For example, they have been used for truckload transportation [20, 50, 8], bus routes [48], railway [5] and industrial procurement [74], and have been proposed for airport arrival and departures slots [47, 46, 68, 58], as well as for allocating radio spectrum for wireless communication services [37, 69]. The advantage of combinatorial auctions is that the bidder can better express his preferences. This is particularly important when items are complements, that is, when a set of items has greater utility than the sum of utilities for the individual items (for example, a pair of shoes is worth more than the value of a left shoe alone plus the value of a right shoe alone). Allowing bidders to better express preferences often leads to improved economic efficiency (allocating the item to those who value them most) and greater auction revenues.

In these kinds of auctions where the allocation of resources is repeated with the same or similar participants and bidder agents have different wealth, the mid-term tendency is for the richer agents to win the resources. Thus, the traditional auctions could produce the inevitable starvation of certain buyers [40], that may choose to leave the auction process. This problem is known as the bidder drop problem [41] and the consequence could be the collapse of the auction in the mid term since when poor agents leave the auction process, the richer bidders have the power to set the prices of resources, provoking a fall in prices.

Another problem is the asymmetric balance of negotiation power that happens when the bid prices are dependent only on the agent's willingness to pay for the resources. In the long run, the effect of this problem could also cause the collapse of the auction process. This problem could be a consequence of the bidder drop problem but could also appear in other situations.

Finally, if the auctioneer can keep some of the units being auctioned (if doing so his revenue is higher), then the resource waste problem can appear since the resources we deal with in this work are perishable. This means that all unsold resources in an auction are lost.

The consequences of the three problems are the same: less revenue for the auctioneer and the collapse of the auction in the worst case.

1.2 Problem statement and hypothesis

Recurrent auctions with perishable resources pose several problems to the auctioneer: the bidder drop problem, the asymmetric balance of negotiation power and the resource waste problem.

The hypothesis of this thesis is that fairness can minimize the effects of these problems, increasing the revenue for the auctioneer in the mid-long term. Agents behave selfishly and try to maximize their own profit and the auctioneer, being selfish too, uses fairness with the aim of increasing its revenue.

1.3 Goals and methodology

The main goal of this thesis is to prove that the fair allocation of resources increases the auctioneers' benefits in the long term in repeated auction processes. The fair allocation will maintain the interest of bidders in staying in the auction, minimizing the bidder drop problem. Fairness also helps the auction mechanisms based on reservation prices to do a better use of resources since a part of them is fairly shared, reducing the resource waste. The aim is to prove these hypotheses in scenarios where agents' wealth is heterogeneous and the resources allocated are perishable.

The goal is also to study the fair mechanisms in static scenarios where the auctioneer in each auction sells the same quantity of resources, and dynamic ones where the supply of resources can be different in each auction.

Finally the last goal is to study the fair auction mechanism in closed markets where bidder agents cannot enter in the repeated auction process when the process is started, and in open markets where different auctioneers are competing and bidders could decide to drop from a recurrent auction and enter another one with another auctioneer at any time.

The methodology used to develop this work has been the following:

1. Analyse the problems that appear in repeated auction processes when we are dealing with perishable resources and state the necessity of fair allocations in repeated auction processes to avoid these problems.
2. Study the existent methods for fair allocation in the literature in auction processes and in more general allocation problems.
3. Design fair auction mechanisms for repeated multi unit auctions.
4. Design a generic simulator for repeated auction processes to perform simulations.
5. Test the designed methods and compare with the other existent in the literature in a previously tested scenario.
6. Extend the designed fair auction mechanism to combinatorial auctions.
7. Test the designed methods and compare with the other existent in the literature in a previously tested scenario.
8. Adapt the fair methods to a practical application.
9. Analysis of the results obtained in all experimentations.
10. Study the possible manipulation of the mechanisms by the bidders.

1.4 Thesis outline

This PhD thesis report is organized as follows:

- **Chapter 1: Introduction.** This chapter gives an overview of this PhD thesis, its motivations, objectives, the methodology used in order to achieve the goals and finally presents the outline of the different chapters.
- **Chapter 2: Background and related work.** This chapter presents some necessary background. The type of auctions treated in this thesis are introduced. The problems that appear in this kind of auctions are also presented. Also previous related work about fairness in resource allocation is described.
- **Chapter 3: Mechanisms for RMUA.** In this chapter new fair mechanisms for recurrent multi-unit auctions (MUCA) are presented.
- **Chapter 4: Mechanisms for RMUCA.** In this chapter new fair mechanisms are presented for recurrent multi-unit combinatorial auctions (RMUCA). These mechanisms are an extension of the mechanisms presented in Chapter 3, adding the capability of dealing with combinatorial environments and trying to avoid some kinds of cheating behaviour by the bidder agents.
- **Chapter 5: Experimentation in a bandwidth allocation domain.** In this chapter the results of the simulated experiments in an allocation bandwidth domain are presented. The selected domain provided by [42] is extended in order to deal with dynamic environments allowing the auctioneer to vary the supply of resources in each moment and allowing bidders to change of recurrent auction during the simulations. Also the domain has been extended in order to deal with combinatorial auctions.

- **Chapter 6: Experimentation in the Waste Water Treatment Plant domain.** In this chapter a practical application of a fair mechanism in a Waste Water Treatment Plant domain is presented.
- **Chapter 7: Manipulations and equilibrium.** In previous chapters the behaviour of bidder agents is assumed to be honest. In this chapter we discuss about the problems produced when the bidder agents cheat to the auctioneer in order to manipulate the mechanism.
- **Chapter 8. Conclusions.** In this chapter, we summarize the main contributions of the thesis, and point out some open problems and research perspectives that we plan to tackle in the near future.

CHAPTER 2
Background and related work

In this chapter we review some background necessary to understand the aim of this thesis, such as the kind of auctions treated in this work and the problems that appear in some situations. Also previous related work on fairness in auctions and in resource allocation is presented.

2.1 AUCTIONS

Auctions have been widely used from ancient times as one of the most popular market mechanism used to match supply with demand. They achieve this goal by allowing buyers and sellers to agree on a price of a resource following a set of rules and procedures well defined [16]. Figure 2.1 shows the steps of a simple auction mechanism. Firstly, the auctioneer starts the auction and offers to bidders the resources that will be auctioned (call for bids). Secondly the bidders send back to the auctioneer their bids if they are interested in buying the resources (bidding phase). A bid is usually composed by the resources desired by the bidder agent and the bid amount that is the maximum price that the bidder is willing to pay for the required resources. The auctioneer collects the bids and then, closes the auction. This means that the auctioneer stops receiving bids. The next step for the auctioneer is to select the winners (auction clearing). Finally the auctioneer distributes the resources to the winners and collects the payments [40].

In an auction process we can distinguish three main components. The two first components are decisions that the auctioneer agent has to take while the third one is a component of the bidder agent.

- The first one is the *winner determination* algorithm or market clearing that decides how the auctioneer selects the winning bids (i.e. how the resources are allocated to the agents).
- The second one is the *pricing mechanism* that determines how the auctioneer decides the price to be paid by the winners. Typically there are two principal families of payment schemes. The first one is the first price auctions where the bidder agents have to pay the bid amount sent in the bid if the bid results as winner. Conversely in the second-price auctions, also known as Vickrey auctions [11, 28], the price paid for the winners bidder agents is the highest bid amount of the loser agents. The Vickrey auctions are very important since they gives bidders an incentive to bid their true value. Also some authors classify the pricing mechanisms into discriminatory and non-discriminatory. When prices are discriminatory it means that each agent could pay a different price, while in non-discriminatory mechanisms all agents pay the same amount of money for the resources. Note that in a first price payment scheme

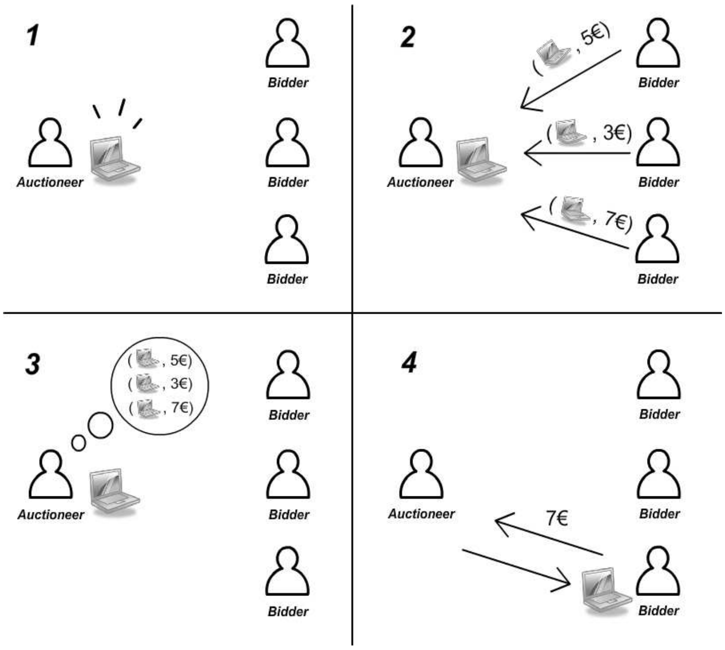

Figure 2.1: Auction example

Auction steps: (1) Call for bids, (2) Bidding phase, (3) Auction clearing, and (4) Payment and allocation.

the prices are discriminatory, while with a second price auction the prices could be discriminatory or not.

- The third component is the *bidding policy* that is the method used by bidder agents to decide which resources to bid for and the price they are willing to pay for them. Note that each bidder could have its own way of taking decisions. Thus, the bidding policy is not necessary one for all the bidder agents.

2.1.1 TYPE OF AUCTIONS

Figure 2.2 shows a general classification of auctions based on five different criteria. The aim of this classification is doing a first introduction to the kind of auction treated in this work. The criterions fulfilled by those auctions are highlighted in bold and the names of auctions are shown inside a box. The kinds of auctions not treated in this thesis are not subdivided in order to make the classification more understandable but they also could be subdivided following the same criteria.

The first criterion is the *role of the participants* in the auction. Auctions can be classified in *reverse* and *forward* auctions. One the one hand in a forward auction, the buyers are the bidders and they compete to obtain the resources and the auctioneer is the seller of the resources. On the other hand a reverse auction is a type of auction in which the roles of buyers and sellers are reversed. In a reverse auction, the buyer is the auctioneer and the bidders are the sellers which compete to obtain business. For example in [25] the problem of supply chain formation is solved via reverse combinatorial auctions.

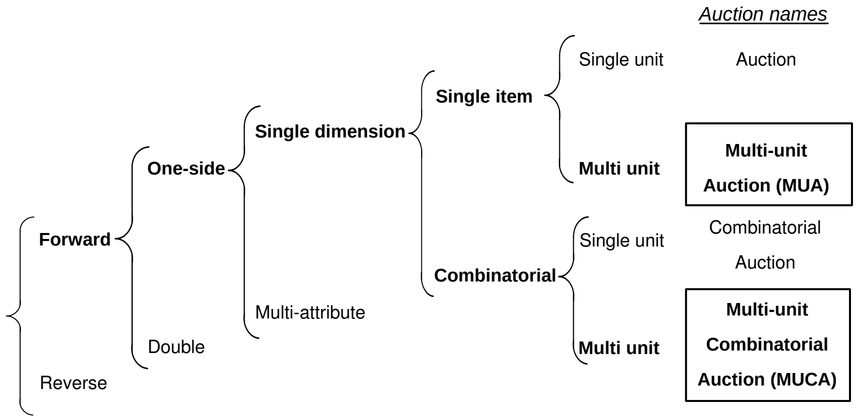

Figure 2.2: Classification of auctions

The second criterion is the *number of bidding sides*. An auction is a one-side auction (or single auction) when participants can take part only in one side of an auction [40]. A participant can be auctioneer or bidder but not both. Conversely in a double auction, participants can take part in both sides of the auction. A participant can be auctioneer or bidder in the same auction. An example of an auction where an agent could be auctioneer and bidder at the same time is for example an auction where an agent buys the components to produce a product and then the agent sells the final product to other agents. The purchase of components ant the contract to sell the final product can be decided in the same auction. There exist two main kinds of double auctions: the continuous double auctions and the call auctions [35]. In continuous double auction the market is cleared continuously, that is each time that a new bid is sent. In contrast, in the call auction the market is cleared periodically.

The third criterion is the *bid composition*. In a single dimension auction the bid is composed by the bid amount and the resources that the bidder agent wants. In contrast in a multi-attribute auction, also called multidimensional auction, the bidders can bid on various attributes beyond the price [42]. For example a bid could be composed by the bid amount, the resources and also the quality or other attributes.

The fourth criterion is based on the *number of different resources* that the agent can bid for. If the bidder can only bid for a single item in each bid the auction is called single-item auction (or just auction) while if bidders can bid for more than one resource the auction is called combinatorial auction. In this latter case, the combination of items are also called packages [16]. Note that the packages are indivisible. The winner determination problem in those kind of auctions is $\mathcal{NP}$-complete [36].

The fifth criterion is based on the *number of available units* of each item. If the auctioneer sells only one unit of each item the auction is called single-unit auction. Otherwise if there are more than one available identical unit of items it is called multi-unit auction.

Figure 2.2 shows in bold the kind of auctions treated in this work. All the auctions treated in this work are forward, one-side and single dimension. Then, on the one hand we work with multi-unit auctions where the auctioneer sells several units of a unique resource (MUA). On the other hand, we work with multi-unit combinatorial auctions where the auctioneer sells several resources and several units of each resource (MUCA). Note that we assume that when the auctioneer sells only one resource, the bidders can only bid for one unit of the resource, if each bidder can bid for different quantities of units of the resource then, the auction is combinatorial too.

These five criterions classify the auctions but there are other important features that have to be discussed. Auctions can be *one-shot* or *recurrent*. We will use the term one-shot in this thesis to differentiate the auction that takes place and ends from the process that involves sequences of auctions with relationships between the results of different auctions. When we refer to an auction we will refer to a one-shot auction, while when we refer to an auction composed by several auction, we will refer as recurrent auction. Finally another feature of auctions is if they are *sealed-bid* or *open-cry*. In open-cry auctions every bidder knows the bid amount offered by other bidders while in the sealed-bid auctions this information is private, only the auctioneer knows all bids sent by bidders. In this work we deal with sealed-bid auctions.

2.2 Winner Determination Problem in MUCA

The winner determination problem (WDP) in combinatorial auctions can be defined as follows: Given a set of bids, find an allocation of items to bidders, including the possibility that the auctioneer retains some items (free disposal condition), that maximizes the auctioneer's revenue. This problem is $\mathcal{NP}$-complete, meaning that a polynomial-time deterministic algorithm that is guaranteed to compute the optimal allocation is unlikely to exist [16].

Furthermore in MUCA the auctioneer has to allocate the units of each item. In an auction a_j the auctioneer auctions a set $R_j = \{\langle r_0, q_0\rangle, ..., \langle r_{|R_j|-1}, q_{|R_j|-1}\rangle\}$ where $\{r_0, r_1, ..., r_{|R_j|-1}\}$ is the set of resources auctioned and $\{q_0, q_1, ..., q_{|R_j|-1}\}$ is the set of available units of each resource. A bidder agent g_i sends to the auctioneer in the auction a_j a set $V_{i,j}$ of bids. Each bid is composed by a package and the price or bid amount. A package is formed by a set of tuples indicating the resources required by the bidder agent and the number of units of each item. The combinatorial auction winner determination problem is to label the bids as winning or losing so as to maximize the auctioneer's revenue under the constraint that the quantity allocated of each item cannot surpass the available quantity, as follows:

$$
\begin{aligned}
max \sum_{\forall i \in G} \sum_{\forall b \in V_{i,j}} \mathcal{C}(b) \cdot win(b) \\
s.t. \sum_{\forall i \in G} \sum_{\forall b \in V_{i,j}} win(b) \cdot r_x(b) \leq q_x, \quad \forall x \in \{0..|R_j|-1\}
\end{aligned}
\tag{2.1}
$$

where $win(b)$ indicates whether bid b is winner ($win(b) = 1$) or loser ($win(b) = 0$), G is the set of all bidder agents, $\mathcal{C}(b)$ is a function that returns the bid amount of bid b and $r_x(b)$ is a function that returns the number of units of resource r_x required by bid b. The WDP for MUCA is also $\mathcal{NP}$-complete.

We are assuming the *free disposal condition*, that is, the auctioneer can keep some of the units being auctioned if doing so his revenue is higher. Otherwise when there is not the free disposal condition, the auctioneer must sell all the units auctioned. In this latter case another constraint should be added to Equation 2.1 to assure that all units are sold. Suppose an example with an auction with two bidders, B1 and B2 and two resources auctioned r_0 and r_1. B1 sends a bid for the item r_0 with a bid amount of 10. B2 sends a bid for both items r_0 and r_1 with a bid amount of 7. With the free disposal condition the solution with higher revenue is to give item r_0 to B1 obtaining a revenue of 10. Otherwise without the free disposal condition the winner must be B2 obtaining a revenue of 7, because if B1 is the winner, the item r_1 is not sold.

With the free disposal condition, the auctioneer can fix reservation prices. A *reservation price* fixes the minimum requirements of the auctioneer. The reservation prices can be fixed for units of resources, for packages of resources or for all the resources auctioned. This value is known only by the auctioneer and is used to decide the winners. For example an auctioneer can fix a reservation price for a resource r_0. This means that the resource r_0 will not be sold with a price lower than the reservation price. Then, all the bids that request the resource with a bid amount lower than the reservation price will not be considered in Equation 2.1. The auctioneer can also set a global reservation price for all the units auctioned and he could cancel the entire auction if the total revenue is lower than the global reservation price. In this latter case, the auctioneer first solves the auction and when he knows the optimal revenue and if it is lower than the global reservation price he could decide to cancel the auction labelling all bids as losers and not selling any resource.

The WDP for combinatorial auctions and for MUCA have received a considerable attention. Authors deal with these problems with four different approaches, which we briefly describe next.

2.2.1 Constraining the problem

Some authors have constrained the set of possible packages that the agents can send in order to ensure a polynomial-time solution does exist [65]. For instance if the bids have at most 2 items each, the winners can be optimally determined in $O(m^3)$ time using an algorithm for maximum-weight matching [61]. A more constrained easy example is the constraint used in Chapter 3. In this case there is an auction with only one resource but many units of the resource, constraining the bids of bidders to an unique item, the problem can be solved in a polynomial time sorting the bids by price and selecting the q_0 bids with highest bid amount where q_0 is the number of items auctioned. As a drawback in all the constrained mechanisms the bidders cannot fully express their preferences.

2.2.2 Heuristic approaches

Other authors have proposed algorithms to search the optimal solution that can deal with large problems but without any guarantees about the running time.

Combinatorial Auction Structured Search (CASS) [21], is a branch and bound search algorithm. CASS structures the search space in order to allow more pruning during the search and that avoids the consideration of most infeasible allocations. Whenever a bid is encountered that does not conflict with the current partial allocation then the search tree branches, where one branch adds the bid to the partial allocation and the other does not. CASS performs a depth-first search, meaning that one branch of the tree is fully explored before the other is considered. When a full allocation $Alloc$ is reached CASS records this allocation as the best $Alloc_{best}$ if $revenue(Alloc) \geq revenue(Alloc_{best})$, and then backtracks, where $revenue(Alloc)$ is the revenue of the allocation $Alloc$.

CABOB (Combinatorial Auction Branch On Bids) [66] is a depth-first branch-and-bound tree search that branches on bids. CABOB calculates an upper bound on the revenue that the unallocated items can contribute by solving the Liner Programming problem (with continuous variables is a relaxed version of the problem) using the LP module of CPLEX. This algorithm uses decomposition techniques and ordering heuristics too.

In [53] the authors propose a set of reduction techniques to transform the problem to another one easier to solve. Some of these techniques allow the elimination of bids, elimination of items and changes in the prices of bids obtaining in many cases equivalent problems with fewer variables. At the end the algorithm has to perform some changes in the solution to obtain the solution of the initial problem.

Finally CAMUS (Combinatorial Auction Multi-Unit Search) [45] is a generalization and extension of the CASS algorithm for the multi-unit combinatorial auctions. Like CABOB and CASS this algorithm performs a depth-first search too.

2.2.3 Integer programming

Although, as we have just described, specific algorithms for the winner determination exist, the Integer Programming tools have demonstrated that they are a powerful way to solve the problems. Also the WDP can be easily modelled as an integer programming problem. For this reasons a lot of researchers have used the Integer Linear programming tools to solve the WDP in their works [73, 67, 24]. There are several integer programming solvers, amongst all we can highlight two of them. On the one hand IBM ILOG CPLEX [15] is the most used by the research community and it is considered as one of the fastest solvers. On the other hand GNU Linear Programming Kit (GLPK) is a free code solver [26] but with a lower performance.

2.2.4 Sub-optimal methods

Other authors have proposed sub-optimal solutions. In [31] Hoos and Boutilier propose an algorithm based on Stochastic Local Search for combinatorial auctions called Casanova and claim that it finds high quality (even optimal) solutions much faster than other methods. The algorithm scores each state of the search and each bid also has a score that represents the increase of the revenue that the bid adds to the current state. The bids are ranked taking into account the score and those with highest score and age (the number of steps since that bid was last used) are selected. The search proceeds for $maxSteps$ steps and is restarted with the empty allocation for a total of $maxTries$ independent searches, with the best allocation found at any step of any search reported as the solution. In [30] the authors examine the performance of hill climbing algorithms for combinatorial auctions and conclude that for some instances deterministic hill climbers perform well but for some other types of problems their performance, although good, is not better than chance.

In this work we do not focus on the way to solve the WDP in a polynomial time. The problem is modelled as a mixed integer linear programming problem (MIP) and solved with linear programming tools. This is sufficient for the size of the problems simulated in this work but when the problem is bigger the exponential grow of the complexity makes unfeasible to solve it with linear programming tools. It is an important issue to take into account when resources are perishable since the auction has to be cleared before the perish of resources.

2.3 Type of resources

The resources auctioned in one auction can have different features. These features can have different consequences in the winner determination strategy. Here we show three different features of resources.

- *Durable or static* vs *time-sensitive*: Static or durable resources do not change their properties during a negotiation process [9]. In an auction process if the resource is not sold, the auctioneer can sell it in the future because its value is maintained. For example an auctioneer offering a bike could decide not to sell the bike if the bid amount received does not achieve the auctioneer's desires. Then the auctioneer can auction again the bike in a future auction. On the other hand time-sensitive resources are *consumable* or *perishable* [42]:
  - A resource is *consumable* if it is depleted by constant use (i.e., fuel is a consumable resource).
  - A resource is *perishable* if it vanishes or loses its value when held over an extended period of time. For example, network bandwidth is a perishable resource, since it only has value if it is used, and it cannot be stored to later increase the bandwidth of a network connection. For example if an agent has a unit of bandwidth in each timestep, if in a timestep x don't use the bandwidth unit, in the timestep x+1 the agent have not 2 units of bandwidth.
- *Divisible* vs *indivisible*: This defines whether the resource can be indefinitely divided into as many units as desired (divisible resource) or it cannot be divided (indivisible resource). In this latter case, however, there may be multiple units of the resource (each of them being indivisible).
- *Controlled* vs *non-controlled*: Although usually the resources belong to an owner that can control the access to them (controlled), in some domains the resources are somehow "public", meaning that anyone can use them, even without having been authorized to do so. Examples of non-controlled resources can be found in natural resources, which are usually accessible to anyone, and for which there are no physical means of controlling this access.

In this work we deal with two different kind of resources, the first one are electronic resources as network bandwidth. The second one is the capacity of a Waste Water Treatment Plant (WWTP). In both cases the resources are perishable: if they are not auctioned they are lost, and they are indivisible. The difference is that the network bandwidth is controlled; the auctioneer can give or not the resources, while the capacity of the WWTP is an uncontrolled resource, the industries could discharge pollutants to the river without the permission of the WWTP.

2.4 Recurrent Auctions (RA)

When perishable resources are auctioned, the auctions could be repeated along time and bidders are continuously competing for the resources. Although a bidder agent won the resources, as they perish, he needs to win the resources again from time to time. In these situations we can use the recurrent auctions. A recurrent auction (RA) is a sequence of one-shot auctions of any kind where the result of one auction may influence the following one. For example an auction takes places and ends, and then when the resources have perished a new auction starts.

2.4.1 Problems in RA with perishable resources

In a RA if bidders have an uneven distribution of wealth and resources are perishable some problems appear. For an uneven distribution of wealth we understand that there are bidder agents with higher true value than other for the same resources. The true value for a resource is a private value of each agent and is the maximum price that is willing to pay for it. In other words the true value is the valuation that the agent has about the resource. Then, the problems caused by this uneven distribution are: resource waste, the asymmetric balance of negotiation power and the bidder drop problem. Next we describe these problems in detail.

Resource waste. If the auctioneer can keep some of the units being auctioned (by doing so his revenue may be higher), the auction is said to have the free disposal condition. However, this free disposal condition has to be minimized when dealing with perishable resources, as it can produce what is known as the resource waste problem. Perishable resources present in many real-world scenarios, cannot be stored in warehouses for future sales; if the resources are not allocated, they lose their value or vanish completely. On the other hand, the auctioneer cannot give the resource for free. So a trade-off between the resource usage and the benefit of the auctioneer should be appropriately handled.

Asymmetric balance of negotiation power. In most traditional auction mechanisms, the bid prices depend only on the bidder's willingness to pay for the resources. This means that only the intentions of bidders, not those of the auctioneers, are reflected in the auction winning prices [42]. In the long run, the effect of this problem may cause the auction to collapse. For example, let us suppose that initially there are N bidders in a recurrent auction. A third of them are poor and bid 1€, while the other two thirds are richer and bid an amount over 5€. After several auctions, the richer agents start lowering their bids down to 3€, while the poor agents raise their bids to 2€. In the end, the richer agents win with a bid close to that of the poor agents. In this case, the richer bidders have the power to set the price, not the auctioneer. In a recurrent auction, these bids can even go under the lower bids, if the poor agents have dropped out of the market. Note that this problem is different from bidder collusion [64], although the effects are the same. In bidder collusion, the bidders form coalitions to force this situation, while the asymmetric problem is caused by the uneven wealth distribution of the agents.

Bidder drop problem. This problem occurs when bidder agents participating in many auctions always lose. These bidders could decide to leave the market because they are not making any profit. This has bad consequences for the auctioneer: the reduction in the number of bidders gradually decreases the price competition because the probability of winning increases for the remaining bidders. Bidders can decrease their bids without losing the chance to win, provoking the asymmetric balance of negotiation power and the consequent overall drop in bid price. In order to avoid collapse, some authors [59] have introduced a reservation price in the auction. In this case the reservation price maintains the balance of the negotiation but produces resource waste. Note that the bidder drop problem could provoke the asymmetric balance of negotiation power but the asymmetrical balance can also appear in other circumstances without the bidder drop problem.

2.5 Fairness in resource allocation

In the recurrent auction mechanism a fair solution means that at long term, all of the participants accomplish their goals in the same degree or in the most equal possible degree, independently of their wealth. The inclusion of this fairness can be somewhat acting against short-term optimality, since the result of an auction may differ from the optimal solution if a suboptimal solution is fairer. However, its mid or long-term effect produces an increase of auctioneer benefits, since it maintains the interest of bidders in continuing in the auction process, so dealing with some of the problems explained in the previous section. This is the approach we have followed in this thesis.

The application of fairness in recurrent allocations can be considered from either a local or a global point of view. A local point of view means treating each allocation problem separately and trying to find a fair solution to each one. With a global point of view we can find that, overall, the set of solutions is fair. The fair auction mechanisms we will present in this thesis are designed to be fair for a complete sequence of auctions, that is, the global view.

Moreover, fairness can be analyzed in light of the agent who is fair. From the point of view of the bidder agent, fairness means that the objective of the agent is not only to maximize benefits in the short term but also to consider fairness at the time of making decisions. Fairness can benefit the whole society and consequently obtain greater individual benefits. In this case the solution to the allocation of resources is given by the interaction, negotiation and coalition between agents, etc. [17]. It is also possible to consider fairness from the point of view of the seller agent. In this case the behavior of bidders could be totally utilitarian and the seller agent imposes fairness to distribute the resources [44, 54]. In this thesis we focus on this second case where bidder agents behave selfishly and try to maximize their own profits.

This is also the case of DP-ORA [42] (studied in depth later on), and the work of Lemaître et al. [44]. The latter proposes to a set of agents a fair division proportional to their investment in an earth observation satellite. In the work of Lemaître et al. each bidder agent has a resource quota assigned taking into account the financial contribution and a fair solution is the one that fulfils the quota in a higher degree. This concept is different from our definition of fairness defined at the beginning of this Section but our definition is more complete since the objectives of heterogeneous agents could be different and they could be satisfied with different resources. Also if we define that an agent is satisfied if his quota is fulfilled, then our definition includes this definition. Also, another difference is that in this case, each one shot auction is fair, that is the local point of view. In the work of Lemaître et al. [44] the aim of having a fair solution is imposed by the domain. This study includes a comparison between fairness constraints and efficiency constraints in the use of the satellite with three different models. The authors conclude that there is no best method. In this sense they are demonstrating the compromise between optimality and fairness. From our experiments, we can see that these results can be true in the short term, but in the long run, fair methods also become efficient (they obtain as many benefits as unfair methods). These results lead us to say that being fair does not mean being “quasi” rational, but rational in the long term (that is, individually, the agents improve their benefits).

Other fairness studies take the bidder point of view, not the auctioneer point of view. That is, the bidders are aware of the process being fair. One of those processes is the envy-free approach. In an envy-free allocation none of the agents would prefer to exchange allocated goods with those allocated to another agent [6]. However, this criteria alone is not sufficient (i.e., allocating no resources to any agent would be an envy-free allocation), since the efficiency (in the sense of utilitarian social welfare) is also important. Other studies [10] have shown how such efficient envy-free allocations can be attained through distributed negotiation among the agents. In such a setting, there is no central agent or authority (i.e., the auctioneer) to decide what the optimal allocation is, but the agents themselves perform a sequence of deals (exchanges of resources and payments) to find an efficient and envy-free allocation. The work presented by [6] and [10], however, deals with an isolated allocation problem, and does not mention how distributed negotiation could be applied when the agents are faced with a sequence of allocation problems. In another study [19] the concept of egalitarian social welfare is defined to measure the degree of fairness in this envy-free scenario, as well as for a general purpose. The concept is based on the welfare measure of the agent that is the worst off. This measure is interesting from the perspective of a single-shot auction, but when dealing with a sequence of auctions, other measures that take into account the degree of satisfaction of agents in the long run should be considered.

Another interesting and related study is based on fairness and human behavior [17]. It presents three models for adding fairness to multiagent systems, in which the inequity aversion shown by humans is modeled (i.e., we tend to avoid situations where there are high inequalities among the members of society). Their work can be situated in the group of studies in which fairness is exhibited by the bidders (distributed settings) because there is no central agent coordinating the whole process. Specifically the authors present a model in which each agent is assigned a priority (for instance, according to his wealth), and the agents behave differently depending on the priorities of the other agents (i.e., a rich agent would be willing to give away more money to a poorer agent). These priorities are assigned a priori, and they do not change over time. The authors also address the repetitive aspect in their model. It is mainly focused on adding punishment mechanisms (agents that do not behave fairly can be punished by the others) and on enabling the use of trust mechanisms to learn who to interact with. They mention that priority updates could be done, but they do not point out how this could actually be performed. In our work priorities are dynamic, and they vary according to what has happened in the auction history.

Some studies aligned with these human studies are [56, 57]. The first [56] analyzes the effect of risk attitudes in agents and fairness. The authors distinguish three kinds of agents: risk-averse, risk-neutral, and risk-loving. All of the agents are trying to maximize their payoffs by using a Q-learning algorithm in a bargaining scenario. The most successful agents, that is, the ones that reach an agreement, are risk-averse agents that propose fair contracts. This confirms that fair behavior is beneficial in the long term. On the other hand, [57] studies the effects of fairness and randomness in a repeated game. The authors distinguish two flavors of fairness: apparent and evident. The former is related to opportunities that are regarded as equal for all participants (like tossing dice), while the latter happens when one player takes the control of the game. The mechanisms proposed in this thesis could be seen as a combination of these two types of fairness. The use of priorities and reservation prices makes the competition fair to all agents, no matter their wealth (apparent fairness). On the other hand, the auctioneer is the sole agent in charge of applying the fair mechanisms (evident fairness).

Table 2.1: Classification of existing literature on fairness in resource allocation

		Local view (single shot)	Global view (repeated game)
Static	Bidder (distributed)	[19] [10]	[17] [56]
	Seller (centralized)	[44]	[40] **This thesis**
Dynamic	Bidder	-	[17]
	Seller	-	**This thesis**

Table 2.1 shows the classification of the previous studies in relation to the local/global point of view and whether fairness is exhibited by the bidder or the seller. This table also classifies the works in static scenarios and dynamic scenarios. By static scenarios we understand scenarios where there are no changes when a simulation has started. Otherwise in a dynamic scenario it is possible to have changes, such as the entry of new bidder agents in a started recurrent auction or the variation of the resources offered by the auctioneer in each auction.

2.5.1 DP-ORA and PI-ORA

Although fairness has been studied for a long time in microeconomics, to our knowledge, there are very few previous studies that take into account fairness in a repeated auction process. The Discriminatory Price Optimal Recurring Auction (DP-ORA) mechanism [40, 41] is an exception. It is based on the supply and demand principle of microeconomics. The mechanism sets a reservation price rp_{ORA} in each auction. This value is the maximum between the $(2 \cdot q_0/3)th$ highest bid value in the current auction and the auctioneer's minimum desired benefit from the sale of a unit of the resource where q_0 is the number of auctioned resources. Then, all bidders with a bid higher than rp_{ORA} become winners. The remaining resources are shared between the loser agents following the VLLF-BDC (Valuable Last Loser First Bidder Drop Control) algorithm. This algorithm divides the surplus resources in two phases. In the first phase the algorithm marks the bidders who lost in the last auction and increased their bid in the current one. Next, the algorithm allocates resources among the highest marked bids. If there are still resources to be allocated, then in the second phase the resources are allocated to the highest non-marked bids. So in some sense, the history analyzed by DP-ORA is as if we were considering a time window of length two (current and previous auction). In this procedure, then the authors analyze the history of current and previous auctions in order to decide upon the current fair distribution, and this fair distribution is performed independently of the wealth of the agents. Regarding the pricing, this mechanism is first-price.

The same authors also proposed Participation Incentive Optimal Recurring Auction (PI-ORA) [39], based on similar principles than DP-ORA but with a second price pricing mechanism. The authors claim that this mechanism is Incentive Compatible and rewards the participation of bidders in the auction by giving them more frequency of winning for each participation.

DP-ORA and PI-ORA are mechanisms for RMUA auctions since only one resource is auctioned and bidder agents can only bid for one unit of the resource. Regarding combinatorial auctions, the same authors propose Participation Incentive Generalized Vickrey Auction (PI-GVA) [43] extending the mechanism PI-ORA and adding a pricing policy based on the mechanism of the Generalized Vickrey Auction (GVA). Although this mechanism is for combinatorial auctions it is designed to deal only with a unique resources. It is combinatorial since the bidder agents can bid for different amount of units of the resource. As PI-ORA, this mechanism gives more frequency of winning to bidders for each participation. This fact is not good when dealing with dynamic markets where the bidder agents can enter or drop from the market. With this mechanism it is very hard for a new bidder to win if there are other bidders that remain in the recurrent auction for a long time.

2.6 Summary

This chapter has reviewed some necessary background in order to understand the concepts of the following chapters and to know the motivation for use fairness in recurrent auctions.

First the kind of auctions with which we are dealing in this thesis have been introduced: recurrent multi-unit auctions and recurrent multi-unit combinatorial auctions. Recurrent auctions are sequences of auctions where the result of one auction may influence the following one. In multi-unit auctions the auctioneer sells several identical units of the resources auctioned and combinatorial auctions are those where the bidders can place bids for combinations of items called packages. In this kind of auctions if bidders have an uneven distribution of wealth and resources are perishable some problems appear. Perishable resources are those that cannot be stored if they are not sold, since they lose their value.

The first problem is the resource waste. Perishable resources present in many real-world scenarios, cannot be stored in warehouses for future sales; if the resources are not allocated, they lose their value or vanish completely. On the other hand, the auctioneer cannot give the resource for free. So a trade-off between the resource usage and the benefit of the auctioneer should be appropriately handled. The second problem is the bidder drop problem. This problem occurs when bidders participating in many auctions are always losing. They could decide to leave the market, since they are not getting any profit. This has bad consequences for the auctioneer: the reduction on the number of bidders gradually decreases the price competition causing the overall drop of prices. The third problem is the asymmetric balance of negotiation power. This problem occurs when the bidders have the power in the negotiation and they are capable of fixing the price of resources. Obviously, in such a situation, they will try to fix the price at the minimum possible value.

To deal with all these problems, we propose some mechanisms based on fairness and reservation prices. In the recurrent auction mechanism a fair solution means that at long term, all of the participants accomplish their goals in the same degree, independently of their wealth. The inclusion of this fairness can be somewhat acting against short-term optimality, since the result of an auction may differ from the optimal solution if a suboptimal solution is fairer. However, its mid or long-term effect produces an increase of auctioneer benefits, since it maintains the interest of bidders in continuing in the auction process.

The application of fairness in recurrent auctions can be considered from either a local or a global point of view. A local point of view means treating each auction separately and trying to find a fair solution to each one. With a global point of view we can find that, overall, the set of solutions is fair. Fairness can also be analyzed in light of the agent who is fair. From the point of view of the bidder agent, fairness means that the objective of the agent is not only to maximize benefits in the short term but also to consider fairness at the time of making decisions. Fairness can benefit the whole society and consequently it allows obtaining greater individual benefits. In this case the solution to the allocation of resources is given by the interaction, negotiation and coalition between agents. It is also possible to consider fairness from the point of view of the seller agent. In this case the behavior of bidders could be totally utilitarian and the seller agent imposes fairness to distribute the resources. This thesis is focused on the global and auctioneers point of view.

Chapter 3
Fair Mechanisms for Recurrent Multi-Unit Auctions

In this chapter we introduce some basic fair mechanisms for recurrent auctions. The mechanisms introduced in this chapter are designed for an environment where the bids are constrained. Only one resource is auctioned but several identical units of the resource are available. Bidders can sent only one bid in each one-shot auction to obtain one unit of the resource. This constraint makes the winner determination problem a polynomial problem. In the next chapter we show mechanisms for combinatorial environments where bidders can send any combination of resources and any amount of units. All the mechanisms of this chapter are first price and we assume that bidders will have an honest behaviour, that is, they try to maximize his utility but they do not try to manipulate the mechanisms. In chapter 7 the problem of agents and manipulations is discussed. We start with some notation about the recurrent auctions, then we explain some previous mechanisms and then we introduce the fair mechanisms presented in this thesis for Recurrent Multi-Unit Auctions (RMUA).

3.1 Definition of RMUA

A Recurrent Multi-Unit Auction (RMUA) is a recurrent auction composed by a sequence of one-shot auctions where only one resource is auctioned but more than one identical units of the resource are offered in each auction. We assume that this kind of auction is not combinatorial, that is the bidders can only bid for one unit of the resource in each one-shot auction. For the combinatorial version of RMUA see Chapter 4 were bidders can place bids for packages of resources and several units of each resource.

Formally, The recurrent auction A is formed by a succession of auctions $A = \{a_0, ..., a_{|A|-1}\}$. In each auction a_i, one resource or item is auctioned. R_i is a set composed in this case for one tuple that indicates the resource r_0 and the number of available units of the resource q_0 ($R_i = \{\langle r_0, q_0 \rangle\}$). A set R_i of an auction a_i can be different of the set R_j corresponding to auction a_j, $i \neq j$.

Auctions are ordered temporarily and we associate to each auction a_i a time step t_i where T is the set of time steps in which the auctions of A occur ($T = \{t_0, ..., t_{|A|-1}\}$ where $t_0 < t_1 < ... < t_{|A|-1}$). G is the set of all bidder agents, $G = \{g_0, ..., g_{|G|-1}\}$, that participate in the recurrent auction A.

A bidder agent g_i sends to the auctioneer agent a bid $b_{i,j}$ in auction a_j. Each bid is composed by one unit of the resource and the bid amount.

3.2 Previous mechanisms

We can find some mechanisms for the resource allocation in RMUA.

- *Traditional Auction* (TA). This is the simplest auction mechanism also called first price sealed bid auction. In the TA mechanism the winners are the bidders with the highest bids. In this auction mechanism if there are more bidders than units of the resource auctioned, all units are sold and consequently any resource waste is produced.
- *Cancellable Auction* (CA). In a CA, if the resulting revenue of an auction does not meet the minimum requirements of the auctioneer, the entire auction is canceled. Thus, the cancellation of an auction wastes the entire stock of resources. For instance, suppose an auction where the auctioneer sells three units of one resource and he has a global reservation price of 15€. There are three bidders: B1, B2 and B3 that send a bid to obtain 1 unit of the resource each. The bid amounts are 6€, 5€ and 3€ respectively. As 6+5+3=14, then the auctioneer does not obtain the desired revenue and the entire auction is cancelled and none of the units are sold.
- *Reservation Price Auction* (RPA). In a RPA the auctioneer defines a reservation price (the same for all bidders) that indicates the minimum price the bidders should pay for a unit of the resource. Only bids higher than the auctioneer's reservation price are accepted, and so, this restricts the number of winners and can waste part of the resources. For instance, suppose the same previous example defined for CA but in this case the auctioneer has a reservation price of 5. Then the bids of B1 and B2 are winners while B3 is loser since his bid amount is lower than the reservation price. In this example two units are sold and one unit is wasted.
- *Discriminatory Price Optimal Recurring Auction* (DP-ORA). Proposed by [40], it is a fair mechanism that sets a different reservation price for one unit of the resource in each auction. Then, all bidders with a bid higher than this reservation price become the winners. The remaining resources are shared between the loser agents according to the algorithm explained in Section 2.5.1.

3.3 Prioritized Auction (PA)

This is the simplest mechanisms presented. The motivation behind PA is to use priorities to prevent the starvation of poor bidders and their dropping out of the auction. The priority assigned to each bidder will increase the probability of poor bidders winning and decrease the probability of the richest winning. This mechanism takes into account the history of each agent in previous auctions. Each agent is assigned a priority value depending on the number of won and lost auctions. The more lost auctions, the higher the priority. The priority values are updated after each auction, and they are used to clear the next auction. The clearing algorithm could use priorities in very different ways: transforming them into new constraints to be satisfied by the solution, letting them directly designate the set of winning agents, among others. Because the history of the agents in a recurrent auction scenario is long, a time window could be used to calculate the priorities.

Formally, we define the priority of agent g_i following Equation 3.1.

$$p_i = \frac{\sum_{j=|A|-LT+1}^{|A|}(1 - x_{i,j})}{LT} \tag{3.1}$$

Table 3.1: Example of PA

auction	bidder	bid	p_i	score ($v_i^{'}$)	result	payment
a_0	B1	5	$\frac{1}{2}$	2.50	W	5
	B2	4	$\frac{1}{2}$	2.00	L	0
a_1	B1	5	$\frac{1}{3}$	1.66	L	0
	B2	4	$\frac{2}{3}$	2.66	W	4

where $x_{i,j}$ is the outcome of the j-th auction (a_j) for agent g_i (1 if the bid of the agent was a winner and 0 otherwise), $|A|$ is the total number of auctions, and LT is the length of the time window.

The use of priorities to modify the value of the bids and select as winners the highest modified bids is proposed. More precisely, given a bid value v_i of an agent with priority p_i, a new bid valuation is computed following Equation 3.2.

$$v_i^{'} = f(v_i, p_i) \tag{3.2}$$

The priority is handled by the auctioneer, and this new value $v_i^{'}$ or score is the one used by the clearing algorithm to find an optimal solution. Note, however, that the winning bidders pay the original v_i price since the mechanisms is first-price. The function f can be designed in many ways, and it allows the introduction of different fairness facets in the auction solution. Thus, the function should increase the chances of winning for a high priority agent, and decrease the chances of a low priority one. For example, the product function (Equation 3.3) is used in this work.

$$v_i^{'} = f(v_i, p_i) = v_i \cdot p_i \tag{3.3}$$

This priority-based mechanism is not strategy-proof. That is, if the bidders are aware of how the winner determination algorithm works, they can manipulate it. So we assume that bidders are honest in the sense that they change their bids only in response to the new prices, not to cheat and take advantage of the mechanism.

The PA mechanism does not produce any resource waste as it always sells all the available units (if there are more bidders requesting resources than resources available) and, what is more, it reduces the effect of the bidder drop problem thanks to the use of priorities.

3.3.1 Example of PA

Table 3.1 shows an example of PA where score is the value used by the auctioneer for clearing the auction, that is, the bid amount after being modified with the priority. In the column result a W denotes that the bid is winner and L that the bid is loser. There are two bidders, B1 and B2, and the recurrent auction is composed by two one-shot auctions.

Algorithm 1 updateReservationPrice(rp_i, bid_i)

$minimum = rp_i \cdot \delta$
$difference = abs(bid_i - rp_i)$
if $bid_i \geq rp_i$ **then**
  $rp_i = rp_i + max(difference/2, minimum)$
else
  $rp_i = rp_i - max(difference/2, minimum)$
end if

In the first one B1 and B2 have a priority of 0.5 and they send a bid amount of 5€ and 4€ respectively. Then, the score for B1 is higher than the score for B2 and consequently B1 wins the resource. In the second auction they send again the same bid amounts but now their priorities are different. As B2 lost in the last auction he has now a higher priority. Consequently B2 wins the second auction. Regarding the payments as the mechanism is first price they pay the bid amount sent.

3.4 Customizable Reservation Price Auction (CRPA)

The motivation for CRPA is to keep prices at an acceptable level. Some authors have suggested the use of a reservation price to accomplish this goal [59], but in an environment where agents have different wealth it is not fair to have the same reservation price for all of them. CRPA proposes a different reservation price for each bidder. In this mechanism the reservation price of a bidder agent g_i is defined as the minimum price at which the auctioneer is willing to sell a good or service to the agent g_i.

That means that the auctioneer does not accept any agent bid under his reservation price. The reservation price is initially the same for all the bidders, but it gradually varies as auctions are held. For each agent, if a bid price is higher than his reservation price, the reservation price for that agent is increased because the agent shows a higher willingness to buy the resource. Otherwise, if the reservation price is higher than the bid price, it decreases. A parameter $\delta \in [0, 1]$ is defined to indicate the minimum percentage of increase and decrease of the reservation price. When a bidder g_i bids with a value higher than his reservation price, then his reservation price is incremented by half of the difference between the reservation price and the bid's value, except if the difference is lower than $\delta \cdot rp_i$. In this case, the reservation price is incremented in $\delta \cdot rp_i$ units. These reservation prices are private to the auctioneer. The procedure is shown in Algorithm 1.

This mechanism is fair since everybody can win or lose irrespective of wealth. In addition, it prevents bidders with high wealth from reducing their price as low as possible to win, and it forces them to increase it to a minimum reservation price. Thus, it solves the problem of the asymmetric balance of negotiation power. However, the use of reservation prices produces resource waste as all the available resources are not always allocated.

This mechanism learns the behavior of the agents and appreciates the effort being made to obtain the resources. Although agents do not know the reservation price that the auctioneer assigns them, they can know that they won by maintaining the bid value at an acceptable level within their capabilities.

Figure 3.1 shows the value of the reservation price and true value during a simulation of

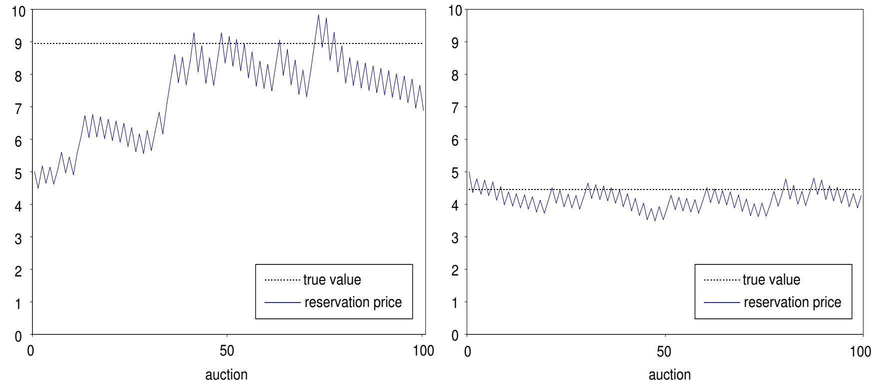

Figure 3.1: Example of the value of the reservation price

Table 3.2: Example of CRPA

auction	bidder	bid	rp_i	result
a_0	B1	6.00	5.00	L
	B2	7.00	5.00	W
	B2	4.00	5.00	L
a_1	B1	6.00	5.50	W
	B2	5.00	6.00	L
	B2	4.00	4.50	L
a_2	B1	5.00	6.05	L
	B2	6.00	5.40	W
	B2	4.50	4.05	L

a recurrent auction composed by 100 auctions[1]. The values correspond to two bidders, the first one, shown on the left, has a true value of 9 (the maximum price that the agent is willing to pay) and the second one (right) has a true value of 4.5. The plots shows that the reservation price starts with the initial value (5 in this case) and takes a value around the true value of the bidders in both cases, with a higher value than the true value but only few times, while the great part of time the reservation price value is lower.

3.4.1 Example of CRPA

Table 3.2 shows an example of CRPA where the auctioneer sells 1 unit of a resource in each auction. The value of δ is set to 0.1. In the first auction, all bidders have the initial reservation price. Then B2 results as winner. In the second auction, the reservation prices for B1 and B2 have been increased while the reservation price for B3 has been decreased. The winner of the resource in the second auction is B1. Note that B2 has decreased his bid under his reservation price, for this reason he is not a winner in the second auction. For the third auction, the reservation price are updated again, the reservation price for B1 has been increased while the reservation price for B1 and B2 have been decreased.

[1] For more details of the simulations see Chapter 5.

Table 3.3: Example of CRPAP

auction	bidder	bid	rp_i	p_i	first phase	second phase
a_0	B1	6	5.00	$\frac{1}{2}$	W	-
	B2	7	5.00	$\frac{1}{2}$	W	-
	B3	4	5.00	$\frac{1}{2}$	L	-
a_1	B1	6	5.50	$\frac{1}{3}$	W	-
	B2	5	6.00	$\frac{1}{3}$	L	L
	B3	4	4.50	$\frac{2}{3}$	L	W
a_2	B1	5	6.05	$\frac{1}{4}$	L	L
	B2	6	5.40	$\frac{2}{4}$	W	-
	B3	4	4.05	$\frac{2}{4}$	L	W

3.5 Customizable Reservation Price Auction with Priorities (CRPAP)

A way of avoiding the resource waste of the previous mechanism is to distribute the remaining resources, that is, the resources that are not being sold because of the reservation prices, among the non-winning bidders. To do so, we propose a two-phase mechanism.

- In the first phase the resources are allocated following the same rules as in CRPA. It means that the auctioneer has a reservation price for each bidder agent and consequently it is possible not to sell all resources.
- In the second phase, if there are still non-allocated resources, the mechanism gives the resources to bidders with higher priority, calculated as PA following Equation 3.1, without considering their bid amounts. It means that the bidders with higher priority will win the resources in this second phase independently if their wealth. This second phase eliminates the resource waste problem and improves the level of fairness of the solutions.

This mechanism is a combination of the CRPA and the PA mechanisms, because it uses the individual variable reservation price and the priority mechanism explained above.

3.5.1 Example of CRPAP

Table 3.3 shows an example of CRPAP where the auctioneer sells 2 units of a resource in each auction. The initial reservation price for bidders is 5 while the initial priority is $\frac{1}{2}$.

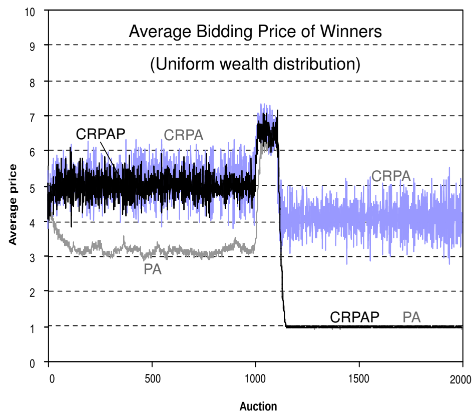

Figure 3.2: Collapse of some fair mechanisms in dynamic markets: x-axis: sequence of auctions; y-axis; average price

In the first phase of the mechanism B1 and B2 results as winners. As all units have been allocated in the first phase no unit is allocated in the second phase. In the second auction the winner in the first phase is just B1. Then in the second phase one unit is allocated to B3 since he is the bidder with higher priority $\frac{2}{3}$, because he lost the first auction and the first phase of the second. In the third auction B2 wins the resource in the first phase while B2 wins the resource again in the second phase.

3.6 Dynamic Reservation Price Auction (DRPA)

When the available resources are always the same, the previous fair mechanism (CRPAP) works correctly. However, if the supply varies, for example, due to technical malfunctions in a network communication scenario, the CRPAP mechanism could also collapse. That is, if there are fewer resources, and the bidders are the same, the number of loser agents increases. This leads to a decrease in the corresponding reservation prices at the same time that their priorities are increased, and then the auction may collapse. Figure 3.2 shows an example of a dynamic environment where there is a decrease of resources at time step 1000. The *y-axis* represents the average price paid by the winners. When the supply is re-established at time step 1100, the markets either collapse or decrease their performance (for more details see Chapter 5). This problem is due to priorities. In theory, priorities help poor agents, but when the supply varies, priorities can also favor medium and rich agents since a lot of poor bidders have disappeared from the market when supply went down. When the supply recovers medium and rich agents are not motivated to maintain the prices at an acceptable level because they can win the resources in the fair distribution even with low priorities. In this situation bidders have the negotiation power and the market collapses.

In order to avoid these problems we propose a mechanism called dynamic reservation price auction (DRPA). It consists in combining the previous fair mechanisms (based on reservation prices and priorities) and adding a mechanism to control that rich bidders do not get the resources in the fair allocation of the second phase. We have called this mechanism "control of fair resources" and at this stage it is implemented by a minimum priority parameter ($minimumPriority$) that avoids the collapse of the auctions when the supply varies.

In the first phase the resources are allocated following the same rules as in CRPA. In the second phase of the algorithm, the idea is to give the resources to bidders with higher prior-

Algorithm 2 DRPA(q_0:number of resources auctioned)

Mark bids with a price higher than the reservation price of his sender
Sort the marked bids by price in descending order into P
Select as winners the x first bids of P, where $x = min(q_0, |P|)$

if there are still available resources ($x < q_0$) **then**
  Mark bids of bidders with a priority higher than $minimumPriority$
  Sort the marked bids by priority of his sender in descending order into D
  Select as winner the y first bids of D where $y = q_0 - x$
end if

Update reservation prices according to the procedure of Algorithm 1
Update priorities according to Equation 3.1

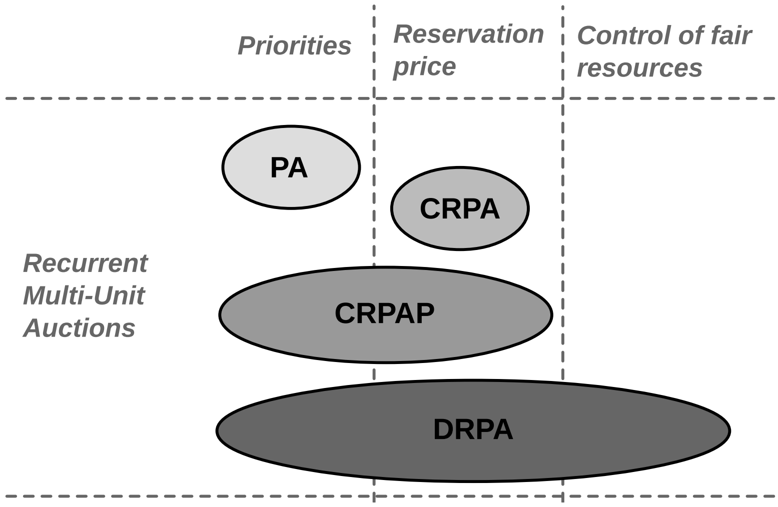

Figure 3.3: Summary of the presented fair mechanisms for RMUA

ity, but only if their priority is strictly higher than a predefined threshold ($minimumPriority$). This parameter prevents bidders with low priorities (that have won resources recently) and low bids from obtaining the resources, thereby avoiding the drop in prices when supply varies. Algorithm 2 shows the pseudo-code of this mechanism.

3.6.1 Example of DRPA

Table 3.4 shows the same example as for CRPAP, but in this case for DRPA. The value of $miminumPriority$ is 0.5. The outcome is the same in a_0 and a_1, but it changes in a_2. In the first phase B2 wins one unit of the resource but in this case no units of resource are allocated in the second phase because the 2 loser bidders in the first phase do not have a priority higher than 0.5. Then in a_2 there is one unit of resource wasted.

3.7 Summary

This chapter has introduced some basic first-price fair mechanisms for non combinatorial recurrent multi-unit auctions. Figure 3.3 shows the four mechanisms presented and the

Table 3.4: Example of DRPA

auction	bidder	bid	rp_i	p_i	first phase	second phase
a_0	B1	6	5.00	$\frac{1}{2}$	W	-
	B2	7	5.00	$\frac{1}{2}$	W	-
	B3	4	5.00	$\frac{1}{2}$	L	-
a_1	B1	6	5.50	$\frac{1}{3}$	W	-
	B2	5	6.00	$\frac{1}{3}$	L	L
	B3	4	4.50	$\frac{2}{3}$	L	W
a_2	B1	5	6.05	$\frac{1}{4}$	L	L
	B2	6	5.40	$\frac{2}{4}$	W	-
	B3	4	4.05	$\frac{2}{4}$	L	L

concepts they are based on.

The first one, called *Prioritized Auction* (PA) achieves fair solutions giving a priority to agents that modify the bid amount sent by bidders. Also this mechanism avoids the resource waste since all resources are always sold except if there is less demand than supply.

The second one, *Customizable Reservation Price Auction* (CRPA) is based on reservation prices. The auctioneer assigns a different reservation price to bidders. Each reservation price is dynamic and changes its value taking into account the bid amount sent by each bidder. The idea behind this mechanism is to maintain the bid amount to a high level but treating with each bidder in a different way taking into account his wealth.

The third one called *Customizable Reservation Price Auction with Priorities* (CRPAP) is based on priorities and reservation prices since it is a mix between PA and CRPA. The mechanism is composed in two phases. In the first the mechanism works like CRPA and in the second, the non allocated resources are shared between the bidders with higher priorities.

Finally *Dynamic Reservation Price Auction* (DRPA) is an improvement of CRPAP. CRPAP works well in several situations but has problems when the richer agents obtain the resources in the second phase. Then this mechanism adds a control of fair resources in order to avoid these situations.

CHAPTER 4
Fair Mechanisms for Recurrent Multi-Unit Combinatorial Auctions

In this chapter we present several mechanisms for Recurrent Multi-Unit Combinatorial Auctions (RMUCA). In this case the auctioneer offers several resources or items and several units of each resource. There are not any constraints for the bidders; they can bid for combinations of resources and different units of each resource following XOR bidding language [16].

First we present PMUCA and DRPMUCA: two fair mechanisms that are the extension of PA and DRPA respectively to the combinatorial environment. PMUCA as PA is based on priorities and DRPMUCA is based on priorities and reservation prices. As a difference of their non-combinatorial versions, PMUCA and DRPMUCA take into account that bidders can manipulate the priorities and they have some solutions to some kinds of manipulation.

Regarding to other mechanisms existent in the literature we can found PI-GVA [43] as a fair mechanism for recurrent multi-unit combinatorial auctions but this mechanism is only valid for auctions where several units of a unique resource are auctioned. For this reason and with the aim of comparing with the mechanism presented here, we present DP-ORMUCA the extension of DP-ORA to the combinatorial environment.

Finally, as all methods are first-price and with the aim of analysing the equilibrium of mechanisms in Chapter 7, we present PGVA, a second price mechanism based on priorities and the Generalized Vickey Auction (GVA).

4.1 DEFINITION OF RMUCA

A Recurrent Multi-Unit Combinatorial Auction (RMUCA) is a recurrent auction composed by a sequence of one-shot MUCAs. In this case the auctioneer offers several resources and several units of each resource. Regarding bidders they can bid for packages of resources. A package is a combination of resources and a quantity of units of each resource. Also they can send more than one bid following the XOR bidding language [16]. With this bidding language bidders express their preferences with XOR bids. For example suppose a bidder that wants the resources r_0 and r_1 or r_2. For r_0 and r_1 he wants to pay a maximum of 5 and 7 for r_2. In the XOR bidding language it is translated in three bids: $b_{i,j,0} = \langle\{r_0, r_1\}, 5\rangle$, $b_{i,j,1} = \langle\{r_2\}, 7\rangle$ and $b_{i,j,2} = \langle\{r_0, r_1, r_2\}, 12\rangle$. Then the auctioneer has to take into account that the three bids come from the same bidder and only one of them can be winner.

The recurrent auction A is formed by a succession of auctions $A = \{a_0, ..., a_{|A|-1}\}$. In each auction a_i, $|R_i|$ resources or items are auctioned where R_i is a set composed by tuples that indicates the resource r_x and the number of units of each resource q_x ($R_i = \{\langle r_0, q_0\rangle, ..., \langle r_{|R_i|-1}, q_{|R_i|-1}\rangle\}$). A set R_i of an auction a_i can be different of the set R_j corresponding to auction a_j, $i \neq j$.

Auctions are ordered temporarily and we associate to each auction a_i a time step t_i where T is the set of time steps in which the auctions of A occur ($T = \{t_0, ..., t_{|A|-1}\}$ where $t_0 < t_1 < ... < t_{|A|-1}$). G is the set of all bidder agents, $G = \{g_0, ..., g_{|G|-1}\}$, that participates in the recurrent auction A.

A bidder agent g_i sends to the auctioneer agent a set $V_{i,j}$ of bids in auction a_j. Each bid is composed by a package and the price or bid amount. A package is formed by a set of tuples indicating the resources required by the agent and the number of units of each item (i.e. $\{\langle bandwidth, 2\rangle, \langle memory, 5\rangle\}$). We define as $\mathbb{S}_i$ the set of all packages sent by agent g_i in the recurrent auction, $\mathbb{S}_i = \{S_{i,0}, ..., S_{i,|\mathbb{S}_i|-1}\}$ where $S_{i,m}$ is m-th the package sent by g_i. Therefore a bid is defined as $b_{i,j,x} = \langle S_{i,m}, c_{i,j,x}\rangle$ where x is the number of bid in the auction a_j sent by agent g_i to obtain the package $S_{i,m}$ ($0 \leq m < |\mathbb{S}_i|$) paying a maximum of $c_{i,j,x}$. We define the functions $\mathcal{S}(b_{i,j,x})$ to know the index of the package of bid $b_{i,j,x}$ and $\mathcal{C}(b_{i,j,x})$ to know the bid price ($\mathcal{C}(b_{i,j,x}) = c_{i,j,x}$).

4.2 Previous mechanisms

The basic unfair mechanisms presented in the previous Chapter can be easily adapted to combinatorial auctions.

- *Traditional Multi-Unit Combinatorial Auction* (TMUCA). This auction is the combinatorial version of the TA auction. Therefore the winners are the bids with the highest bid amount. The only difference between TA and TMUCA is that in TMUCA the auction is combinatorial.

- *Cancellable Multi-Unit Combinatorial Auction* (CMUCA). In a CMUCA, if the resulting revenue of an auction does not meet the minimum requirements of the auctioneer, the entire auction is canceled. As in CA, the cancellation of an auction wastes the entire stock of resources.

- *Reservation Price Multi-Unit Combinatorial Auction* (RPMUCA). In a RPMUCA the auctioneer defines a reservation price for each different package (the same for all bidders) that indicates the minimum price the bidders should pay for the package. Only bids with a bid amount higher than the corresponding reservation price can be winners.

4.3 Prioritized MUCA (PMUCA)

The PMUCA mechanism takes into account the past history of each agent. The auctioneer assigns to each bidder a set of priorities, one priority for each different package that the bidder agent has sent in the recurrent auction. The value of each priority depends on the number of lost auctions since the bidder won the package for the last time. The more auctions the bidder has lost the greater the priority. The priority values are calculated by the auctioneer and are only known to him. The priority values are calculated after the reception of bids and are used to solve the auction modifying the price $c_{i,j,x}$ of the bid $b_{i,j,x}$ generating a new bid $b'_{i,j,x}$ with a new price $c'_{i,j,x}$. The auctioneer stores in a set L_i the counters of lost auctions for each bidder g_i, one counter for each element of $\mathbb{S}_i$ ($L_i = \{l_{i,0}, ..., l_{i,|\mathbb{S}_i|-1}\}$).

However, the outcome from such fair winner determination, that is, changing the price from $c_{i,j,x}$ to $c'_{i,j,x}$, could be easily learnt by dishonest agents. That is, a bidder that is not actually interested in an auction run could send a fake bid with the aim to lose and then to obtain a greater priority in the next auction where the agent is truly interested. Thus, a mechanism should not incentivize the participation in the auctions where the bidder is not actually interested.

On the other hand a mechanism that works with combinatorial auctions must take into account the different nature of items. A bidder could send a bid for an item of little value to obtain a high priority and then use the priority to bid for a high value item. For example a bidder could send a bid for a pencil until he obtains a high priority, assuming the risk of winning the pencil since the cost of the pencil is low. Then, when the bidder obtains a high priority, he can use the priority to bid for a car.

In order to avoid these situations we define a *cycle* as a set of consecutive auctions where the priority of the agent g_i for the package $S_{i,m}$ is not decreasing. Each agent has a different cycle for each package. When a cycle ends the priority is initialized with an initial value. A cycle ends and another starts when a bidder agent wins the package or when the agent sends a bid for the package with a price higher than the bid price that the agent sent at the first auction of the cycle. If a bidder agent sends more than one bid, the agent could have a different priority for each bid since each bid requests a different package. We define $k_{i,m}$ as the price of the bid in the first auction of the current cycle of agent g_i and package $S_{i,m}$. We define K_i as the set of all the $k_{i,m}$ of agent g_i. $K_i = \{k_{i,0}, ..., k_{i,|\mathbb{S}_i|-1}\}$.

The priority $p_{i,m}$ of an agent g_i and a package $S_{i,m}$ is calculated with the following equation:

$$p_{i,m} = \begin{cases} l_{i,m} < \gamma & p_{i,m} = \lambda + \frac{1-\lambda}{\gamma} \cdot l_{i,m} \\ \\ l_{i,m} \geq \gamma & 1 \end{cases} \tag{4.1}$$

Where λ is the initial priority and γ indicates the number of lost auctions necessary so that the priority arrives to his maximum value (1.0). $l_{i,m}$ is the number of lost auctions in the current cycle for package $S_{i,m}$. The expression $\frac{1-\lambda}{\gamma}$ shows the increase of priority for each lost auction. After priorities are calculated, the modified bids $b'_{i,j,x}$ are generated. The bid $b'_{i,j,x}$ of an agent g_i that has sent a bid $b_{i,j,x}$ in the auction a_j is:

$$b'_{i,j,x} = \langle S_{i,\mathcal{S}(b_{i,j,x})}, \mathcal{C}(b_{i,j,x}) \cdot p_{i,\mathcal{S}(b_{i,j,x})} \rangle \tag{4.2}$$

Then the auction is solved using any standard combinatorial auction solving method, but with the $b'_{i,j,x}$ bids. When winners are determined, the mechanism updates the sets L_i and K_i (see Algorithm 3). For each bidder g_i if any of his bids has been winner, an end of the current cycle is produced for each package $S_{i,m}$ corresponding to the bids sent by agent g_i, therefore all counters $l_{i,m}$ of agent g_i that corresponds to bids sent in the auction are initialized. In the case that all bids have been losers, then all counters corresponding to sent bids by g_i are incremented one unit except if the price is lower than $k_{i,m}$.

We assume that there are not two bids from the same bidder with the same package with

Algorithm 3 updateLandK

```
for each bidder g_i do
  if agent g_i has won in current auction a_j then
    for each bid b_{i,j,x} in V_{i,j} do
      l_{i,S(b_{i,j,x})} ← 0
      k_{i,S(b_{i,j,x})} ← C(b_{i,j,x})
    end for
  else
    for each bid b_{i,j,x} in V_{i,j} do
      if (k_{i,S(b_{i,j,x})} < C(b_{i,j,x})) then
        l_{i,S(b_{i,j,x})} ← 0
        k_{i,S(b_{i,j,x})} ← C(b_{i,j,x})
      else
        l_{i,S(b_{i,j,x})} ← l_{i,S(b_{i,j,x})} + 1
      end if
    end for
  end if
end for
```

different prices in the same auction since one of the bids would be dominated by the other and would never be winner [21, 65].

Note that the number of elements in each set L_i and K_i could be very big. Therefore this problem must be taken into account when we apply the mechanism, for example limiting the number of possible combinations. We will take care of this issue in the future work.

4.3.1 Example

Table 4.1 shows an example where an agent g_i participates in a recurrent auction composed by 3 one-shot auctions where $\lambda = 0.5$ and $\gamma = 5$. The bidder sends bids for 3 different packages $S_1 = \{\langle r_1, 1\rangle, \langle r_2, 2\rangle\}$, $S_2 = \{\langle r_3, 3\rangle\}$ and $S_3 = \{\langle r_3, 10\rangle\}$. Note that S_2 and S_3 require the same resource r_3, but they request different quantities of r_3, thus being two different packages. The example shows the view of agent g_i to see the change of values but we assume that there are other agents in the recurrent auction.

Table 4.1 shows the bids sent in each auction and the values of the set L_i. In the first auction he sends 3 bids but none of them have resulted as winner. In the following auction the priority for S_1 and S_3 have been increased since the bid amount in a_1 is higher than the bid amount sent in a_0 and consequently a change of cycle has been produced. In the second auction the bidder sends two bids and the bid $b_{i,1,1}$ results as winner. Therefore the priority for S_1 and S_2 is initialized to 0.5. The priority for S_3 continues with the same value as in a_1 since the bidder did not send a bid for package S_2.

4.4 Dynamic reservation price MUCA (DRPMUCA)

This mechanism is the extension of DRPA to combinatorial auctions. As DRPA, DRPMUCA is based on priorities and reservation prices. The purpose of reservation prices is twofold. On the one hand reservation prices incentive bidders to pay a higher value for resources.

Table 4.1: Example of PMUCA

auction	bids	l_{i,S_1}	l_{i,S_2}	l_{i,S_3}	p_{i,S_1}	p_{i,S_2}	p_{i,S_3}	result
a_0	$b_{i,0,1} = \langle S_1, 5\rangle$ $b_{i,0,2} = \langle S_2, 7\rangle$ $b_{i,0,3} = \langle S_3, 15\rangle$	0	0	0	0.5	0.5	0.5	loser
a_1	$b_{i,1,1} = \langle S_1, 5\rangle$ $b_{i,1,2} = \langle S_2, 8\rangle$	1	1	1	0.6	0.5	0.6	winner ($b_{i,1,1}$)
a_2	$b_{i,2,1} = \langle S_1, 5\rangle$ $b_{i,2,2} = \langle S_2, 8\rangle$ $b_{i,2,3} = \langle S_3, 15\rangle$	0	0	1	0.5	0.5	0.6	winner ($b_{i,2,3}$)

On the other hand reservation prices introduce fairness in the system therefore each agent has more chances to win independently of his wealth.

However when we work with dynamic reservation prices in the combinatorial environment new ways for the bidder's manipulation appears. On the one hand the reservation price has to take into account if it makes reference to one unit of one item or several units. Conversely the bidder could send bids with low bid amount for one unit of the resource in order to decrease the reservation price and in the following auction send a bid for a bigger amount of resources. On the other hand a reservation price cannot be valid for different items since they can have very different prices. For example a pen cannot have the same reservation price than a car. Therefore the reservation price as priorities has to take into account the different quantities of items and the different nature of items.

In DRPMUCA the auctioneer has a set RP_i of reservation prices for each bidder agent g_i. In RP_i there is a reservation price for each package sent by g_i ($RP_i = \{rp_{i,0}, ..., rp_{i,|\mathbb{S}_i|-1}\}$). The reservation price $rp_{i,m}$ is defined as the minimum price at which the auctioneer is willing to sell the package $S_{i,m}$ to the agent g_i. This means that the auctioneer will not accept a bid of agent g_i for package $S_{i,m}$ with a price lower than $rp_{i,m}$. The reservation prices are dynamically changing according to the sent bids in each auction.

DRPMUCA is composed by three phases. In the first phase the auction is solved by the traditional way (the highest bid amounts are the winners) but only taking into account the bids $b_{i,j,x}$ that fulfil the condition $\mathcal{C}(b_{i,j,x}) \geq rp_{i,\mathcal{S}(b_{i,j,x})}$. In this first phase the bids are not modified. Once determined the winners of the first phase, the idea of the second phase is to sell the resources that are not being distributed in the first phase between the loser bidders with higher priority without taking into account the bid price. But in order for an agent become a winner in the second phase, the priority of the bid has to be greater than a parameter $minimumPriority$. This minimum priority value avoids the rich agents to obtain the resources at low price due to the fair distribution. We have called this mechanism *control of fair resources*. The priority is calculated using the equation 4.1. Then each bid $b_{i,j,x}$ that belongs to loser bidders with a priority greater than $minimumPriority$ are modified in order to obtain the modified bid $b'_{i,j,x}$:

$$b'_{i,j,x} = \langle \mathcal{S}(b_{i,j,x}), p_{i,\mathcal{S}(b_{i,j,x})}\rangle \tag{4.3}$$

This modified bid has the same package than $b_{i,j,x}$ but in this case the bid amount is not $\mathcal{C}(b_{i,j,x})$. The bid amount is the priority of the bid $p_{i,\mathcal{S}(b_{i,j,x})}$.

Algorithm 4 updateRP

for each bidder g_i **do**
  for each package $rp_{i,m}$ in RP_i **do**
    if bidder g_i has sent a bid $b_{i,j,x}$ for $S_{i,m}$ **then**
      if $\mathcal{C}(b_{i,j,x}) > rp_{i,m}$ **then**
        $rp_{i,m} = rp_{i,m} + max(\frac{\mathcal{C}(b_{i,j,x})-rp_{i,m}}{2}, rp_{i,m} + rp_{i,m} \cdot \delta)$
      else
        $rp_{i,m} = rp_{i,m} - rp_{i,m} \cdot \delta$
      end if
    else
      $rp_{i,m} = rp_{i,m} - rp_{i,m} \cdot \delta$
    end if
  end for
end for

A new auction is solved with the modified bids. Finally, in the last phase of DRPMUCA, the information related to priorities (L_i and K_i sets) are updated following Algorithm 3 and reservation prices as follows. For each agent, if the price of a bid that requests the package $S_{i,m}$ is greater than $rp_{i,m}$, $rp_{i,m}$ will be incremented for the next auction since the bidder is showing that he can pay more for the package. Conversely if the price is lower, $rp_{i,m}$ will be decremented. Note that changes in $rp_{i,m}$ are independent of whether the bids are winners or losers, or they participate or not (if they do not participate it is equivalent to sending a bid with price 0 for all of the packages, and the reservation price is decreased).

As in CRPA and DRPA, δ is defined between [0,1] as the minimum percentage of increment or decrement. When a $rp_{i,m}$ is incremented, the increment is the maximum between the half of the difference between the price and the $rp_{i,m}$ and $rp_{i,m} \cdot \delta$. When a $rp_{i,m}$ is decremented, the new $rp_{i,m}$ is $rp_{i,m} - (rp_{i,m} \cdot \delta)$. Reservation prices are updated at the end of each auction and are used to solve the next auction. The algorithm 4 shows the update of each RP_i.

4.4.1 Example

Table 4.2 shows an example of the DRPMUCA mechanism where a bidder agent g_i participates in a recurrent auction composed by 5 one-shot auctions where $\lambda = 0.5$, $\gamma = 5$ and $minimumPriority$ is 0.5. The bidder sends 2 bids in each one-shot auction for 2 different packages S_1 and S_2. As in the previous example we focus on the view of data about bidder agent g_i but we assume that there are other agents participating in the recurrent auction.

In the first auction both bids result as losers. He loses in the first phase and does not participate in the second because the priority of his bids are not higher than the $minimumPriority$ parameter. Then, in the second auction the priority has been increased. Also the reservation prices have been changed taking into account the bid amount sent by the bidder. In the second auction the bid $b_{i,0,1}$ result as a winner. Then for the third auction the values of priority for packages S_1 and S_2 are initialized with the initial value (λ). In this case the bidder g_i does not participate in the second phase of the algorithm.

In a_2 and a_3, the bidder do not win the resource achieving a priority of 0.7 in the fifth auction. In this latter auction, the bidder is a loser of the first phase but wins the resource

Table 4.2: Example of DRPMUCA

auction	bids	l_{i,S_1}	l_{i,S_2}	p_{i,S_1}	p_{i,S_2}	rp_{i,S_1}	rp_{i,S_2}	1st phase	2nd phase
a_0	$b_{i,0,1} = \langle S_1, 4\rangle$ $b_{i,0,2} = \langle S_2, 15\rangle$	0	0	0.5	0.5	5.00	5.00	loser	-
a_1	$b_{i,1,1} = \langle S_1, 5\rangle$ $b_{i,1,2} = \langle S_2, 15\rangle$	1	1	0.6	0.6	4.50	10.00	winner ($b_{i,0,1}$)	-
a_2	$b_{i,2,1} = \langle S_1, 5\rangle$ $b_{i,2,2} = \langle S_2, 15\rangle$	0	0	0.5	0.5	4.95	12.50	loser	-
a_3	$b_{i,3,1} = \langle S_1, 5\rangle$ $b_{i,3,2} = \langle S_2, 15\rangle$	1	1	0.6	0.6	5.44	13.75	loser	loser
a_4	$b_{i,4,1} = \langle S_1, 5\rangle$ $b_{i,4,2} = \langle S_2, 15\rangle$	2	2	0.7	0.7	4.89	15.12	loser	winner ($b_{i,4,2}$)

in the second phase with the bid $b_{1,4,2}$ due to the high priority.

4.5 Discriminatory Price Optimal Recurring MUCA (DP-ORMUCA)

In this section we make a generalization of the mechanism DP-ORA proposed by Lee and Szymanski [42]. DP-ORA is the only previous winner determination mechanism of the literature that deals with fairness in multi-unit auctions. In [43] the same authors propose a mechanism called Participation Incentive Generalized Vickrey Auction (PI-GVA) but this mechanism is not valid to compare with our proposed mechanism since PI-GVA only allows one item to be auctioned in the recurrent auction. For this reason we have followed the main ideas of DP-ORA in order to adapt the mechanism to combinatorial auctions. Since DP-ORA is designed for a non-combinatorial scenario, we know that is not the best way to create a new mechanism. However, it can be useful in order to compare it with the performance of our mechanisms. We have called the generalization of DP-ORA Discriminatory Price Optimal Recurring Multi-Unit Combinatorial Auction (DP-ORMUCA).

DP-ORA algorithm is a mechanism based on the demand-supply principle of micro-economics. The mechanism fixes a reservation price rp_{ORA} in each auction. This value is the maximum between the $\frac{2 \cdot q_0}{3}$th higher bid value in the current auction and the auctioneer's minimum desired benefit of the sold resource where q_0 is the number of auctioned resources. Then, all bidders with a bid greater than rp_{ORA} become winners. The remaining resources are shared between the loser agents following the VLLF-BDC (Valuable Last Lost First Bidder Drop Control) algorithm. This algorithm divides the surplus resources in 2 phases. In the first phase the algorithm marks the bidders who lost in the last auction and increased their bid in the current one. Then, the algorithm allocates resources amongst the highest marked bids. If there are still resources to be allocated, then in the second phase the resources are allocated to the highest non marked bids. So in some sense, the history analyzed by DP-ORA is as if we were considering a time window of length two (current and previous auction).

In our generalization, the mechanism is composed by three phases. In the first phase an auction is applied where the winners are the bids with highest bid amounts but not all of the units of items are auctioned. For each resource only 66.66% of units are auctioned. If $R = \{\langle r_0, q_0\rangle, ..., \langle r_{|R|-1}, q_{|R|-1}\rangle\}$ then the set $R' = \{(r_0, q'_0), ..., \langle r_{|R|-1}, q'_{|R|-1}\rangle\}$ is auctioned, where $q'_i = \lfloor \frac{2 \cdot q_i}{3} \rfloor$.

Then, in the second phase, the resources not sold in the first phase are auctioned. In this second phase the bids from loser bidders (none of their bids has resulted winner) are marked if they fulfil the following conditions: the bid pertains to a bidder who was loser in the last auction that participated to win the same package, and the price offered this time is higher. Then, in the second phase a second auction is done with the marked bids. The winners are again the highest bids.

Finally in the third phase, resources not assigned are shared and all loser bidders that have not been marked in the second phase participate in this phase. A third auction takes place in this phase with the non marked bids and the winners are the highest bid amounts.

4.5.1 Example of DP-ORMUCA

Table 4.3 shows an example of DP-ORMUCA. Assume we have an auction x where 3 bidders participate: B1, B2 and B3. Suppose that is not the first one-shot auction of the recurrent auction. They send the following bids in the first auction: $b_{1,x,1} = \langle S_1, 6\rangle$, $b_{1,x,2} = \langle S_2, 7\rangle$, $b_{1,x,3} = \langle S_3, 15\rangle$, $b_{2,x,1} = \langle S_4, 6\rangle$, $b_{2,x,2} = \langle S_5, 10\rangle$ and $b_{3,x,1} = \langle S_6, 4\rangle$ where $S_1 = \{\langle r_1, 2\rangle, \langle r_2, 4\rangle\}$, $S_2 = \{\langle r_1, 3\rangle\}$, $S_3 = \{\langle r_3, 10\rangle\}$, $S_4 = \{\langle r_1, 3\rangle, \langle r_2, 3\rangle\}$, $S_5 = \{\langle r_2, 3\rangle, \langle r_3, 5\rangle\}$ and $S_6 = \{\langle r_1, 1\rangle, \langle r_2, 3\rangle\}$. The auctioneer auctions the set R of resources ($R = \{\langle r_1, 7\rangle, \langle r_2, 7\rangle, \langle r_3, 10\rangle\}$). In the first phase of the mechanism the auctioneer auctions $R' = \{\langle r_1, 5\rangle, \langle r_2, 5\rangle, \langle r_3, 7\rangle\}$. By this way the winner is $b_{1,x,1}$. Note that with the XOR bidding language only one bid of each bidder can be winner. Then, in the second phase the auctioneer auctions the remaining resources $R = \{\langle r_1, 5\rangle, \langle r_2, 3\rangle, \langle r_3, 10\rangle\}$. In this phase, the auctioneer marks the bids that fulfil the necessary conditions. The bids of B1 are not marked since B1 resulted as winner in the first phase. $b_{2,x,1}$ and $b_{2,x,2}$ are marked supposing that the bidder sent the bids $b_{2,x-1,1} = \langle S_4, 5\rangle$ and $b_{2,x-1,2} = \langle S_5, 7\rangle$ in the previous auction resulting as loser. Then $b_{3,x,1}$ is not marked supposing that he sent a bid amount of 5 in the previous auction. Then the auction is cleared with the bids $b_{2,x,1}$ and $b_{2,x,2}$ and the winner is $b_{2,x,2}$. In the third phase the auctioneer auctions $R = \{\langle r_1, 5\rangle, \langle r_2, 0\rangle, \langle r_3, 5\rangle\}$ and the only participant is $b_{3,x,1}$ since he was not marked in the second phase. $b_{1,x,1}, b_{1,x,2}, b_{1,x,3}, b_{2,x,1}$ and $b_{2,x,2}$ do not participate because bidders B1 and B2 have won in the previous phases. In this last phase there is not any winner because $b_{3,x,1}$ requires 3 units of the resource r_2 and the auctioneer is not selling any unit of this resource in this phase.

Then in the auction $x+1$ the bids received by the auctioneer are the following: $b_{1,x+1,1} = \langle S_2, 7\rangle, b_{1,x+1,2} = \langle S_3, 15\rangle, b_{2,x+1,1} = \langle S_4, 6\rangle, b_{2,x+1,2} = \langle S_5, 10\rangle$ and $b_{3,x+1,1} = \langle S_6, 4\rangle$. The auctioned resources are $R = \{\langle r_1, 7\rangle, \langle r_2, 7\rangle, \langle r_3, 10\rangle\}$ therefore in the first phase the resources auctioned are $R' = \{\langle r_1, 5\rangle, \langle r_2, 5\rangle, \langle r_3, 7\rangle\}$ and the winner is $b_{2,x+1,2}$. In the second phase the only market bid is $b_{3,x+1,1}$ since B3 was loser in the previous auction and he has sent a higher bid amount. The bids of B2 are not marked since he has won in the first phase and the bids of B1 are not marked since he won in the previous auction. Consequently $b_{3,x+1,1}$ results as winner. Finally in the third phase the set $R = \{\langle r_1, 6\rangle, \langle r_2, 1\rangle, \langle r_3, 5\rangle\}$ is auctioned and the bids that participate are $b_{1,x+1,1}$ and $b_{1,x+1,2}$, resulting $b_{1,x+1,1}$ as winner.

4.6 Prioritized Generalized Vickrey Auction (PGVA)

In Chapter 7, we discuss about the manipulation that bidders could do in order to take advantage of mechanisms. Some of the manipulations can be avoided with a second price mechanism. For these reason and with the aim to study the behaviour of bidder agents we

Table 4.3: Example of DP-ORMUCA

auction	bidder	bids	1st phase	Marked	2nd phase	3rd phase
a_x	B1	$b_{1,x,1} = \langle S_1, 6\rangle$	W	✗	-	-
		$b_{1,x,2} = \langle S_2, 7\rangle$	L	✗	-	-
		$b_{1,x,3} = \langle S_3, 15\rangle$	L	✗	-	-
	B2	$b_{2,x,1} = \langle S_4, 6\rangle$	L	✓	L	-
		$b_{2,x,2} = \langle S_5, 10\rangle$	L	✓	W	-
	B3	$b_{3,x,1} = \langle S_6, 4\rangle$	L	✗	-	L
a_{x+1}	B1	$b_{1,x+1,1} = \langle S_2, 7\rangle$	L	✗	-	L
		$b_{1,x+1,2} = \langle S_3, 15\rangle$	L	✗	-	L
	B2	$b_{2,x+1,1} = \langle S_4, 6\rangle$	L	✗	-	W
		$b_{2,x+1,2} = \langle S_5, 10\rangle$	W	✗	-	L
	B3	$b_{3,x+1,1} = \langle S_6, 4\rangle$	L	✓	W	-

have created a new mechanism based on priorities and a pricing mechanism based on the Generalized Vickrey Auction (GVA).

As in PMUCA, the auctioneer assigns to each bidder a set of priorities, one priority for each different package that the bidder agent has sent in the recurrent auction. The priority values are calculated as in PMUCA following Equation 4.1.

The difference is in the pricing mechanism. In this case the auction is not first price, therefore the bidders do not pay the bid amount sent, they pay a lower amount. The payment is based on the payment rule of Vickrey Clarke Groves (VCG) auction [11, 28] or Generalized Vickrey Auction (GVA). In the GVA auction a winner bidder has to pay the difference between the total revenue for the auctioneer of the auction supposing that the winner bidder is not participating in the auction and the total revenue for the auctioneer supposing that the winner bidder do not participate in the auction and the resources that the bidder have won are not auctioned. Suppose 3 bidders B1, B2 and B3 and two units of a resource auctioned. Each bidder wants one unit of the resource and offers a bid amount of 5, 7 and 3 respectively. Then, in the GVA the winners are B1 and B2 and both have to pay 3. The revenue for the auctioneer without B1 is 10 because B2 and B3 would be the winners (7+3). Then, the revenue without B1 and without one unit of the resource would be 7 because B2 would be the winner. Then 10 less 7 equal to 3. The payment for B2 is (5+3)-5=3. Note that when the auction is combinatorial the auctioneer has to solve one auction to know the winners and two more auctions for each bidder to know the payments.

In PGVA the winner are determined as in PMUCA taking into account the bids modified with the priority. But after calculating the winners, the payments are calculated taking into account the original bid amounts. Then the problem that can appear is that when the payments are calculated, as the winners are not the highest bids the result of the GVA payment can be higher than the bid amount since the second price could be higher than the winner price. To avoid this we modify the payment multiplying the result of the GVA payment by λ.

Then, the payment follows the Equation 4.4.

$$payment(b) = \left(\sum_{\forall i \in G} \sum_{\forall x \in V_{i,j}} win(x)^{\neg b} \cdot \mathcal{C}(x) - \sum_{\forall i \in G} \sum_{\forall x \in V_{i,j}} win(x)^{\neg b*} \cdot \mathcal{C}(x) \right) \cdot \lambda \quad (4.4)$$

Table 4.4: Example of PGVA

auction	bidder	bid	priority	score	result	payment
a_0	B1	3	0.5	$3 \cdot 0.5 = 1.5$	L	0
	B2	4	0.5	$4 \cdot 0.5 = 2.0$	L	0
	B3	5	0.5	$5 \cdot 0.5 = 2.5$	W	$((6+4)-6) \cdot 0.5 = 2.0$
	B4	6	0.5	$6 \cdot 0.5 = 3.0$	W	$((5+4)-5) \cdot 0.5 = 2.0$
a_1	B1	3	0.6	$3 \cdot 0.6 = 1.8$	L	0
	B2	4	0.6	$4 \cdot 0.6 = 2.4$	L	0
	B3	5	0.5	$5 \cdot 0.5 = 2.5$	W	$((6+4)-6) \cdot 0.5 = 2.0$
	B4	6	0.5	$6 \cdot 0.5 = 3.0$	W	$((5+4)-5) \cdot 0.5 = 2.0$
a_2	B1	3	0.7	$3 \cdot 0.7 = 2.1$	L	0
	B2	4	0.7	$4 \cdot 0.7 = 2.8$	W	$((5+6)-6) \cdot 0.5 = 2.5$
	B3	5	0.5	$5 \cdot 0.5 = 2.5$	L	0
	B4	6	0.5	$6 \cdot 0.5 = 3.0$	W	$((5+4)-4) \cdot 0.5 = 2.5$
a_3	B1	3	0.8	$3 \cdot 0.8 = 2.4$	L	0
	B2	4	0.5	$4 \cdot 0.5 = 2.0$	L	0
	B3	5	0.6	$5 \cdot 0.6 = 3.0$	W	$((6+4)-6) \cdot 0.5 = 2.0$
	B4	6	0.5	$6 \cdot 0.5 = 3.0$	W	$((5+4)-5) \cdot 0.5 = 2.0$
a_4	B1	3	0.9	$3 \cdot 0.9 = 2.7$	W	$((6+5)-6) \cdot 0.5 = 2.5$
	B2	4	0.6	$4 \cdot 0.6 = 2.4$	L	0
	B3	5	0.5	$5 \cdot 0.5 = 2.5$	L	0
	B4	6	0.5	$6 \cdot 0.5 = 3.0$	W	$((5+4)-4) \cdot 0.5 = 2.5$
a_5	B1	3	0.5	$3 \cdot 0.5 = 1.5$	L	0
	B2	4	0.7	$4 \cdot 0.7 = 2.8$	L	0
	B3	5	0.6	$5 \cdot 0.6 = 3.0$	W	$((6+4)-6) \cdot 0.5 = 2.0$
	B4	6	0.5	$6 \cdot 0.5 = 3.0$	W	$((5+4)-5) \cdot 0.5 = 2.0$

Where $win(x)^{\neg b}$ is equal to 1 if the bid x results a winner in the auction without bid b (otherwise equal to 0). And $win(x)^{\neg b*}$ represents the result of the auction without b and without the items required in b.

4.6.1 Example of PGVA

Table 4.4 shows an example where 4 bidder agents want one resource in each auction. The auctioneer offers two resources in each auction and the recurrent auction is composed by 5 one-shot auctions. The value of λ is 0.5 and the value of γ is 5. The process to decide the winners is the same as in PMUCA. The difference arises in the payment. In the first auction the winners are B3 and B4 and they have to pay 2. The solution of the original auction without bidder B3 is 10 since the winners are B2 and B6 (6+4=10). Then the solution to the original problem without B3 and with only one unit of the resource auctioned is 6 (the winner would be B4). Then, the payment in a GVA is $(6 + 4) - 6 = 4$. In the PGVA mechanism the payment of GVA is multiplied by λ and consequently the payment is 2.

Looking at the auction a_2 the winners are B2 and B4 and the GVA payment of the original problem is 5 for B2. Note that in this case the GVA payment of the original problem is greater than the bid amount sent by the bidder agent. Multiplying the GVA payment by λ the mechanism avoids this problem.

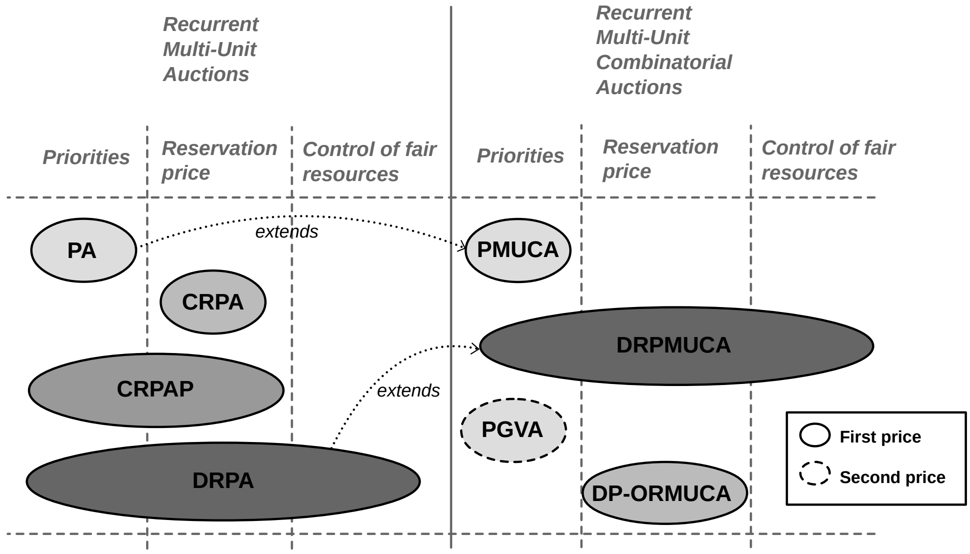

Figure 4.1: Summary of all presented fair mechanisms

4.7 Summary

This chapter has presented two fair mechanisms for recurrent multi-unit combinatorial auctions. The first one is PMUCA and is the extension of PA to combinatorial auctions. The second one is DRPMUCA that is the extension of DRPA. In the combinatorial version of the mechanisms, these have a priority for each different package that each bidder has sent during the recurrent auction instead of having a unique priority for each bidder. The same occurs with reservation prices in DRPMUCA, a reservation price is defined for every different package that each bidder has sent. Also in both mechanisms the way of calculating the priorities has been modified with respect to their predecessors in order to avoid some kinds of manipulations.

Also two other mechanisms have been presented with different purposes. On the one hand DP-ORMUCA is the naive adaptation of DP-ORA to combinatorial auctions. The aim of this adaptation is to have a mechanism to compare our mechanism in combinatorial environments based on the ideas of DP-ORA. On the other hand PGVA is presented as a variation of PMUCA mechanism with a second price payment. This new mechanism will be used in Chapter 7 to study the possible manipulations of bidders in a second price fair mechanism.

Figure 4.1 shows all mechanisms presented in this chapter and in the previous one and the concepts they are based on. PMUCA and PGVA, as their predecessor PA, are based only on priorities to obtain a fair solution but with the difference that they are adapted to combinatorial auctions and PGVA has a second price payment. Then, DRPMUCA ,as DRPA, is based on three concepts: the priorities to obtain a fair solution, the dynamic reservation prices to maintain the power of negotiation for the auctioneer and the control of fair resources. Finally DP-ORMUCA is only based on reservation prices.

Chapter 5
Experimentation in an e-services allocation domain

In [40, 41] a suitable scenario for recurrent auctions is presented. The topic is the allocation of electronic services (e-services). An e-service is defined as a modular internet-based service that requires various computational resources such as network bandwidth, computational cycles, RAM memory or storage in a hard disk to guarantee the Quality of Service (QoS) [42, 62].

An example of e-services are the Grid Computing Services (GCS). In last years the interest in GCS has been growing. The GCS buyers demand computing services and the GCS provider, that is the owner of the resources, temporarily allocates the necessary computer hardware and software resources to the buyer's application to produce the desired QoS [78]. The main reason to use an auction-based mechanism in this domain is that the GCS provider needs a tool for expressing his pricing policies and needs to maximize the resource utilization [42].

In this chapter we experimentally evaluate our hypothesis: Fairness improves revenue in the long term. In [40, 41] a simple version of the e-service scenario is presented. In this scenario an auctioneer sells several identical units of bandwidth between bidders. Bidders want to acquire one unit of bandwidth in each auction. Then, in order to evaluate the presented mechanisms, we have experimented in an extended version of the e-services allocation domain.

Starting from the Lee and Szymanski scenario [42] we have created new more complex scenarios. In this chapter we present the experimentation done in 9 different scenarios. In order to make the readability easy we have enumerated the scenarios from 1 to 9 and Figure 5.1 shows the relation between them. The arrows mean that the one scenario is an extension of another one. For example scenario 2 is an extension of scenario 1 adding changes in the supply offered by the auctioneer.

We divide the experimentation presented in this chapter in two main blocks, the first block is dedicated to the experimentation done in non-combinatorial scenarios (scenarios from 1 to 4), that is where the one-shot auctions are RMUA and the mechanisms of Chapter 3 are used. These results are shown in Section 5.3 while in Section 5.4 we present the experimentation done in the second block with the mechanisms introduced in Chapter 4. This block contains the combinatorial scenarios (scenarios from 5 to 9). These two blocks can be divided again in closed markets where the bidders disappear form the system when they drop out of a market, and open markets where the bidders can dynamically change from one market to another.

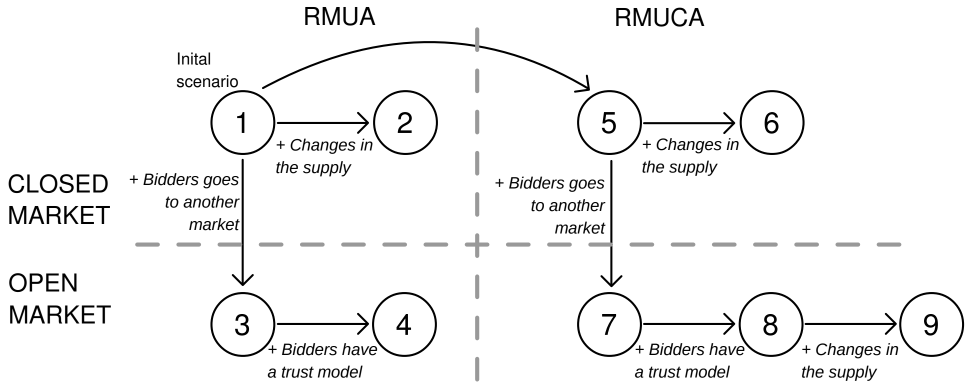

Figure 5.1: Schema of the performed experiments

5.1 Bidder Agent Design

Three main components can be distinguished in the bidders used for the simulations in this chapter. Each component is in charge of taking different decisions. They are the following:

- The first component is the *bidding policy*. The bidder agent has to decide the bid amount to send for the resources that he wants.
- The second component is the *drop policy* in charge of deciding when the agent wants to leave the auction or wants to continue participating in the recurrent auction. This component models the bidder drop problem.
- The third one is the *new auctioneer selection* and is in charge of deciding the new auctioneer when the agent has decided to drop from the auction. This component is only used by bidders in open markets.

5.1.1 Bidding Policy

To model the bidding policy we have used the adaptation strategy defined in [40]. This strategy, defined for RMUA, is the following. The initial bidding price is randomly selected from a uniform distribution over the range $[w_i/2, w_i]$, where w_i represents the upper bound on the willingness of bidder agent g_i to pay (also known as wealth or true value). Based on the assumption that each bidder tries to maximize his expected profit and is honest, the following bidding policy has been considered. If a bidder has lost in the previous auction round, he increases his bidding price by a factor of $\alpha > 1$ to increase his probability of winning in the current round. The increase in the bidding price is limited by the upper bound of the bidder's willingness to pay. If a bidder won in the last auction round, then with equal probability of 0.5, he either decreases the bidding price by a factor β or leaves it unchanged. The decrease attempts to maximize expected profit. The parameters α and β are set in the experiments to 1.2 and 0.8, respectively, since they are the same values used in [40]. Although an analysis of sensibility of these values is needed, these values have been selected in order to be able to compare the results obtained in this thesis with the result of other authors. In each auction bidders want to acquire 1 unit of the resource, therefore each bidder will send only one bid composed of one resource unit and a price between the 10% of his wealth and his wealth.

In order to implement the bidding policy in combinatorial scenarios we have adapted the previous strategy. For each possible package $S_{i,m}$ bidders have a $z_{i,m}$ value that indicates the actual price that they offered by the package $S_{i,m}$ and a value $w_{i,m}$ that indicates the maximum price that they can pay for the package. $z_{i,m}$ is dynamic during the auctions while $w_{i,m}$ is chosen at the beginning of the simulation and it maintains its value during all the recurrent auction. The initial value of $z_{i,m}$ is a random value between $w_{i,m}/2$ and $w_{i,m}$. If a bidder loses in an auction a_j, the bidder increments the value of $z_{i,m}$ multiplying $z_{i,m}$ by α for all the packages that the agent has requested in the auction a_j in order to increment the probability of winning in the next auction. We consider that a bidder loses the auction a_j if none of his bids results as winner. In the opposite, if the bidder won in the auction a_j, all the prices of the packages requested are decremented multiplying them by β the 50% of the times. The other 50% the prices remain with the same value. The values of α and β are fixed to 1.2 and 0.8 respectively as in MUA. The minimum price that a bidder g_i can offer for a package $S_{i,m}$ is the 10% of the $w_{i,m}$ value. Before starting the simulation a value of wealth is assigned to each bidder following several statistical distributions. This value will be used to set the values of $w_{i,m}$.

5.1.2 Drop policy

The drop policy depends on whether the agent has a trust model or not. In the former case, we have used the same concept of Tolerance to Consecutive Losses defined in [40], while on the latter case, we have used the index of desirable resources, IDR, explained below.

The TCL denotes the maximum number of consecutive losses that a bidder can tolerate before dropping out of an auction. The TCL value of each bidder agent is uniformly distributed over the range [2, 10] and is a private value of the bidder. For instance, a bidder with a TCL value equal to 4 will drop the auction if he does not win any resource in 5 consecutive auctions. The TCL is used in the scenarios where the agent does not have trust model. In these scenarios where the agent has a trust model, the drop policy is modeled with the IDR.

Trust model

In some scenarios agents use a trust model of the auctioneers to decide dropping from the auction and to decide the new auctioneer to join. The trust model of each bidder agent is composed of two components:

- The first component is direct trust. Each agent has direct trust in each auctioneer he has interacted with. It is based on the direct experiences of the bidder. This trust is an estimator of the resources the bidder will obtain from the auctioneer [27].

  In this scenario the TCL mechanism to model bidder dropout used in the previous scenarios is replaced by the index of desirable resources, IDR. Each bidder has a minimum percentage of resources that the agent needs (the IDR). This is a private value of each bidder, and it is uniformly randomly assigned from the interval [0.1, 0.4]. For example, if an agent has an IDR value of 0.2, it means that the agent wants to win at least two resources out of every 10 auctions. Then, the direct trust of this agent on his current auctioneer is computed as the percentage of obtained resources over the number of auctions he has participated in. If this percentage is lower than the IDR, then the bidder is not satisfied with his auctioneer, and will leave it, in the case that the agent completely knows the auctioneer (see knowledge explanation below). We assume that bidder dissatisfaction is the only motive to change an auctioneer. We do not consider other motivations such as better prices since we are dealing with sealed-bid auctions where bidders do not know the prices offered by the other bidders.

- The second component of trust is reputation (also called indirect trust), which is related to the experience of other agents. After every auction, each bidder randomly chooses another agent to ask about his auctioneer. If the asked agent is satisfied with his auctioneer, he recommends his auctioneer to the other agent. Otherwise the asked agent does not recommend any auctioneer. The agent will use these recommendations when he decides to leave his current auctioneer and join a new one. The bidder agent chooses the auctioneer with the highest number of recommendations. We assume that agents are honest and do not lie when they are giving recommendations.

Agents also have a parameter called *minimumKnowledge* (MK). This parameter indicates the minimum number of auctions needed to determine if an agent knows his auctioneer. When an agent has participated in more than MK auctions with his auctioneer, the agent can say that he knows enough about the auctioneer to leave if he is not achieving his objectives. In the same way, an agent would not recommend his auctioneer to another agent if he did not know enough about his auctioneer.

5.1.3 Auctioneer selection

In the markets where a bidder can join different auctioneers, after a bidder decides to leave his auctioneer he has two ways to decide the new auctioneer. When the agent is equipped with a trust model, the agent chooses the auctioneer with more recommendations. Otherwise the bidder agent chooses his new auctioneer randomly between all available auctioneers.

5.2 Fairness measure

The satisfaction of an agent is somewhat abstract and relative, as not all agents have the same needs and are not satisfied in the same way. For example, a bidder getting one resource out of four auctions may be satisfied with that, while another agent may need to win the resource in three out of four auctions to be satisfied. If both bidders won two resources out of four auctions, the first agent would be satisfied while the second would not. Thus a metric should be defined according to the different preferences of the individual agents in the market. The aggregation of individual preferences can be modeled using the notion of social welfare [9]. Welfare engineering addresses how to define the appropriate criteria and social mechanisms so that resource allocations converge to the optimal social criteria. There are different measures proposed in the literature including the satisfaction of the minimum needs of a large number of agents, fair division, leximin ordering and envy freeness (a good summary of all of them can be found in [9]). However, the measures studied so far deal with a one-shot allocation process instead of a recurrent scenario. We need to define a new measure that takes into account the sequence of winning and losing bids of an agent in a series of auctions. This measure must provide an aggregation of bidder satisfaction values of each auction round.

An option is to measure the satisfaction of a bidder through the prices of the bids that he sends. Then we assume that if a bidder sends a price c_0 in a bid b_0 and in another bid b_1 he sends a price c_1, if $c_0 < c_1$, then we suppose that the bidder is more interested in winning the bid b_1, consequently we assume that if he wins b_1, it will cause a greater satisfaction. Then we define the satisfaction of an agent g_i in an auction a_j following Equation 5.1.

$$satisfaction(i,j) = \frac{\sum_{\forall b \in V_{i,j}} (\mathcal{C}(b) \cdot win(b))}{maxc(V_{i,j})} \tag{5.1}$$

Where $V_{i,j}$ is the set of bids sent by agent g_i in the auction a_j. $Win(b)$ indicates if the bid b has resulted winner (value 1) or loser (value 0). $\mathcal{C}(b)$ indicates the price of the bid b and $maxc(V_{i,j})$ returns the greater bid price of the $V_{i,j}$ set. In other words we define the satisfaction as the sum of prices of his winning bids divided by the maximum that the agent could win. Recall that auctions are sealed bid and a bidder does not know the bids of the other bidders. We can therefore assume that there is no envy among the bidders. Next we define the satisfaction level of an agent g_i in the recurrent auction A as the average of the satisfaction degree on each auction, following Equation 5.2.

$$satisfaction(i,A) = \frac{1}{|P(A,i)|} \cdot \sum_{\forall a_j \in P(A,i)} (ff(t_j, LT) \cdot satisfaction(i,j)) \tag{5.2}$$

where $P(A,i)$ is the set of auctions belonging to A where agent g_i has participated, t_j is the time when auction a_j took place, $ff(t_j, LT)$ is a forgetting function to give less weight to older auctions and LT is the time window size.

Once we have a measure for each agent, the level of fairness of an auctioneer auc after a sequence of auctions can be defined as the inverse of the standard deviation of the average satisfaction of agents belonging to the auctioneer, following Equation 5.3.

$$fairness(auc) = \frac{1}{\sqrt{\frac{1}{|G|-1} \cdot \sum_{\forall g_i \in G} \left(satisfaction(i,A) - \overline{satisfaction(A)}\right)^2}} \tag{5.3}$$

Where A is the set of auctions performed by auctioneer auc, G is the set of agents that have participated in any auction of the A set, and $\overline{satisfaction(A)}$ is the average of the degree of satisfaction of the agents, following Equation 5.4.

$$\overline{satisfaction(A)} = \frac{\sum_{\forall g_i \in G} satisfaction(i,A)}{|G|} \tag{5.4}$$

With this measure, $fairness(auc)$, we quantify how fair the different mechanisms are. A mechanism that treats all the bidders equally fair would have a high $fairness(auc)$ value, independently of the amount of items being awarded by the auctioneer and the revenue obtained. Auctioneers look to maximize their benefits and the methods we propose, in particular, use fairness to achieve this goal. But their decision making does not take into account the evaluation measure defined in Equation 5.3. This measure is only used to compare the different mechanisms.

5.3 Experimentation in a non-combinatorial environment

In order to evaluate the performance of the fair RMUA mechanisms of Chapter 3, we have experimented in four different scenarios:

- **First scenario:** In this scenario the same framework used in other related work [41, 55] has been replicated. The supply is constant, and no other marketplaces are available.
- **Second scenario:** In the second scenario, we have done two experiments, adding variations in the supply of the resource to simulate dynamic environments.
- **Third scenario:** In the third scenario the resource supply is constant as in scenario 1 but we have changed the way bidders drop out: if a bidder decides to leave his auctioneer, he joins the market of another, randomly selected auctioneer instead of disappearing from the system.
- **Fourth scenario:** The fourth scenario extends the third scenario. In this case bidders use trust and reputation information to choose their next auctioneer.

In each scenario, there are eight auctioneers executing their auctions in parallel and each auctioneer has an initial population of 100 bidders. In the two former scenarios, when a bidder leaves his auctioneer, he disappears from the simulation (closed market). On the other hand, in the last two scenarios, when a bidder leaves his auctioneer he can join the market of any other auctioneer (open market). It is therefore likely that some auctioneers will finish with more participants than those they started with. Hence, in these scenarios the different auctioneers (and thus, the different mechanisms) are competing against each other to attract more bidders.

In order to compare their performances, we have used the total revenue of the auctioneers during the recurrent auction, since their ultimate goal is to maximize their revenue. Total revenue is then analyzed regarding how fair the mechanisms are, since our hypothesis is that fairness improves revenue in the mid-long term. As secondary metrics, we have also used the percentage of resource waste and the number of bidders that remain in the auction at the end of the recurrent auction, in order to evaluate to what extent we are solving these problems of recurrent auctions, while improving revenue. Finally in the last scenario we have also taken into account the number of recommendations that agents have done about each auctioneer, meaning that more recommendations is an indicator of the mechanism being beneficial for more bidders.

Thus, each of the eight auctioneers of the simulation follows a different mechanism: there are five fair mechanisms (PA, CRPA, CRPAP, DRPA, DP-ORA) and three unfair mechanisms (TA, CA, RPA). The fair mechanisms are those presented in Chapter 3 and DP-ORA explained in Section 2.5.1 from the literature. The unfair mechanisms are the basic mechanisms explained in Section 3.2. From this point on, we will refer to the mechanisms by their abbreviations and we will add a superscript F for fair methods and N for unfair methods to make the reading easier.

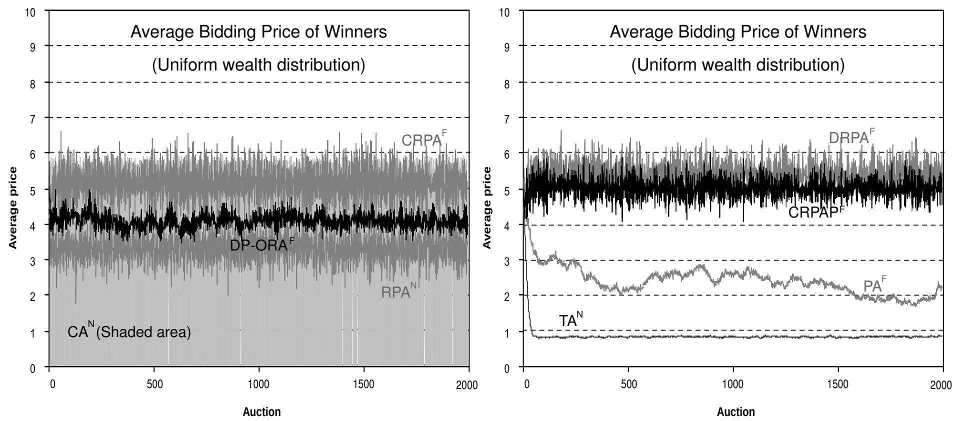

Figure 5.2: Average bidding price in scenario 1 (Uniform wealth distribution, 1 simulation). For the sake of clarity, the results are split into two plots. Left: CA^N, CRPA^F, DP-ORA^F, RPA^N. Right: TA^N, PA^F, CRPAP^F, DRPA^F.

Table 5.1: Results for all mechanisms with a uniform distribution of wealth in scenario 1 (no dynamics). Averaged results of 10 simulations with the standard deviation in brackets.

	Mechanism	Total Revenue	% Resource Waste	Number of Bidders
Fair	PA^F	263226.26 (53303.95)	0.00% (0.00)	81.80 (1.03)
	CRPA^F	501216.90 (38955.67)	10.50% (2.03)	81.50 (2.01)
	CRPAP^F	495684.78 (6798.01)	0.00% (0.00)	91.10 (1.10)
	DRPA^F	503950.25 (21380.26)	0.00% (0.00)	90.20 (1.13)
	DP-ORA^F	434270.21 (25110.21)	0.00% (0.00)	94.00 (1.33)
Unfair	TA^N	94585.65 (6558.26)	0.00% (0.00)	69.30 (1.49)
	CA^N	355414.14 (39840.06)	34.24% (7.15)	54.40 (4.97)
	RPA^N	336669.83 (42836.59)	38.26% (7.86)	50.50 (6.43)

5.3.1 Results in the first scenario: no dynamics

In this scenario the number of resources in each auction is constant (50 units) and when a bidder g_i loses more than TCL_i consecutive auctions, he drops out of the auction and disappears from the system. Figure 5.2 shows the average resource price at which each of the eight auctioneers has sold the resources during the 2000 auctions of one simulation. The x-axis represents the temporal sequence of the auctions, and the y-axis is the average price at which the resources have been sold, which is the total benefit obtained by the auctioneer divided by the 50 units of resource, irrespective of whether all the resources have been sold or not. The wealth of bidders has been distributed following a uniform distribution in [2, 10]. The results have been drawn in two plots for clearer readability. The numerical data is shown in Table 5.1, where the total revenue, the resource waste produced by each mechanism, and the number of bidders remaining with the auctioneer at the end of 10 simulations are also shown. The table values are the average of 10 simulations with the standard deviation in brackets.

In Figure 5.2 we can see how TA^N (right plot) collapses very quickly. Table 5.1 shows that

Table 5.2: Results for fair mechanisms with a exponential distribution of wealth in scenario 1 (no dynamics). Averaged results of 10 simulations with standard deviation in brackets.

	Mechanism	Total Revenue	% Resource Waste	Number of Bidders
Fair	PA^F	134113.39 (17848.66)	0.00% (0.00)	77.20 (1.61)
	$CRPA^F$	489161.87 (28122.32)	17.35% (2.78)	76.10 (2.47)
	$CRPAP^F$	511654.82 (32149.30)	0.00% (0.00)	90.80 (0.92)
	$DRPA^F$	492633.98 (30998.73)	0.00% (0.00)	90.40 (0.84)
	$DP\text{-}ORA^F$	293116.79 (18438.55)	0.00% (0.00)	96.20 (3.58)
Unfair	TA^N	96529.49 (6234.67)	0.00% (0.00)	61.80 (1.39)
	CA^N	325410.58 (3572.25)	39.87% (0.60)	50.30 (0.67)
	RPA^N	228621.02 (18923.73)	58.23% (3.45)	33.90 (2.84)

this is due to the bidder drop problem (it has only an average of 69.3 bidders at the end of the simulations). This drop of bidders means that the remaining bidders have the power to set the price and influence the consequent fall of prices. Thanks to the reservation prices, the RPA^N and CA^N mechanisms[1] can maintain the price at a higher level than TA^N as they are not affected by the asymmetric balance of negotiation power. However, the reservation prices produce a resource waste of 34.24% and 38.26% of the resources respectively, and these mechanisms are also affected by the bidder drop problem (an average of 54.4 and 50.5 bidders, respectively, at the end of simulations). The mechanism $CRPA^F$, as well as RPA^N (recall the difference between these two methods: $CRPA^F$ has an adaptable reservation price for each bidder, while RPA^N has a unique reservation price for all bidders) maintain the balance of negotiation power and the incentive for bidders to bid with higher prices, thereby achieving higher total revenue. $CRPA^F$ also maintains a high number of bidders in the auction (81.5 bidders) due its fair behavior, but produces some resource waste (but less than CA^N and RPA^N). Other fair methods, such as $DP\text{-}ORA^F$, $CRPAP^F$ and $DRPA^F$, show similar behaviors as those of $CRPA^F$, but without resource waste. They maintain the prices at an acceptable level and maintain a high level of bidders at the end of the simulations. Finally, PA^F is the only fair mechanism that is affected by the asymmetric balance of negotiation power, and this causes a price decrease that will collapse in the long term. Observe, however, that the asymmetric balance of negotiation power is due to the particularities of our experimental scenario: there are 50 units of resources and less than 100 bidders. Then, when some of the poorest bidders have dropped out of the auction, more than 50% of the bidders become winners; therefore the number of winning bidders is significantly higher than losers. Winning bidders are then lowering prices instead of raising them, making the average price fall at long-mid term.

Figure 5.3 shows the average and the standard deviation of total revenue earned in 2000 auctions for each auctioneer in 10 simulations, as well as the fairness level achieved by each mechanism. Fairness is expressed according to our satisfaction measure (see Equation 5.3). In general, fair mechanisms have better performance than unfair ones. The four mechanisms with a higher revenue are also those with a higher fairness level: $DRPA^F$, $CRPA^F$, $CRPAP^F$ and $DP\text{-}ORA^F$. Thus, fairness provides highest revenue in the long term.

[1]The CA^N mechanism is displayed as a gray area because whenever an auction is canceled, the prices fall down to zero, and so when plotting the results there are lots of lines reaching the x axis.

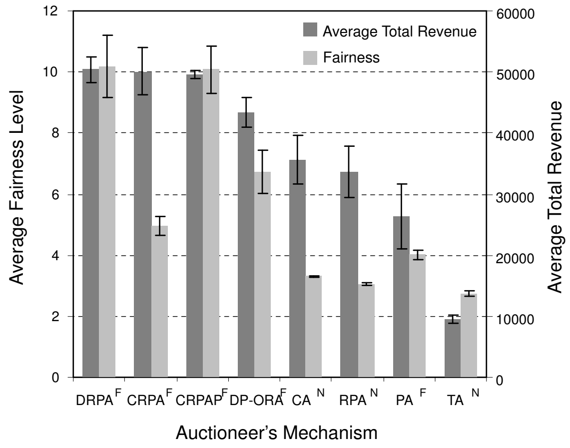

Figure 5.3: Total revenue and fairness obtained by all mechanisms in scenario 1 (average and standard deviation of 10 simulations).

Table 5.3: Results for fair mechanisms with a Gaussian distribution of wealth in scenario 1 (no dynamics). Averaged results of 10 simulations with standard deviation in brackets.

	Mechanism	Total Revenue	% Resource Waste	Number of Bidders
Fair	PA^F	468783.48 (29296.04)	0.00% (0.00)	86.90 (1.96)
	CRPA^F	482505.96 (6383.20)	8.78% (0.97)	82.70 (0.82)
	CRPAP^F	499247.06 (4932.84)	0.00% (0.00)	90.20 (1.03)
	DRPA^F	502299.17 (4909.11)	0.00% (0.00)	90.40 (0.97)
	DP-ORA^F	485362.19 (9632.47)	0.00% (0.00)	95.00 (0.94)
Unfair	TA^N	143687.43 (69252.21)	0.00% (0.00)	77.80 (2.29)
	CA^N	354506.32 (30767.49)	33.64% (5.91)	57.40 (5.25)
	RPA^N	35082.90 (3950.66)	35.08% (3.95)	53.90 (3.95)

Tables 5.2 and 5.3 show the results obtained by the mechanisms in scenario 1 when the wealth of agents follows an exponential distribution (this means few rich agents and many poor ones) and a Gaussian distribution (few rich, few poor and many agents in the middle class), respectively. The results are similar to those obtained with the uniform distribution. Note, however, that with the exponential distribution of wealth, CRPA^F produces more resource waste, so its performance is slightly affected, as is that of DP-ORA^F.

Figure 5.4 shows the evolution of the average number of bidders in 10 simulations with each of the methods during 2000 auctions in the right plot and the detail of the 100 first auctions in the left plot. The number of bidders stabilizes during the first 20 auctions and from then on changes are much smaller and stable. The plots show the difference between fair methods (DRPA^F, CRPAP^F, CRPA^F, PA^F and DP-ORA^F) with an average value higher than 80 bidders and unfair ones (TA^N, CA^N and RPA^N) with a value less than 70. In this domain the stabilization of bidders causes a stabilization of prices (see Figure 5.2) without changes to the supply. The bidders that remain in the system pressure the market at a constant rate, so revenue is also stabilized.

Finally, Figure 5.5 shows how bidders drop out of the different mechanisms, depending

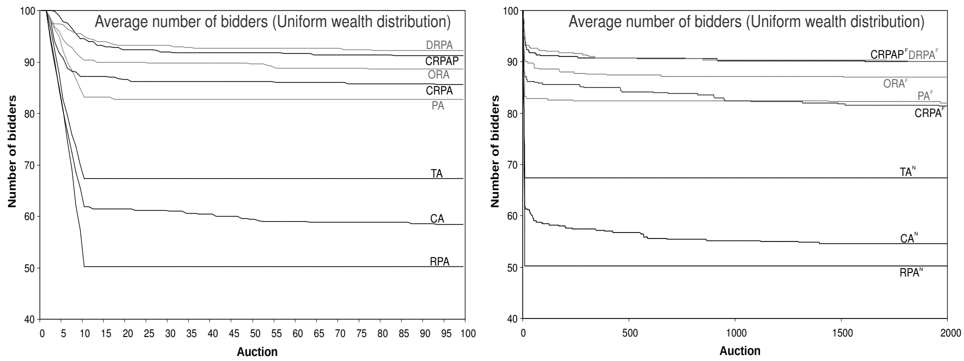

Figure 5.4: Average number of bidders in scenario 1 (Uniform wealth distribution, 10 simulations). At right the result of the 2000 auctions, at left the detail of the 100 first auctions.

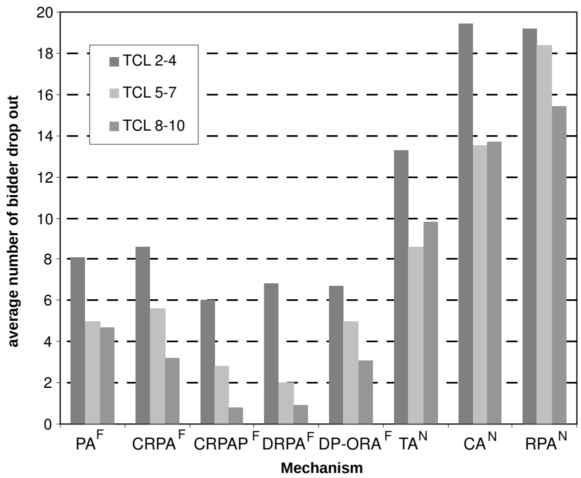

Figure 5.5: Average number of bidder drops in 10 simulations depending on the bidder's tolerance (TCL).

on their tolerance to losses (TCL). The first thing to note is that unfair mechanisms (CA^N, TA^N and RPA^N) are those with a higher drop out degree, as quantitative results of Table 5.1 corroborate. In general, and as it could be expected, the lowest the value of TCL, the highest the frequency of dropping out of an auction. Particularly, all fair mechanisms follow a skewed right distribution pattern. In unfair methods, however, the wealth of bidders has a huge importance, and poor bidders leave the auction even if they have a high TCL. For this reason the pattern is less skewed than for fair methods.

As a summary, the results of this scenario indicate that the mechanisms that incorporate fairness and reservation prices minimize the problems of recurrent multi-unit auctions. Fairness gives bidders incentives to stay in the auction, and reservation prices help maintain the equilibrium in the negotiation power. In addition, this combination maintains resource prices at a high level. However, this scenario is static: in a real environment there are other factors that can change the nature of the auctions. For this reason, we introduce some of these changes into the scenario.

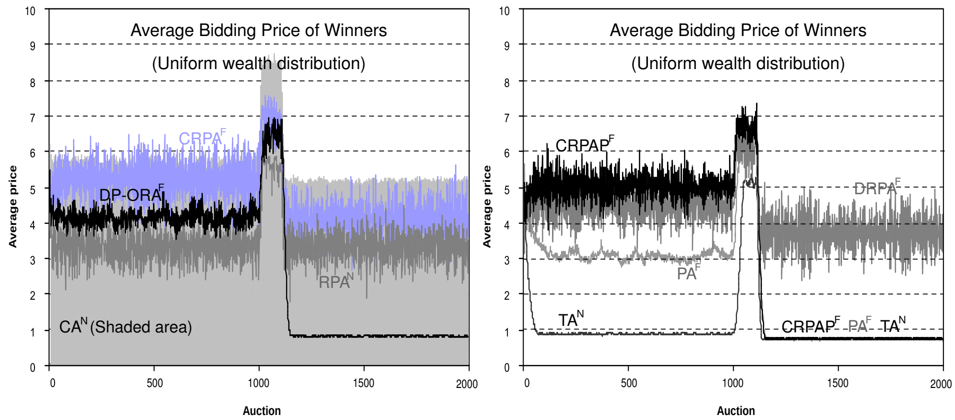

Figure 5.6: Average bidding price in scenario 2 with a temporal reduction of supply (Uniform distribution of wealth, 1 simulation). Left: CA^N,CRPA^F,DP-ORA^F,RPA^N. Right: TA^N,PA^F, CRPAP^F, DRPA^F.

5.3.2 Results in the second scenario: variation of supply

Reality is not static, and in a bandwidth communication domain it is feasible to expect malfunctions, technical problems with the network, and maintenance issues that decrease the available supply. To model this we have performed two experiments to vary the supply of the auctioneers. The first one consists of a sudden reduction of the supply. The initially available supply is set to 50 units, but it is reduced from 50 to 30 units at time step 1000, and then it is restored back to 50 units at time step 1100. From that time onwards, it does not change anymore. In the second experiment, the resource quantity intermittently oscillates between 40 and 60 units. The supply is initially set to 40 units, and it is gradually increased, reaching 60 units at time step 500. Then the supply gradually decreases, arriving to 40 units again at time step 1000. This oscillation is repeated every 1000 auctions.

Figure 5.6 shows the average price in one simulation of the first experiment. We can see how prices rise for all methods during the time with scarce units of resource (less supply, prices go up). During this period all methods suffer the drop of the poorest bidders, and as a consequence, some of the mechanisms are not able to return to their same or close steady-state when the supply is restored. Particularly, DP-ORA^F, CRPAP^F and PA^F are fair methods that are not able to return to their steady-state. We can find the explanation on the fair distribution of the resources. These mechanism focus on avoiding resource waste, and they are always trying to sell all the resources. That is, if we classify the bidders in three classes, rich, middle class and poor agents, the bidders from the middle class put pressure on the upper class. If bidders from the high class relax, the bidders of the middle class get the resources, and the rich ones do not get the resources, consequently they maintain prices at an acceptable level. When bidders of the middle or upper class get the resources at low prices due to the fair distribution, then they have no incentive to increase their bids, and prices begin to decrease. In this circumstance, the bidders of the upper class have the power to fix the price, and obviously they try to decrease it to the minimum possible, and the market collapses. This does not happen with RPA^N and CRPA^F because they sacrifice resource waste for maintaining the prices at an acceptable level. Finally, DRPA^F does not collapse because of the control of fair resources and it is trading off reservation prices and resource waste.

Table 5.4: Results for all mechanisms with a uniform distribution of wealth in scenario 2 (variation of supply). Averaged results of 10 simulations with standard deviation in brackets.

	Mechanism	Total Revenue	% Resource Waste	Number of Bidders
Fair	PA^F	208304.84 (43389.46)	0.00% (0.00)	60.20 (1.47)
	$CRPA^F$	451891.36 (19727.05)	23.66% (1.00)	53.50 (1.35)
	$CRPAP^F$	316905.30 (21666.03)	0.00% (0.00)	56.40 (0.52)
	$DRPA^F$	451442.78 (40175.99)	18.97% (0.79)	56.20 (1.23)
	DP-ORA^F	285722.23 (18388.61)	0.00% (0.00)	58.40 (1.26)
Unfair	TA^N	97984.91 (5299.34)	1.17% (1.04)	48.70 (1.15)
	CA^N	228217.64 (64154.85)	60.02% (8.73)	15.00 (15.81)
	RPA^N	328682.72 (29768.08)	38.67% (5.23)	47.10 (2.56)

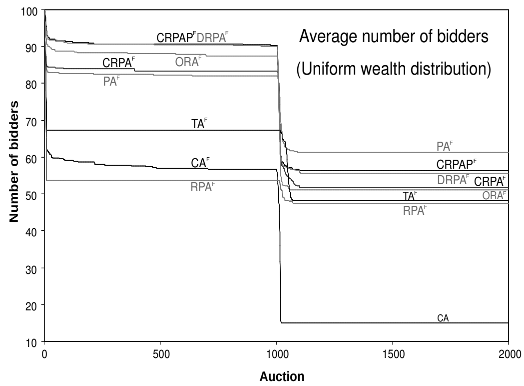

Figure 5.7: Average number of bidders in scenario 2 (uniform wealth distribution, 10 simulations).

Table 5.4 shows how the performance has dropped for all mechanisms that have failed to keep the price after a reduction on the resource supply. The mechanisms that have obtained more revenue are $CRPA^F$ and $DRPA^F$, but they have produced resource waste. On the other hand, the mechanisms that have not produced resource waste have collapsed. Therefore, in these situations it is necessary to produce some resource waste to maintain prices at acceptable levels.

Figure 5.7 shows the evolution of the average number of bidders in 10 simulations with each of the methods during 2000 auctions in this experiment. We can see how the number of bidders is drastically reduced at time step 1000, when supply fluctuation begins. If we correlate these results with those in Figure 5.6, we can see that the reduction of bidders reduces auctioneer revenue. So, we cannot guarantee any stabilization of prices when supply fluctuation appears, and we corroborate the importance of keeping agents interested in the auction for the stability of prices.

In the second experiment the units of resource offered by the auctioneer gradually vary oscillating between 40 and 60 units each 500 auctions. This oscillation seems feasible in a network communication domain. The decrease in supply from 50 to 40 could be caused by technical problems due to some temporarily unavailable links. On the other hand, the increase in supply can be caused by the temporary availability of some bandwidth that

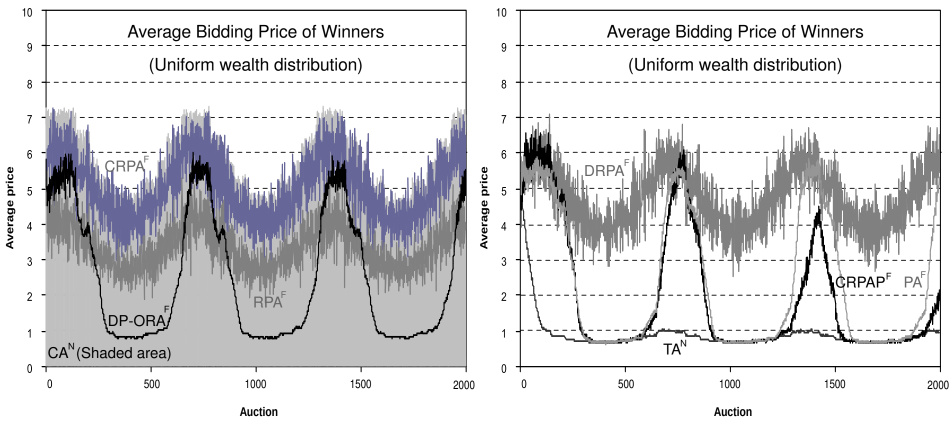

Figure 5.8: Average bidding price in scenario 2 with an oscillation of supply (Uniform wealth distribution, 1 simulation). Left: CA^N,CRPA^F,DP-ORA^F,RPA^N. Right: TA^N,PA^F, CRPAP^F, DRPA^F.

is usually not sold and reserved for backup purposes. The plots in Figure 5.8 show the ups and downs of prices as resources vary. CRPA^F and DRPA^F are the mechanisms that show better performance, as in periods of abundant resources they maintain the prices at a higher level than the other mechanisms. As already shown in Figure 5.6, the prices rise with low supply, but with CRPAP^F it seems that the rises are becoming smaller every time and in the long term the auction collapses. This experiment shows how the dynamics in supply can cause problems in the auction mechanisms even with fair methods. The only fair mechanisms that maintain the stability in such situations are CRPA^F and DRPA^F.

From the results we can conclude that previous fair mechanisms with reservation prices can collapse in a scenario where the supply of the auctioneer is reduced over time. This occurs to the methods that distribute a quantity of resources fairly (DP-ORA^F and CRPAP^F). On the other hand, DRPA^F avoids the collapse by introducing a minimum priority that prevents the fairly distributed resources from being allocated to middle and upper class agents.

5.3.3 Results in the third scenario: arrival of new customers

In environments where agents need resources, it is logical to think that if an agent leaves his supplier, his need for resources does not disappear and therefore the agent will try to find those resources elsewhere. Thus, in this scenario, when an agent leaves an auctioneer, he randomly joins the market of another auctioneer in search of the resources he needs. Thus, after each auction, some bidders might leave an auctioneer, while others could arrive. Each bidder is initially assigned to participate in a given market controlled by an auctioneer using his corresponding auction mechanism. However, when the bidder decides to randomly change of auctioneer, he leaves his current market and he joins the market of another auctioneer which uses another auction mechanism. Note that the bidders that change to a new auctioneer are usually poor because they are usually losers with their previous auctioneers. When a bidder changes auctioneer, his configuration values (wealth and TCL) remain the same, but the TCL counter is set to 0, and the auctioneer of the new market sets the priority of the agent to default. Both measures, the TCL counter and priority, are dynamic and depend on the agent-auctioneer interactions; since the bidder moves to a new market, no previous interaction exists, and then the default values should be assigned.

Table 5.5: Results for uniform distribution of wealth in scenario 3 (arrival of new customers). Averaged results of 10 simulations with standard deviation in brackets.

	Mechanism	Total Revenue	Improv. (scen. 1)	% Resource Waste	Number of Bidders
Fair	PA^F	448882.08 (26294.13)	71%	0.00% (0.00)	109.70 (4.32)
	CRPA^F	532526.97 (37561.61)	6%	0.90% (0.16)	111.00 (4.24)
	CRPAP^F	526125.96 (33562.50)	6%	0.00% (0.00)	113.70 (4.42)
	DRPA^F	547996.64 (30969.23)	9%	0.00% (0.00)	114.30 (3.26)
	DP-ORA^F	508243.53 (38068.57)	17%	0.00% (0.00)	117.20 (4.83)
Unfair	TA^N	277304.95 (16488.65)	193%	0.00% (0.00)	95.20 (3.05)
	CA^N	353185.90 (35803.38)	-1%	34.56% (6.43)	71.00 (5.77)
	RPA^N	328840.91 (31884.12)	-2%	39.67% (5.78)	67.90 (4.33)

Table 5.5 presents the averaged results after 10 simulations in this scenario. We expected a general increase in the revenue of all the auctioneers, because now bidders are not disappearing from the simulation, but moving from one auctioneer to another (and in the end, more bidders are kept in the simulation). The results show that, effectively, most of the mechanisms improve overall, some of them improve drastically, and only two, CA^N and RPA^N, have slightly decreased their gains. The *Improvement* column in Table 5.5 shows the increase or decrease of revenue in proportion to scenario 1. TA^N has been greatly benefited by the arrival of new bidders and has increased its profits an average of 193%. Despite this large increase, the TA^N mechanism is still the one with the worst revenue. As shown in the *Number of Bidders* column, fair mechanisms end up with more bidders than they had initially. The fair mechanism that has increased its revenue the most is the PA^F with a growth of 71%, followed by DP-ORA^F with 17% and DRPA^F with 9%. All of the differences between scenario 1 and scenario 3 for fair methods are statistically significant according to the $t - test$.

Summarizing all the results of this scenario, we can say that fair mechanisms (PA^F, CRPA^F, CRPAP^F, DRPA^F and DP-ORA^F) are more able to retain newly arrived bidders. The bidders who go to other auctioneers because they did not find the resources they wanted, sometimes obtain the resources in a fair auction and, consequently, they remain with the new auctioneer and help to maximize the auctioneer's revenue.

5.3.4 Results in the fourth scenario: customers with trust

Trust and reputation are increasingly used in electronic marketplaces. For example, in eBay auctions, users can view the reputation of sellers based on the opinions of users who have previously bought from them, and this information can be used to decide whether to trust these sellers or not. Reputation in this market is vital: buyers have to trust sellers because sellers could not send the products or the products might not have the expected quality. Having a good reputation is a key element for success in a competitive market; customers will move to the most reputable suppliers. The reputation of a supplier can be the factor that determines whether an agent decides to sign a contract with one supplier or another [23].

For these reasons, we added a trust model to the agents in the last scenario. As a result, the agents have different degrees of trust toward their suppliers. The objective is to approximate the agents' behavior to that of a real environment. With this trust model, an agent leaves an auctioneer in which he has not enough trust. In addition, when he decides to leave his supplier, he joins the auctioneer with the highest reputation, instead of moving randomly as

Table 5.6: Results for uniform distribution of wealth in scenario 4 (customers with trust). Averaged results of 10 simulations with standard deviation in brackets.

Mechanism	Total Revenue	% Resource Waste	Number of Bidders	Improv. (scen. 3)	Number of Recommendations
PA^F	445684.32 (43506.40)	0.00% (0.00)	110.50 (5.06)	0.73%	178005.50 (2667.90)
$CRPA^F$	529515.67 (44930.74)	0.82% (0.21)	115.20 (3.08)	3.78%	185570.00 (1296.40)
$CRPAP^F$	536566.79 (17068.58)	0.00% (0.00)	122.10 (7.52)	7.39%	187322.90 (1052.01)
$DRPA^F$	546594.38 (19530.43)	0.00% (0.00)	115.10 (5.97)	0.70%	186343.20 (1183.79)
$DP\text{-}ORA^F$	496080.97 (37991.97)	0.00% (0.00)	128.60 (3.13)	9.73%	197076.80 (1556.35)
TA^N	254016.99 (20741.33)	0.00% (0.00)	94.70 (3.68)	-0.52%	160800.80 (635.67)
CA^N	374335.30 (25401.71)	30.67% (4.54)	63.20 (3.76)	-10.98%	117431.10 (6393.71)
RPA^N	323737.43 (47015.53)	40.67% (8.60)	50.60 (8.64)	-25.48%	96442.90 (13863.98)

Table 5.7: Summary of results.

	Mechanism	Bidder Drop Problem	Resource Waste	Asym. Balance of Negotiation Power	Fairness	Revenue
Fair	PA^F	low	very low	high	high	low
	$CRPA^F$	low	medium	very low	high	very high
	$CRPAP^F$	low	very low	medium	very high	medium
	$DRPA^F$	low	low	very low	very high	very high
	$DP\text{-}ORA^F$	very low	very low	medium	very high	medium
Unfair	TA^N	very high	very low	very high	very low	very low
	CA^N	high	very high	low	low	low
	RPA^N	high	very high	very low	very low	low

in the previous scenario.

Table 5.6 shows the results obtained in this scenario. Examining the data we can see that the fair mechanisms obtain the highest number of recommendations and this means that they have increased the number of bidders with respect to scenario 3 (see column *Improvement*). All unfair mechanisms have decreased the number of bidders, while fair mechanisms have increased it. In conclusion, we can say that agents are more satisfied with fair mechanisms and this popularity means that auctioneers with them get more customers.

5.3.5 Discussion

With the results from all of the scenarios we can generate the summary of Table 5.7. This table shows the obtained revenue, the level of fairness of each mechanism and to what degree the mechanisms are affected by the recurrent multi-unit auction problems described in Chapter 2. Regarding the bidder drop problem, the least affected mechanism is DP-ORA^F, but the mechanisms PA^F, CRPA^F, CRPAP^F and DRPA^F are a short distance below it. Regarding the resource waste problem, the mechanisms TA^N, DP-ORA^F, PA^F and CRPAP^F are not affected by this problem, which slightly affects DRPA^F. The rest of the mechanisms are affected in a serious way. The asymmetric balance of negotiation power problem does not affect the mechanisms DRPA^F, RPA^N, and CRPA^F. DP-ORA^F and CRPAP^F have a medium level because they may be affected by this problem in dynamic situations. Thus, according to our hypothesis, obtaining the maximum revenue can be achieved by a fair mechanism, as DRPA^F does. DRPA^F and CRPA^F achieve the highest revenue for the auctioneer and both mechanisms behave the best when supply varies and there is market competition. However, if we look at the results in more detail, CRPA^F is always behind the revenue obtained by DRPA^F, except for the case of varying supply where CRPA^F obtains just a bit more than CRPA^F. Moreover, CRPA^F causes higher resource waste, and it keeps fewer bidders interested than DRPA^F does. Finally, it is important to note that CRPA^F has shown certain instability regarding resource waste and number of bidders when the wealth distribution of bidders varies, while DRPA^F behaves similarly with all wealth distributions. Therefore, we can conclude that the DRPA^F outperforms the previous ones.

Nevertheless, we should verify in a future whether the mechanisms behave differently when using other values for the simulation parameters (i.e. TCL, IDR, wealth, etc.), as well as for their internal parameters (i.e. α, β, γ, etc.). The values of agent wealth, bidding price distribution, reservation prices modifications (α, β) and tolerance of consecutive losses (TLC) have been taken from [41] in order to make our work comparable to DP-ORA. On the other hand, the minimum priority, minimum knowledge, and the index of desirable resources (IDR) have been empirically set in this work. Thus, some kind of sensibility analysis should be performed in order to assess the effect of each parameter on the behavior of the mechanisms.

5.4 Experimentation in a combinatorial environment

An e-service allocation scenario has been created based on extending the one described in [40] to multi unit combinatorial auctions. Each auctioneer is an e-service auctioneer that owns 60 units of bandwidth that are distributed in five groups. The first group is dedicated to voice (20 units), the second group is dedicated to high quality voice (10 units), the third group is dedicated to video (10 units), the fourth group is dedicated to high quality video (10 units) and the fifth group is dedicated to data (10 units). Then the auctioneer can provide five different resources: Voice (VO), High Quality Voice ($HQVO$), Video (VI), High Quality Video ($HQVI$) and Data (D).

There are 100 bidder agents that are requesting electronic services. Bidders can be classified in six groups.

1. The agents of the first group (20 agents) are doing a video conference and send a bid to obtain the package $\{\langle VI, 1\rangle, \langle VO, 1\rangle\}$.
2. The second group (15 agents) is watching TV and want a good quality, and bid for $\{\langle HQVI, 1\rangle, \langle HQVO, 1\rangle\}$ xor $\{\langle VI, 1\rangle, \langle HQVO, 1\rangle\}$ xor $\{\langle HQVI, 1\rangle, \langle VO, 1\rangle\}$ xor $\{\langle VI, 1\rangle, \langle VO, 1\rangle\}$. Obviously for the first bid they offer a higher price but if they cannot win the first bid they want to win any of the alternatives.
3. The third group (30 agents) is composed by bidders that are doing phone calls and they want $\{\langle VO, 1\rangle\}$.
4. The members of the fourth group (10 agents) want $\{\langle HQVO, 1\rangle\}$ xor $\{\langle VO, 1\rangle\}$ since they are listening to music.
5. In the fifth group there are 15 agents that need $\{\langle D, 1\rangle\}$.
6. Finally the agents of the last group (10 agents) need $\{\langle D, 2\rangle\}$ because they want to download files at a higher velocity.

In the simulations of the fifth and sixth scenario there are 5 auctioneers. Each auctioneer uses a different mechanism for clearing the auction. The auctioneers uses the main fair mechanisms presented in Chapter 4: PMUCA and DRPMUCA and the 3 unfair mechanisms described in Section 4.2: TMUCA, CMUCA and RPMUCA. Then, in the seventh, eighth and ninth scenarios a new auctioneer has been added, the DP-ORMUCA described in Section 4.5. In all simulations there are one hundred bidders for each auctioneers and the wealth of bidders has been distributed following 3 statistical distributions (uniform, exponential and gaussian). In order to evaluate the performance of the mechanism under dynamic situations and competing markets, five different scenarios have been designed. They are enumerated continuing the numeration of the scenarios of non-combinatorial environments.

- **Fifth scenario:** This scenario is the extension of scenario 1 to combinatorial auctions. The supply is constant and the market is closed but there are several resources and bidders bid for packages of resources instead of bid for just one unit of one resource.
- **Sixth scenario:** The sixth scenario has the same characteristics than the fifth but with changes in the supply offered by the auctioneer.
- **Seventh scenario:** This scenario extends the fifth scenario. When a bidder is not achieving his goals, he changes of auctioneer. The new auctioneer is selected randomly. Bidders do not use the trust model.
- **Eighth scenario:** In this scenario when a bidder changes of auctioneer he selects the new auctioneer with the best reputation. Therefore agents are equipped with the trust model.
- **Ninth scenario:** In this scenario variations on the supply are added to the eighth one. There are two possible variations. On the one hand the resources auctioned between time step 1000 and 1100 are reduced in a 40%. On the other hand, the supply oscillates.

As in the previous section, we will refer to the mechanism by their abbreviation and we will add a superscript F for fair mechanisms and N for unfair mechanisms to make the reading easier.

5.4.1 Results in the fifth scenario: no dynamics in RMUA

Figure 5.9 shows the average resource price at which each of the 5 auctioneers has sold the resources during the 2000 auctions of one simulation. In the fifth scenario, where the market is closed and the supply offered by the auctioneer do not change. The x-axis represents the temporal sequence of the auctions, and the y-axis is the average price. The wealth of bidders has been distributed following a uniform[2] distribution in [2, 10]. The numerical data is shown in Table 5.8, where the total benefits, the resource waste produced, the fairness level, and the number of bidders remaining with the auctioneer at the end are shown. The table values are the average of 20 simulations with the standard deviation between brackets.

[2] All experiments have been also simulated with wealth distributions following a exponential distribution (this means few rich agents and many poor ones) and a gauss distribution (few rich, few poor and many agents in the middle class). The results are similar to those obtained with uniform distribution.

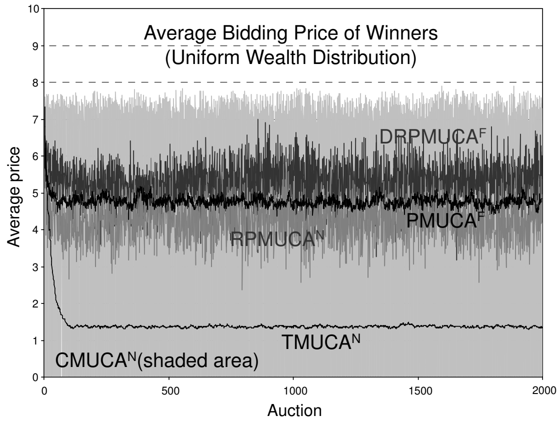

Figure 5.9: Average bidding price in scenario 5 (uniform wealth distribution)

Table 5.8: Results for all mechanisms with a uniform distribution of wealth in scenario 5. Averaged results of 20 simulations

	Name	Total benefits	Resource waste	Number of bidders	Fairness
Fair	PMUCA^F	550119.74 (60183.99)	5729.30 (1480.90)	68.60 (2.43)	3.51 (0.08)
	DRPMUCA^F	666314.48 (41969.16)	18384.25 (2283.99)	66.50 (2.18)	4.10 (0.12)
Unfair	TMUCA^N	178297.63 (29690.01)	2439.00 (1835.44)	52.25 (1.58)	2.71 (0.08)
	RPMUCA^N	549565.30 (53360.16)	38255.10 (6779.03)	45.25 (3.64)	3.10 (0.03)
	CMUCA^N	532021.85 (19758.86)	46737.40 (2932.32)	37.60 (1.04)	3.46 (0.06)

Results on Table 5.8 show that the bidder drop problem affects in a major way TMUCA^N, CMUCA^N and RPMUCA^N. Note that CMUCA^N appears in the plot as an area because the average prices are 0 when the auction is cancelled. In the case of TMUCA^N, the drop of bidders has provoked the collapse of the auction. Figure 5.9 shows that the average price of TMUCA^N has fallen to very low prices in less than 100 auctions. The bidders that have not dropped have obtained the power of negotiation and consequently have fixed the price at the minimum possible. The rest of the methods, despite the drop of bidders, have maintained the power of negotiation thanks to the reservation prices. Regarding the resource waste, RPMUCA^N and CMUCA^N have been the mechanisms most affected. They have wasted 31.87% and 38.94% of resources respectively. Below these mechanisms, DRPMUCA^F has lost 15.32% of resources and finally the mechanisms non based on reservation prices are the ones that have wasted less resources. Note that these methods can also have resource waste due to the combinatorial nature of the problem. Regarding the total benefits, DRPMUCA^F has been the mechanism that has obtained the first position followed by RPMUCA^N, PMUCA^F and CMUCA^N. Finally regarding fairness, DRPMUCA^F is the mechanism with a higher value followed by PMUCA^F. We can see that the methods with higher fairness obtains the highest benefits.

5.4.2 Results in the sixth scenario: variation of supply in RMUCA

As already considered in scenario 2, in a bandwidth communications domain it is feasible to expect malfunctions, technical problems with the network, and maintenance issues that decrease the available supply. In a second experiment the market is also closed as in the previous scenario but the supply has been reduced in the auctions during the time

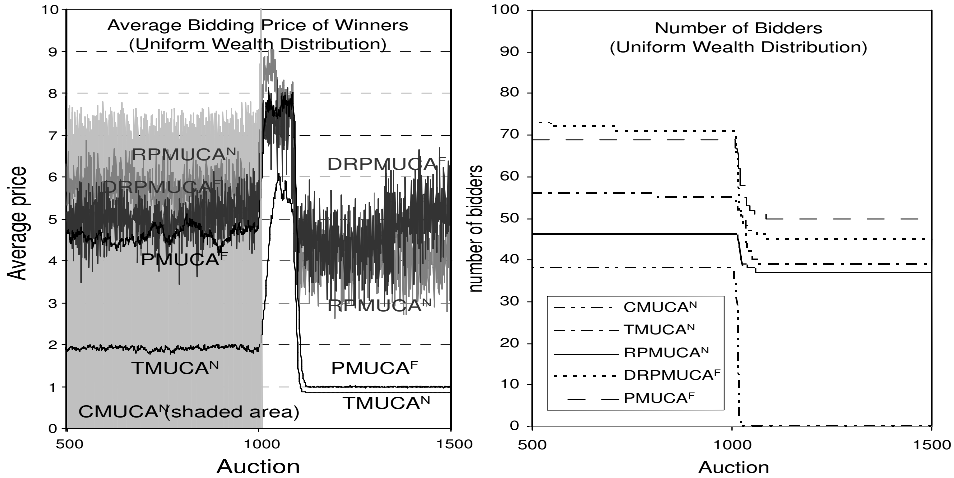

Figure 5.10: Average bidding price in scenario 6 (left). Number of bidders in the recurrent auction (right). Detail between time step 500 and 1500

steps between 1000 and 1100 by a 40%. Figure 5.10 (left) shows the average price in one simulation of this experiment. We can see how prices rise for all methods during the time with scarce units of resource (less supply, prices go up). During this period all methods suffer the drop of the poorest bidders, and as a consequence, some of the mechanisms are not able to return to their same or close steady-state when the supply is restored. Only DRPMUCA^F and RPMUCA^N achieve an acceptable average price when the supply is restored. The average total benefits in 20 simulations for RPMUCA^N is 508869.65 lower than the 635399.09 obtained by DRPMUCA^F.

In this scenario the effect of bidder drop problem is higher. All the methods have lost more bidders than in the previous one. In Figure 5.10 (right) we can see the drop of bidders produced at time step 1000. PMUCA^F is the method that has maintained the greatest number of bidders but when the supply has returned to its normal value, the method has collapsed. This fact is produced by the distribution of the resources; this problem was already described in Section 5.3.2. When bidders of the upper class get the resources at low prices due to the fair distribution, then they have no incentive to increase their bids, and prices begin to decrease. This does not happen with DRPMUCA^F, because it sacrifices resource waste for avoiding that rich agents obtain the resources due to the control of fair resources.

5.4.3 Results in the seventh scenario: arrival of new customers in RMUCA

In this scenario the supply offered by the auctioneer is constant but the market is open, that is, when a bidder is not achieving his goals (he loses more times than his TCL value) he changes randomly his auctioneer.

Figure 5.11 shows the average resource price at which each of the 6 auctioneers has sold the resources during the 2000 auctions of one simulation. In this scenario an auctioneer with the DP-ORMUCA mechanism has been added to the simulations. The x-axis represents the temporal sequence of the auctions, and the y-axis is the average price. The

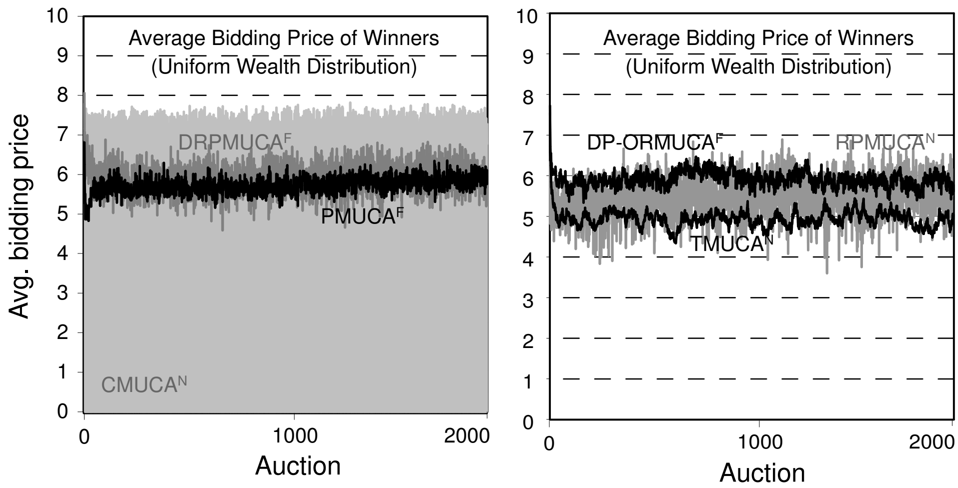

Figure 5.11: Average bidding price in scenario 7 (uniform wealth distribution).

Table 5.9: Results for all mechanisms with a uniform distribution of wealth in scenario 7. Averaged results of 20 simulations

	Mechanism	Total benefits	Resource waste	number of bidders
Fair	PMUCA^F	728411.98 (32648.43)	4009.60 (1774.66)	129.35 (6.35)
	DRPMUCA^F	724449.36 (33234.60)	9728.85 (2280.29)	112.95 (6.58)
	DP-ORMUCA^F	653070.42 (42105.04)	3772.45 (1368.39)	100.20 (5.07)
Unfair	TMUCA^N	557211.02 (37468.50)	2303.45 (1314.12)	95.10 (5.66)
	RPMUCA^N	623749.57 (51788.70)	27839.25 (4908.05)	87.30 (6.04)
	CMUCA^N	540319.67 (23578.23)	45115.90 (3627.67)	75.10 (6.71)

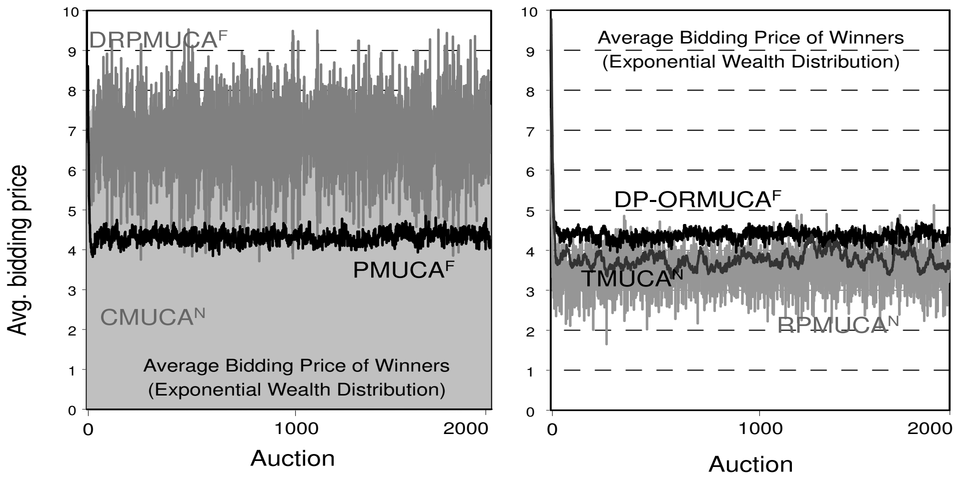

Figure 5.12: Average bidding price in scenario 7 (exponential wealth distribution).

wealth of bidders has been distributed following a uniform distribution in [2, 10]. The numerical data is shown in Table 5.9, where the total benefits, the resource waste produced by each mechanism and the number of bidders remaining with the auctioneer at the end are shown. The table values are the average of 20 simulations with the standard deviation between brackets.

Figure 5.11 shows that fair mechanisms maintain their prices at a higher level than unfair ones. Note that CMUCA^N appears in the plot as an area because the average prices are 0 when the auction is cancelled. Fair mechanisms obtain a higher number of bidders due to the fair distribution of resources. The sum of bidders of the three fair mechanism is the 57% of the market at the end of simulations.

PMUCA^F and DRPMUCA^F are the mechanisms that achieve greater benefits. Table 5.9 shows that the number of bidders achieved by PMUCA^F is 129.35. This mechanism started with the 16.66% of total bidders and finishes with the 21.55%.

In this simulation there is a direct relation between the capacity of retaining bidders in the auction and the total benefits, consequently the methods that present a fair behaviour have a better performance.

Regarding the resource waste, RPMUCA^N and CMUCA^N have been the mechanisms most affected. They have wasted the 23.19% and the 37.59% of resources respectively. Below these mechanisms, DRPMUCA^F has lost the 8.1% of resources and finally the mechanism non based on reservation prices are the ones that have wasted less resources. Note that these methods can also have resource waste due to the combinatorial nature of the problem.

When this experiment is done with a Gaussian distribution of wealth (this means few poor agents, few rich agents and a lot of middle class agents) the results are very similar, but when the wealth follows an exponential distribution (this means few rich and a lot of poor agents) the results for PMUCA^F and DP-ORMUCA^F are worse. Table 5.10 shows that all mechanisms have obtained fewer benefits with the exponential distribution except DRPMUCA^F (Figure 5.12 shows that average prices are situated in lower levels than with the uniform distribution except for DRPMUCA^F). In this situation DRPMUCA^F has sacri-

Table 5.10: Results for all mechanisms with a exponential distribution of wealth in scenario 7. Averaged results of 20 simulations

	Mechanism	Total benefits	Resource waste	Number of bidders
Fair	PMUCA^F	535626.97 (30834.01)	4690.30 (1790.65)	121.60 (6.02)
	DRPMUCA^F	741077.96 (84887.52)	11538.50 (2129.10)	119.00 (6.04)
	DP-ORMUCA^F	487037.81 (37459.22)	4943.55 (1796.52)	104.00 (5.38)
Unfair	TMUCA^N	402252.74 (25778.61)	2401.20 (1811.60)	99.05 (8.53)
	RPMUCA^N	423794.95 (41126.43)	54782.15 (5751.65)	77.80 (8.06)
	CMUCA^N	523630.06 (23249.84)	48356.80 (3114.01)	78.55 (5.09)

ficed some part of resources, wasting the 9.6% in order to maintain the prices at higher level. Although PMUCA^F is still the method with a higher number of bidders, DRPMUCA^F obtains a significantly higher benefits. Then in this situation, it is not sufficient the fair distribution, since reservation prices help to maintain the negotiation power of the auctioneer. The auctioneer that uses PMUCA^F mechanism has a weak power of negotiation. In this experiment thanks to the continuous entrance of new bidders, the PMUCA^F mechanism does not arrive to collapse but in situations with no arrival of new bidders this mechanism could collapse as in the seventh scenario.

5.4.4 Results in the eighth scenario: customers with trust in RMUCA

In this scenario the market is open and each agent has a trust model and when the bidder decides to change of auctioneer, he selects the new auctioneer taking into account the reputation.

Table 5.11 shows the results of 20 simulations. In this case the market quota obtained by fair mechanisms is higher than in the previous experiment (58.88%). This increment mainly comes from the unfair methods that use reservation prices (RPMUCA^N and CMUCA^N) that have fallen to very low values (CMUCA^N retains only 39.25 bidders). In this case the reservation prices punish the mechanisms, excepts if they are combined with fairness.

The fair methods have obtained very similar benefits, but DRPMUCA^F wastes a higher number of resources. Bidders achieve their goals in fair mechanisms and consequently they recommend their auctioneer to other bidders. These recommendations are translated in a higher number of arrivals to fair mechanisms and a decrement in the arrivals to unfair mechanisms.

Regarding the simulations done with the exponential distribution of wealth, the differences are similar as explained in the previous experiment, a decrease for PMUCA^F and DP-ORMUCA^F, and DRPMUCA^F presents the best performance.

Table 5.11: Results for all mechanisms with a exponential distribution of wealth in scenario 8. Averaged results of 20 simulations

	Mechanism	Total benefits	Resource waste	Number of bidders	Arrivals	Depart.	Recom.
Fair	PMUCA^F	723638.30	2179.25	123.30	15507.35	15384.05	89210.90
		(40356.63)	(1214.68)	(14.06)	(963.94)	(959.66)	(3.11)
	DRPMUCA^F	717589.08	10505.80	121.85	14652.85	14531.00	86779.60
		(56583.61)	(3150.51)	(10.89)	(852.16)	(848.65)	(1.99)
	DP-ORMUCA^F	716175.84	2602.30	108.15	13711.90	13603.75	84067.10
		(40909.95)	(752.22)	(10.25)	(609.28)	(605.89)	(1.57)
Unfair	TMUCA^N	653746.66	1532.80	109.45	13607.15	13497.70	83763.75
		(45497.13)	(953.82)	(10.04)	(928.22)	(922.97)	(1.60)
	RPMUCA^N	601594.80	31681.85	98.00	11480.85	11382.85	77331.75
		(54104.53)	(5445.79)	(10.88)	(987.33)	(979.45)	(3.48)
	CMUCA^N	402150.80	64835.15	39.25	4685.25	4646.00	45430.70
		(190096.91)	(26101.29)	(27.00)	(2114.03)	(2090.07)	(8.51)

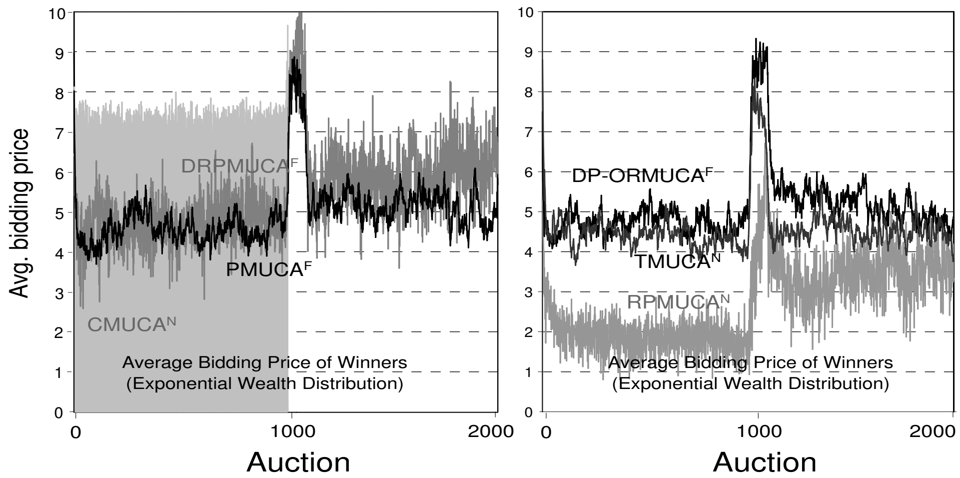

Figure 5.13: Average bidding price in scenario 9 (exponential wealth distribution) with a scarcity resources period.

5.4.5 Results in the ninth scenario: variation of supply and customers with trust in RMUCA

Finally the ninth scenario adds to the previous one variations in the supply offered by the auctioneer.

Figure 5.13 shows the average price with a variation of supply between time step 1000 and 1100 of 40%. We can see how prices rise for all methods during the time with scarce units of resource (less supply, prices go up). During this period all methods suffer a big movement of bidders that provoke the collapse of CMUCA^N mechanism. This collapse provokes that all methods improve their average prices when the supply is restored. Table 5.12 shows that fair mechanisms obtain the highest benefits and a market quota of 62.99%.

The more beneficiated mechanism is PMUCA^F that has obtained the 23,5% of the bidders improving the results of the previous experiment and obtaining the highest total benefit. When the great movement of bidders is produced, the PMUCA^F auctioneer has the best reputation between auctioneers (90177.20 recommendations) and consequently it achieves the best number of arrivals. In this situation the weakness in the power of negotiation of

Table 5.12: Results for all mechanisms with a exponential distribution of wealth in scenario 9. Averaged results of 20 simulations

Mechanism	Total benefits	Resource waste	Number of bidders	Arrivals	Depart.	Recom.
TMUCA^N	671420.27	1306.30	112.15	14220.30	14108.15	82409.15
	30202.72	896.07	8.68	803.66	803.35	1.43
RPMUCA^N	650298.47	26598.35	109.90	13020.65	12910.75	78973.45
	43465.11	4017.09	11.68	1124.15	1120.67	2.83
CMUCA^N	164967.85	95290.45	0.00	2089.25	2089.25	19219.70
	113073.92	15458.50	0.00	1324.56	1324.56	3.36
PMUCA^F	766711.12	1390.15	141.05	17068.00	16926.95	90177.20
	34115.82	776.37	8.64	1172.77	1169.35	3.08
DRPMUCA^F	766005.60	9385.35	121.30	15562.25	15440.95	85936.50
	31396.45	1675.28	7.01	640.49	639.31	2.31
DP-ORMUCA^F	742965.01	2217.85	115.60	14408.40	14292.80	82672.85
	30722.33	744.72	7.53	862.78	864.34	1.70

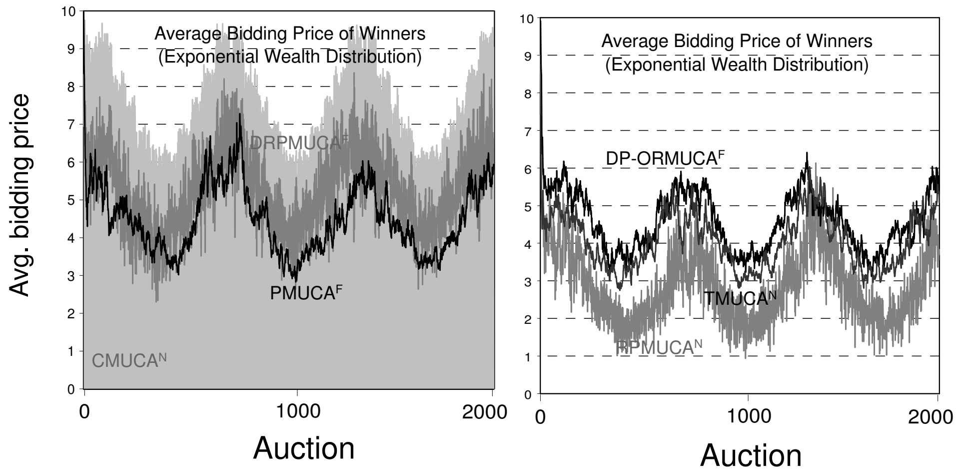

Figure 5.14: Average bidding price in scenario 9 (exponential wealth distribution) with oscillation of supply.

PMUCA^F is solved by the reputation of the mechanism achieved thanks to the fair distribution, but with the exponential distribution the total benefit obtained by PMUCA^F is 620218.13 while for DRPMUCA is 686068.23. Finally, the average prices obtained with oscillation in the supply are shown in Figure 5.14. The average prices values are similar to those obtained with the reduction of supply when the supply is restored.

5.4.6 Discussion

With the results from the simulations done in the five combinatorial scenarios the Table 5.13 can be generated. This table shows the obtained revenue, the level of fairness of each mechanism and to what degree the mechanisms are affected by the problems described in Section 2.4.1. In general the results are very similar those obtained in the non combinatorial scenarios.

Regarding the bidder drop problem the fair mechanisms are the less affected. Especially PMUCA^F is the mechanism that obtains the best performance. Contrarily, CMUCA^N is the most affected obtaining 0 bidders at the end of some simulations in dynamic environments.

Table 5.13: Summary of results.

	Mechanism	Bidder Drop Problem	Resource Waste	Asym. Balance of Negotiation Power	Fairness	Revenue
	PMUCA^F	very low	very low	high	high	medium
Fair	DRPMUCA^F	low	medium	low	very high	very high
	DP-ORMUCA^F	low	very low	low	high	high
	TMUCA^N	very high	very low	very high	very low	very low
Unfair	CMUCA^N	very high	very high	low	medium	very low
	RPMUCA^N	high	very high	low	low	medium

Regarding resource waste all the mechanisms based on reservation prices are affected, especially CMUCA^N and RPMUCA^N with a very high degree. Then, DRPMUCA^F is also affected but in a lower degree. Finally DP-ORMUCA^F, PMUCA^F and TMUCA^N are affected only a bit. In this case all methods are affected in a major or minor way due to the combinatorial nature of the problem. The results regarding the negotiation power as in the non combinatorial scenarios shows that the methods based on reservation prices are less affected.

Regarding the relation between fairness and benefits obtained by the auctioneer the mechanisms based on fairness and reservation prices obtain the higher benefits taking into account all the simulated conditions. The mechanism PMUCA^F based only on priorities achieves a very high benefits in static scenarios due to the large number of bidders that remains in the auction but a very low results in dynamic scenarios due to the loss of negotiation power by the auctioneer. In this latter scenarios this fair mechanism collapses.

5.5 Summary

In this Chapter we have experimentally evaluated the fair mechanisms presented in Chapters 3 and 4. The experimentation done in this chapter scenarios can be divided in the experiments done in static and dynamic scenarios.

The experiments in a static environment show that the mechanisms that incorporate fairness and reservation prices minimize the problems of recurrent multi-unit auctions (bidder drop problem, resource waste and asymmetric balance of negotiation power). Fairness gives bidders incentives to stay in the auction and reservation prices help to maintain the equilibrium in negotiation power.

However, experiments in dynamic scenarios show that even fair mechanisms with reservation prices can collapse when the supply of the auctioneer is reduced during an elapse of time. This occurs to the methods that fairly distribute a quantity of resources. The DRPA^F and its combinatorial version DRPMUCA^F mechanisms proposed here avoid collapsing by introducing a control of fair resources consisting in a minimum priority that prevents the fairly distributed resources from arriving to the middle-upper class agents. We can also say that in scenarios where customers can move from one auctioneer to another, fair mechanisms are more able to retain the newly arrived customers. That is, when a customer leaves an auctioneer and joins another one, if the new auctioneer uses a fair mechanism to allocate resources, the customer's probability of achieving his goals is higher than if the auctioneer was unfair. On the other hand, when bidders use trust and reputation information to decide which auctioneers to join, fair auctioneers achieve greater popularity among bidders and, consequently, the number of arrivals is higher than for unfair mechanisms. In particular, we have experimentally tested how two of our proposed mechanisms, the dynamic reservation price auction (DRPA^F) and its combinatorial version (DRPMUCA^F) present the highest averaged performance of all the simulated conditions, including the variation of supply, and makes a profit for the auctioneer while avoiding, in most cases, the resource waste problem.

CHAPTER 6
Experimentation in WWTP

In this chapter we present the application of a fair mechanism in order to deal with the coordination of industrial discharges in an Urban Waste water System (UWS). This is a real-world problem proposed by the Laboratory of Chemical and Environmental Engineering (LEQUIA) group of the University of Girona.

In this chapter we will show experimentally how this problem can be dealt with an auction-based management of industrial discharges. Then, we will show how adding fairness to the proposed solution the performance of the WWTP is improved even more.

In this domain, a fair mechanism is useful because the starvation of certain industries do not cause the drop of the industries but could provoke that they stop obeying the coordinator decisions. This is possible because of another particularity of this domain: the resources are not controlled by the auctioneer. The resource in this case is the Waste Water Treatment Plant (WWTP) capacity. The coordinator has to coordinate the discharges without exceeding the WWTP capacity, but he cannot avoid the discharges if the industries want to perform it anyway.

6.1 DOMAIN DESCRIPTION

Urban Wastewater Systems (UWS) have been usually considered as the sum of several elements that are managed separatedly to finally discharge into the water body (i.e. river) as the end-of-pipe measure. The current tendency, promoted by the Water Framework Directive (European Directive 2000/60/CE), is to treat the UWS as a single area of operations where hydraulic infrastructures, WasteWater Treatment Plant (WWTP) and point-source discharges have to be managed from an integrated point of view. The WWTP is the central unit of UWS. It receives the polluted wastewater coming from the city, rain events, and different industries connected to the sewer. Nowadays the most common wastewater treatment used is the activated sludge process. The system consists of an aeration tank in which the microorganisms responsible for treatment (i.e. removal of carbon, nitrogen and phosphorous) are kept in suspension and aerated followed by a liquid-solids separation, usually called secondary settler. Finally, a recycling system returns a fraction of solids removed from the liquid-solids separation unit back to the reactor, whereas the other fraction is wasted from the system [51].

The treatment capacity of the plant is limited, therefore all pollutants arriving at the WWTP should be under certain limits; otherwise, wastewater could not be optimally treated, increasing the impact to the river. Currently, there exist regulations intended to achieve this goal by assigning a fixed amount of authorized discharges to each industry. However, they are not sufficient to guarantee the proper treatment of the wastewater. The problem is that, although these regulations enforce industries to respect the WWTP capacity thresholds, they do not take into account that simultaneous discharges by different industries may exceed the WWTP's thresholds. In such a case, no industry would be breaking the rules, but the effect would be to exceed the WWTP capacity. Besides, industry discharges add complexity to the wastewater treatment system, given that the high variability in influent pollutants composition hampers the WWTP operation. Being aware of this problem, the Laboratory of Chemical and Environmental Engineering (LEQUIA) of the University of Girona presented us the challenge of developing a mechanism to deal with these issues. Although a free market system for allocating water resources has always been the goal of the economists, the authors are aware of very few cases in USA and Australia where it really works. Colorado has a sophisticated water rights market, the State Water Project in California has a system to allow water users to purchase water (it is more a "first come, first served" than a true auction), the State of Idaho has a water banking system on the Snake River that is based on selling water from storage in state owned reservoirs, the State of Kansas has a water marketing program to sell state-owned storage space in federal reservoirs (similar to the California State Water Plan), the State of Arizona has local units of government established for the specific purpose of storing water underground for subsequent use by participants, and similar attempts at water auctioning have been made for the Murray-Darling system in Australia. The general idea is that there is not yet free market based on auctions for water transfer, but there are some water rights transfers, highly regulated but still very inefficient.

This wastewater treatment problem could be solved using a centralized approach for which there is a vast literature [7, 79], where given all the planned discharges from the industries, a new schedule for each of them would be generated, in a way that the resource capacities of the plant were not exceeded at any time. Centralized approaches imply that a central scheduler would make all the decisions. However, such decisions should be made by each of the industries, since they may not be willing to disclose private information related with the production process upon which their decisions are based. Thus, in order to preserve privacy, other coordination mechanisms should be considered.

To allow for a more participative mechanism, a distributed approach can be taken. In this case, the agents can interact with the scheduler or between them in order to reach an agreement on the schedules. This approach can be divided into two main classes, depending on who is the responsible of decision making:

- *Partial decentralized approach*. In this kind of scheduling, as in the classical one, there is a single entity that solves the problem. However, there is some interaction between the agents and the scheduler, so that the decisions are not totally taken by the latter. An example of such approach are market-based mechanisms, such as auctions [12, 77], where agents bid for using the resources and the auctioneer must decide which agents can do so.
- *Decentralized approach*. In this approach there is no central entity, but the agents are themselves the ones solving the scheduling problem. They communicate with each other in order to reach a solution. This approach includes negotiation protocols, in which agents trade resources until they are all satisfied with the allocation [38], and also distributed constraint optimization problems [52, 63].

In this chapter an auction based mechanism is proposed to deal with the WWTP problem. Auctions are currently being used in several industrial scenarios [4], as the electricity market in which different kinds of energies are auctioned in order to favour the use of non

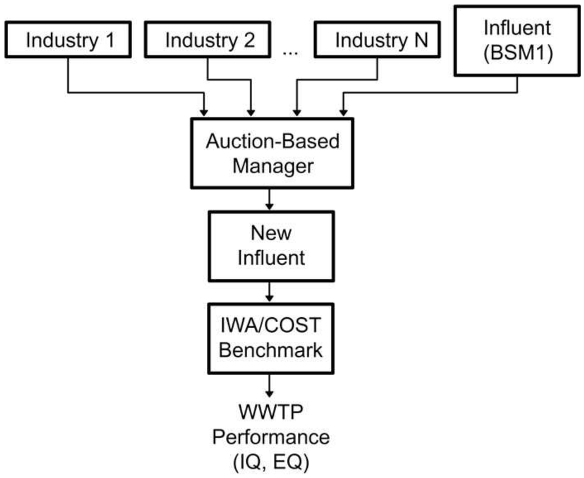

Figure 6.1: Coordination system.

pollutant sources of energy [32]. Recently, auctions have been also considered to deal with natural resources, as CO_2 emissions [72]. In these models, each industry bids for CO_2 emission credits, in such a way that high pollutant industries pay for a lot of emission credits (unless they install some kind of filters in their factories), while industries with non pollutant processes do not need any emission credit, keeping their manufacturing process at a lower cost. In this context, it seems suitable to raise the possibility of using auctions to deal with wastewater resources, as in an UWS. Moreover, this approach is in line with a more integrated management of the river basin [1, 18] taking into account not only the plant, but also the rest of the components of the treatment system, such as the industries and their discharges.

In the wastewater treatment scenario there is a key element, the treatment plant, which assumes the role of coordinating the discharges of the industries. Then, the wastewater treatment plant's hydraulic and pollutants capacities are modelled as individual resources (one for hydraulic capacity and one for each pollutant) shared by all the industries. Each time a conflict in a resource occurs (i.e. the hydraulic or some pollutant capacities is exceeded) an auction is held in order to determine which of the conflicting discharges will be authorized to discharge and which will have to be delayed. For such purpose it is assumed that each industry has a retention tank of a given capacity, where it can store a discharge whenever it is not authorized, and empty it later on. Also it is assumed that each industry can estimate in advance the discharges that it will generate according to the production process. Although this estimation may differ from the real discharges, they help in the process of coordinating all the discharges and so, adjusting properly the UWS management capacity.

Figure 6.1 shows a scheme of the coordination system. The auction-based manager receives the discharges of industries and the urban influent (modeled with BSM1 [29]). Then, the auction-based manager performs the coordination process by replanning the industrial discharges and producing a new influent. Finally the output of the coordination is analyzed with the IWA/COST simulation benchmark [14]. To model such UWS a multiagent approach has been followed.

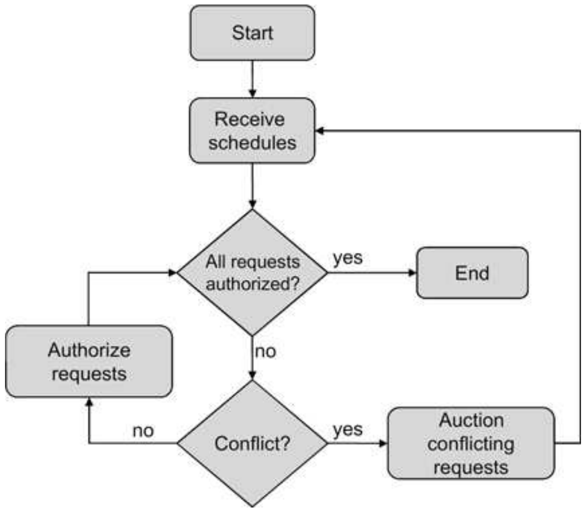

Figure 6.2: Auction-based manager.

6.2 Experimental setup

6.2.1 Multi-agent modeling

Multi-agent systems allow the implementation of complex interactions among the different agents through an appropriate coordination mechanism [2]. In the UWS scenario, the WWTP agent owns the resources (hydraulic and pollution capacities) while the industry agents want to use them.

The process for coordinating the different discharges coming from the industries is depicted in Figure 6.2 and is described in Algorithm 5. Firstly, the industries inform the WWTP about their scheduled discharges. These schedules contain the set of discharges that they plan to perform in a given period of time, and for each discharge the information about its starting time, duration, flow and pollutant levels is also included. Hence, a schedule from an industry i is described as $SC_i = \{d_1, ..., d_n\}$ where n is the number of discharges contained in the schedule and each discharge d_i is defined as $d_i = \{st_i, dur_i, \overline{q}_i\}$, where st_i stands for the start time, dur_i is the duration and $\overline{q}_i$ is a vector containing the flow and pollutant levels of the discharge. The start time of discharges can be modified depending on the industries location: when a difference between the discharge time and the discharge arrival to the WWTP exists this delay should be added to st_i.

Once the WWTP agent has received all the industries' discharge schedules for a given day (or any different predefined period of time), it starts checking for conflicts. A conflict arises when the discharges planned to be performed at a given time violate at least one constraint. The mechanism starts searching for conflicts at the initial time step and advances in a sequential way, treating one conflict at a time in chronological order. Whenever a conflict is detected, the involved industries (the industries whose discharges are scheduled at the time of the conflict) are informed about it, and an auction is started to solve it, eventually forcing some industries to modify their schedules. When the conflict is solved the mechanism continues searching for the next conflict until all the discharges have been authorized, and each industry has a schedule that does not produce any conflict. For this mechanism it does not matter if we use a planning horizon of one day, one week or one month. Actually, an auction is performed each time a conflict is detected. Thus, the mechanism is indepen-

Algorithm 5 Coordinator agent pseudo-code

```
receive schedules from agents
while not all requests authorized do
  for all time steps do
    if no conflict during current time then
      authorize current requests
    else
      solve conflict
      inform agents about resolution
      break for loop
    end if
  end for
  receive updated schedules from agents
end while
```

dent of the period that the WWTP agent wants to plan. We propose that industry agents send their schedules one day in advance but it could be weekly, monthly, etc. without incrementing the complexity. A point in favour of making the planning one day in advance is that the resulting schedule (i.e. when all conflicts have been solved) affects only one day. On the other hand, if the schedule were to be for a whole week, the industries would be attached to it for a longer period, which would prevent them to change their planned activity (unless they decide not to follow what they agreed to do). Thus, using planning horizon of one day gives industries more flexibility to adapt their plans. The unauthorized discharges should not cause problems in the production processes of the industries. In case an industry agent has to reschedule its discharges, its behavior is the following: it first tries to store the rejected discharge into the retention tank; the discharge of the tank is then scheduled as the first activity of the agent once the current conflict has finished. Conversely, if the industry has its tank already full, the discharge will be performed anyway. However, the influent coming from the domestic use does not have any retention tank and, consequently, its discharges cannot be modified.

Note that it is not necessary to know in real-time the industrial discharges, since the coordination process is done offline, for example one day before.

6.2.2 Auction mechanism

Once the involved discharges in a conflict have been detected, their corresponding agents (industries) are informed about the conflict and a new auction process begins. The industries which are not involved in a conflict could also participate in the auction, however they would be winners for sure, since their items requests do not conflict with any other requests, thus they would be assigned the resources they wanted. Thus, we can directly set them as winners and there is no need to have them participate in the auction, the outcome of it being the same.

The WWTP agent assumes the auctioneer role who is in charge of selling its hydraulic and pollution capacities and the industry agents assume the bidders role. The goal of the auction is to select a subset of discharges, which will be authorized to be performed, while the remaining should have to be delayed (stored in the tank). The selection criterion is based on the bids submitted by the agents. A bid of an agent i is composed by a bundle

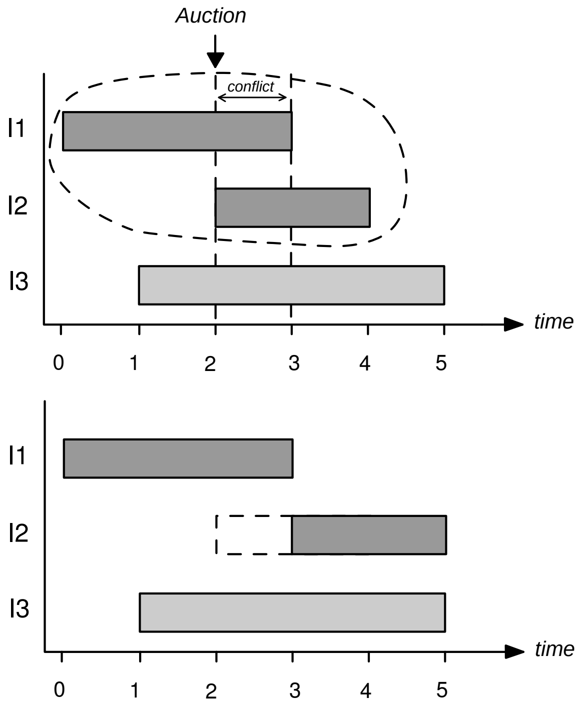

Figure 6.3: Example of request conflicts. Top: conflict between industry I1 and industry I2. Bottom: conflict solved delaying the discharge of I2.

of different items, the quantity of each item that the agent wants and the price that the bidder wants to pay ($b_i = \langle \overline{q}_i, v_i \rangle$). In our mechanism we have one item for each pollutant and one item for the global hydraulic requirement. The bid's price represents the urgency the industry has in performing the discharge. A high price indicates that the agent really needs (or wants) to perform the discharge, while a low bid indicates that the agent could delay the discharge and therefore it can afford the loss of the opportunity to perform it at the auctioned time. For example the bid value v_i of the industry agent i could be calculated dividing the tank occupation of the industry by the total capacity of its tank. Even though we have used the tank capacity for bidding generation, other policies can be designed by industries according to their strategies.

The auction process based on conflicts allows industries to express their interest of discharging at a given time through the bidding policy. Other approaches could be also considered as to run a unique auction for a day. But this situation is very hard for the industries to decide the bid because they do not know if the previous discharges have been performed or not. In a conflict-based auction like the one proposed here the bidders know the result of previous auctions and can estimate the urgency of obtaining the next discharge authorization.

The auctioneer clears the auction (i.e. determines which discharges to authorize) by solving the Winner Determination Problem (WDP) [35]. Particularly, since the auctioneer offers multiple (but limited) units of different items (hydraulic capacity and pollutants), and bidders submit bids for a certain number of units of each resource, we are dealing with a multi-unit combinatorial auction.

The available units of each resource are determined by the capacities of the plant. For example the available units of the resource that represents a pollutant is determined by the maximum concentration that the plant can absorb. As an example, assume there are 3 industries (I1, I2 and I3) and a WWTP with a hydraulic capacity of 1000 units and being able to accept up to 100 units of a pollutant c. In a first stage, industries send their schedules to the WWTP agent. Then, the WWTP agent starts searching for conflicts from the initial time step. If the planned discharges at a given time do not produce any conflict, they are temporarily authorized. Otherwise, if in a given time step, the WWTP agent realizes that industry I1 wants to perform a discharge with a hydraulic capacity of 400 units and 50 units of pollutant c, and at the same time the industry I2 plans to discharge 350 units of hydraulic capacity and 60 units of pollutant c and I3 to discharge 50 units of hydraulic capacity, given that the sum of pollutant c units exceeds the limit accepted by the WWTP (i.e. $50 + 60 + 0 > 100$), a conflict occurs. At this moment I1 and I2 are informed about it and the auction starts. Note that the industry I3 is not involved in the conflict since it is not requiring any unit of the pollutant c. The WWTP agent offers the capacity of the plant, in this case 950 units of hydraulic capacity, since the hydraulic capacity required by I3 is not auctioned, and 100 units of the pollutant c. Then industries send their bids: industry I1 sends a bid composed by a price of 10 and requests 400 units of hydraulic capacity and 50 units of the pollutant c; on the other hand, I2 sends a bid composed by a price of 7 and requests 350 units of hydraulic capacity and 60 units of pollutant c. Then the auctioneer clears the auction. In this case the winner is I1, since it offered a higher amount, and there is no room for accepting any other bid (i.e. authorizing the discharge of I1 leaves the WWTP with 550 units of hydraulic capacity and 50 units of pollutant c unused, which are not enough to satisfy the request of industry I2). Then I1 is informed that its discharge has been authorized, while I2 is informed that its discharge has not. At this moment I2 will have to resubmit a new schedule in which the unauthorized discharge is scheduled later. This process continues until the WWTP agent reaches the end of the schedules with all discharges having been authorized. Figure 6.3 graphically shows this example where the discharge of I2 is delayed.

6.2.3 Adding fairness

The auction process is repeated every time a new conflict is detected. This leads to a Recurrent MUCA model (RMUCA), where the same bidders are continuously competing for the same resources. One of the main concerns in recurrent auctions is to keep the agents interested in participating in the auction. If only a small subset of the agents wins the auctions, the rest of the agents may decide to leave the marketplace since they are not getting any benefit, in what is known as the bidder drop problem, as described in Section 2.4.1. In the WWTP domain to leave the auction process means that industries do not agree with the coordination process and they start to perform their discharges without taking into account the coordinator decisions.

To avoid, or somehow decrease, the bidder drop problem, the recurrent auction process should have some degree of fairness, so that every agent has some possibility of winning from time to time. This would keep the agents attracted in taking part in the auction, which would benefit the global performance of the system. To introduce fairness in the system we have chosen a variation of the PMUCA mechanism.

Since we are dealing with coordinated but uncontrolled resources, priority helps the coordinator to model possible agents behaviors that use the resource even when they are not authorized to do so. That is, although agents are honest, if they have their schedules

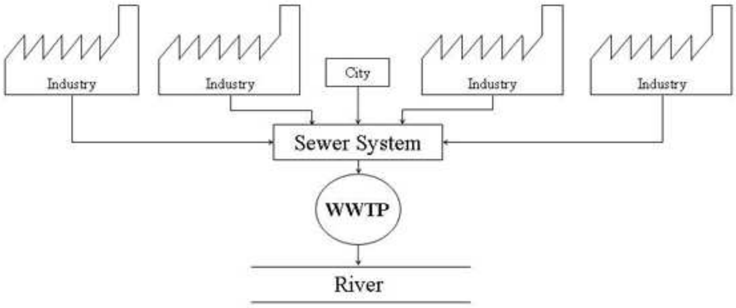

Figure 6.4: Case study.

Table 6.1: Average flow, BOD, COD, TKN and TSS concentrations of the urban influent and each industry with standard deviation in brackets.

	Flow (m^3/day)	BOD (mg/l)	COD (mg/l)	TKN (mg/l)	TSS (mg/l)	Tank Flow (m^3/day)	Tank Capacity (m^3)
Urban influent	18446.33 (5135.90)	112.92 (27.53)	360.00 (90.16)	51.47 (12.11)	198.57 (58.56)	0.00	0.00
Slaughterhouse	2576.02 (200.01)	336.84 (0.00)	1200.00 (0.00)	103.78 (0.00)	54999 (0.00)	2500.00	520.00
Textile	1682.08 (184.43)	336.8 (0.00)	1499.99 (0.00)	22.50 (0.00)	99.99 (0.00)	1500.00	333.33
Paper	5000.00 (0.00)	333.33 (0.00)	1500.00 (0.00)	58.80 (0.00)	750.00 (0.00)	5000.00	1041.66
Paper	659.63 (287.29)	200.00 (0.00)	1500.00 (0.00)	12.52 (0.00)	300.00 (0.00)	1000.00	104.16

continuously delayed, their buffers can become full and forced to use the uncontrolled resource. Thus, priorities try to capture this information related to the urgency to fulfill the agents necessities; or the other way around, they avoid having disobedient agents.

6.2.4 Case study

Our case study is a simplified UWS with 4 industries (slaughterhouse, textile, paper and pharmaceutical) connected to the sewage system that directs the wastewater from the city to a WWTP (Figure 6.4). Once the wastewater has been treated, it is discharged to a stretch of a river.

In Table 6.1 we can see the average flow of discharges and the pollutant concentrations (the Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Kjeldhal Nitrogen (TKN) and Total Suspended Solids (TSS)) of the urban influent and each industry. Then, for the industries we can also see the tank flow and the retention tank capacity. The tank volumes were suggested by experts of the domain based on industrial discharge profiles. Then, Figure 6.5 at left shows the flow of the 4 industries, the flow of the influent coming from the domestic use and the sum of all flows along a week. We can see that the flow increases caused by industries. Figure 6.5 right shows a zoom of industries' flows. Table 6.1 shows that the industrial discharges have a BOD, COD, TKN and TSS concentrations higher than the urban influent concentrations.

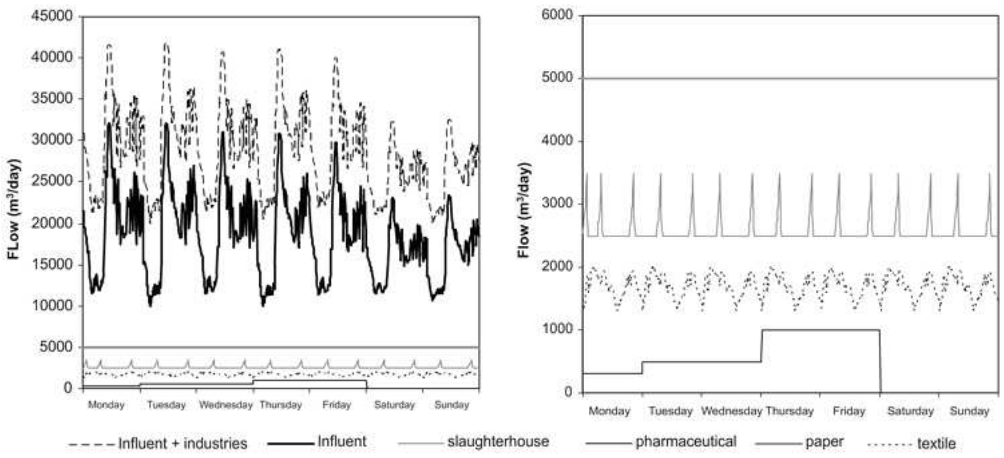

Figure 6.5: Flow of the influent, the industries and total flow (left). Flow of the industries (right).

The first industry considered is a slaughterhouse that discharges a constant flow of 2500 m^3/day but two times every day the industry has a peak of production. During these peaks, the flow discharged is increased up to 3500 m^3/day. The average flow of this industry is 2576.02 m^3/day and the standard deviation is 200.01 m^3/day. Note that the discharges performed by the slaughterhouse have a high concentration of TSS (549.99 mg/l). The tank of the slaughterhouse is 520 m^3 with a flow of 2500 m^3/day.

The second one is a textile industry, whose discharges flow oscillates during all the days between 1300 m^3/day and 2000 m^3/day. The tank of the textile industry is 336 m^3 with a flow of 1500 m^3/day.

The third one is a paper industry that discharges a constant flow of 5000 m^3/day during the seven days of the week. These discharges have a high concentration of TSS. The tank of the paper industry is 1041.66 m^3 with a flow of 5000 m^3/day.

The last one is a pharmaceutical, which is increasing its discharge flow during the week and does not discharge during the weekend. On Mondays the flow is 300 m^3/day, then on Tuesdays and Wednesdays is 500 m^3/day and finally on Thursdays and Fridays is 1000 m^3/day. Then the average flow is 659.63 m^3/day with a standard deviation of 287.29 m^3/day. The tank of the pharmaceutical is 104.16 m^3, and the tank can be emptied with a flow of 1000 m^3/day.

Industries discharges are added to the effluent of the city which is fixed and cannot be coordinated. Altogether represent the WWTP influent. Thus, the output of the auction system is a set of coordinated discharges that is entered as input for the WWTP.

As a model for the WWTP, the IWA/COST Simulation Benchmark has been used. This simulation protocol has resulted in more than 100 publications worldwide [33] and provides several tools such as control evaluation, prediction, estimation of biomass activities and effluent quality parameters. The Benchmark Simulation Model N1 (BSM1) layout contains the Activated Sludge Model N1, ASM1 [29] for two anoxic and three aerobic tank reactors, followed by the Takacs ten-layer model for the secondary settler [71]. Model influent files include 14-days weather disturbances (i.e., dry, rain and storm weather) with 15-minutes sampling. In our case, the dry BSM1 influent has been selected and modified with a set of data to represent industries discharges. Among the results of the simulation performance evaluation, the BSM1 provides the Influent Quality index (IQ) and the Effluent Quality index (EQ) which are a weighted calculation of the amount of pollutants (i.e. carbon and nitrogen in different forms) present in both the influent and the effluent of the model. They are used for the plant performance evaluation based on the total kilograms of pollutants present in the influent and the effluent [14]. IQ and EQ represent the standardized evaluation indices within the simulation protocol of the BSM for comparing simulation results (i.e. [13, 3]). We have essentially considered the IQ and EQ values for the evaluation of the auction system. Likewise, the outcome of the benchmark permits us to observe the effects of the coordination mechanism on the quality of the treated wastewater.

6.2.5 Scenario

In order to compare the results obtained with and without auction-based management, four different scenarios have been defined:

- The first scenario considers the influent (dry) without industrial discharges. This scenario shows the wastewater IQ and EQ when simulating with only domestic wastewater (i.e. BSM1 default influent file). This scenario represents the ideal scenario where the industrial discharges do not affect to the river quality.
- The second scenario adds the industrial discharges to the influent, without using the auction-based management mechanism. This scenario is useful to calculate the impact of industrial discharges in the WWTP effluent. None of the discharges violate current legislation but there is a deterioration of water quality (increase of IQ and therefore EQ) due to the industrial discharges. We have measured such deterioration. This is a baseline scenario and any optimization mechanism should improve the results of it.
- The third scenario is the same as the second one but using the auction-based management mechanism. This scenario is useful to determine the benefits of the proposed system in terms of EQ.
- The fourth scenario adds to the auction-based mechanism the priorities calculated as in the PA mechanism following the Equation 3.1. Also in this scenario bidders could disobey the WWTP decisions.

In order to coordinate the industrial discharges and improve the effluent quality, the following constraints have been defined:

- Hydraulic capacity constraint. This constraint ensures that the total flow arriving to the WWTP (from the influent and industrial discharges) does not exceed a certain threshold at any time. This threshold is called the Maximum Flow (MF).

$$\forall ts \in [0, TS] : \forall c \in C : \sum_{i=0}^{N} flow_{i,ts} \leq MF \qquad (6.1)$$

  where TS is the final time of the simulation, N is the set of industries (including the influent) and $flow_{i,ts}$ is the flow discharged by industry (or influent) i at time ts.

Table 6.2: Results obtained with the benchmark BSM1 in different scenarios.

		IQ $(\frac{Kg.poll.\cdot unit}{day})$	EQ $(\frac{Kg.poll.\cdot unit}{day})$	Increment $(\frac{Kg.poll.\cdot unit}{day})$	Reduction	Constraints
Domestic influent (scenario 1)		42042.81 (20195.42)	7556.54 (2219.93)	-	-	-
Influent and industries	w/o auction (scenario 2)	59092.21 (20080.39)	9127.37 (2303.71)	1570.83	-	-
	With auction (scenario 3)	59163.90 (16527.12)	8958.64 (1935.64)	1402.11	10.74%	R1
		59139.67 (16225.36)	8901.23 (1931.82)	1344.70	14.40%	R2
		59157.73 (15854.09)	8900.13 (2073.70)	1343.60	14.47%	R3
		59126.16 (16086.98)	8886.15 (1906.97)	1329.61	15.36%	R4
		59158.62 (18489.36)	9043.95 (2162.55)	1487.42	5.31%	R5
		59132.39 (13378.48)	8797.63 (1729.65)	1241.10	20.99%	R6

- Pollution constraints. These constraints ensure that the concentrations of certain components arriving to the WWTP do not exceed their respective thresholds at any time. There are 4 constraints, for the following components: COD (Chemical Oxygen Demand), BOD (Biological Oxygen Demand), TKN (Total Kjeldhal Nitrogen) and TSS (Total Suspended Solids). Each constraint is defined as follows:

$$\forall ts \in [0, TS] : \forall c \in C : \frac{\sum_{i=0}^{N} conc_{i,c,ts} \cdot flow_{i,ts}}{\sum_{i=0}^{N} flow_{i,ts}} \leq MC_c \qquad (6.2)$$

  where C is the set of components (COD, BOD, TKN and TSS) and $conc_{i,c,ts}$ is the concentration of component c produced by the industry i or influent at time ts. MC_c is the maximum concentration threshold for component c.

Six different constraint threshold sets have been considered. R1 is related to the maximum flow (MF of Equation 6.1), setting it to 32000 m^3/day. The R1 pollutant thresholds (MC of Equation 6.2) are set to ∞. R2 sets the Maximum TSS to 275 mg/l and the other thresholds to ∞. R3 dictates a Maximum TKN of 55 mg/l and the other thresholds are set to ∞. R4 states BOD = 234 mg/l and the other thresholds to ∞. R5 states Maximum COD = 575 mg/l and the other thresholds to ∞. Finally R6 contains a threshold for all the constraints (Equation 6.1 and 6.2): Maximum flow = 32500 m^3/day, Maximum TSS = 275 mg/l, Maximum TKN = 50 mg/l, Maximum BOD = 260 mg/l and Maximum COD = 100 mg/l [14]. The values of the constraints thresholds were fixed by the experts of the domain according to their experience.

6.3 Experimental results

The experimental results have been obtained with the simulation protocol BSM1 in the three first scenarios previously described. In order to evaluate the system the effluent quality has been considered. Then, in the fourth scenario, the number of overflows, the maximum flow overflowed and the total volume overflowed have been used in order to evaluate the improvement on the system adding priorities.

Table 6.2 shows the results obtained with the different scenarios. The first column is the

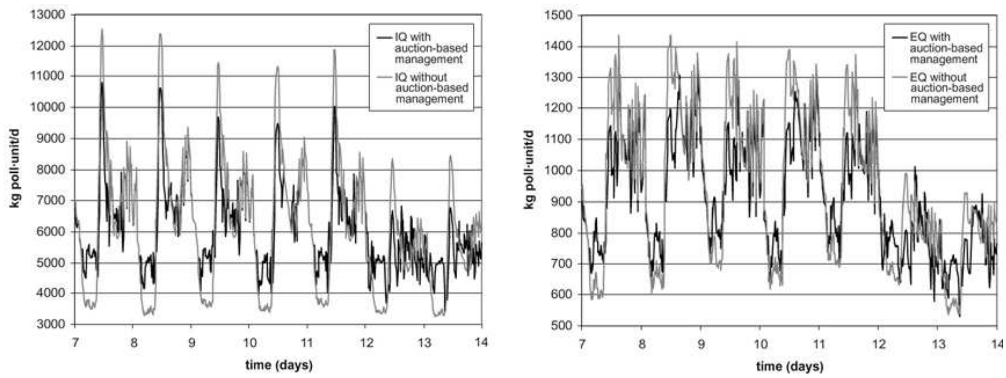

Figure 6.6: Influent Quality index (IQ) during the 7 simulated days (left), Effluent Quality index (EQ) during the 7 simulated days (right).

Influent Quality Index (IQ) measured by BSM1, integrating the last seven days of weather simulation [14] with the standard deviation in brackets. The second column corresponds to the EQ measured by the benchmark with the standard deviation too. The third column (Increment) represents the difference in the EQ value between the first and the other scenarios; this value represents the impact of the industrial discharges in the wastewater. The fourth column shows the reduction in percentage on the value Increment when using the coordination mechanism. Finally, the fifth column (Constraints) indicates the set of constraints thresholds used for the coordination.

The results of Table 6.2 show that the value of EQ obtained in the first scenario is 7556.54 $Kg.poll. \cdot unit/day$. When the industrial discharges are added to the influent in scenario 2, the value of EQ becomes 9127.37 $Kg.poll. \cdot unit/day$, therefore the industries are causing an increase of 1570,83 $Kg.poll. \cdot unit/day$. The other data of the table corresponds to the executions of the benchmark in the third scenario with coordinated data and using different sets of constraints, showing that when the auction-based management mechanism is used, the EQ is reduced and consequently, the impact of industrial discharges (Increment) is smaller. In the best case (set of constraints R6) the impact is reduced up to 20.99%. According to the t-test, the values of the mean and standard deviation of EQ in the second scenario and the best EQ obtained in the third scenario (set of constraints R6) are statistically extremely significant.

Figure 6.6 (left) graphically shows the values of IQ during the seven days with and without auction-based management. This picture shows that the auction-based management has lowered the upper values and raised the lower values. The steadiness in the IQ profile is important as it improves wastewater treatment by reducing the variability of the influent composition. This circumstance allows the WWTP to process more efficiently the pollutants and consequently achieve better results regarding EQ. Figure 6.6 (right) shows the comparison between the EQ values during the seven days with and without auction-based mechanism. Analogously to the Influent Quality Index (IQ), the values have also been homogenized.

Figure 6.7 shows the final schedule of the textile industry and the pharmaceutical industry after the coordination process. Then we can compare the final schedules and the initial schedules that appear in Figure 6.5 and we can see the impact of the coordination process. We can observe that periodically some gaps appear where the discharges are not authorized and later the industries can recover discharging from the tank.

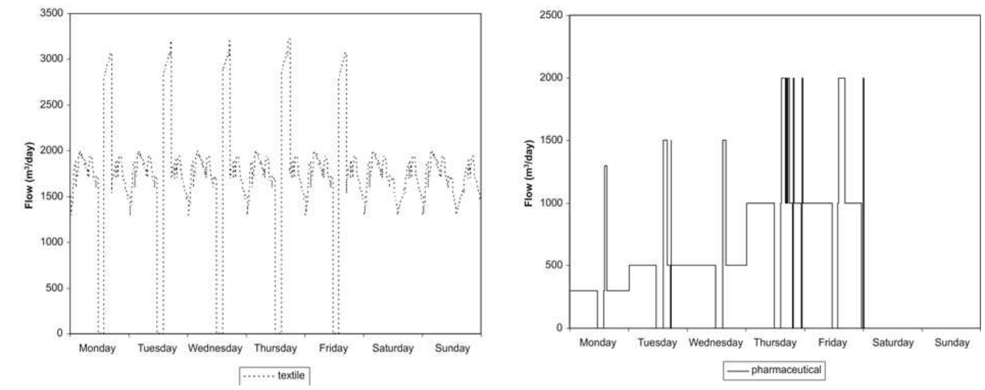

Figure 6.7: Final schedule of textile industry (left) and the pharmaceutical (right).

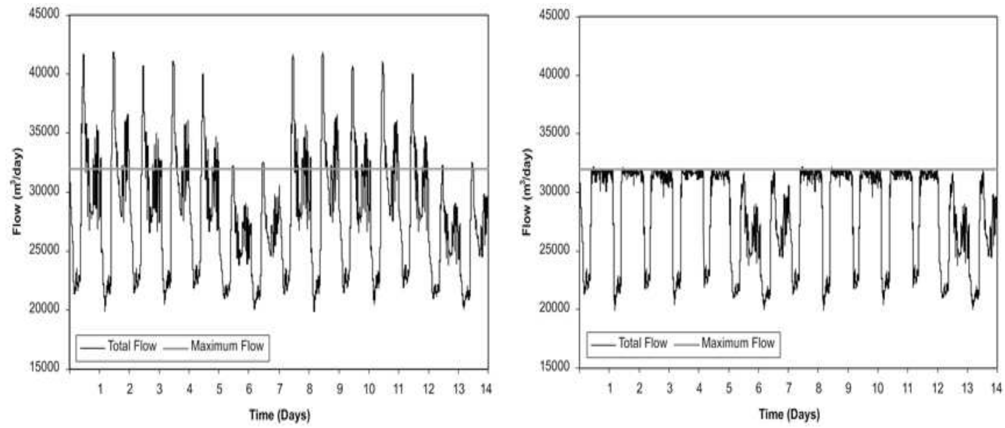

Figure 6.8: Incoming total flow without (left) and with (right) coordination.

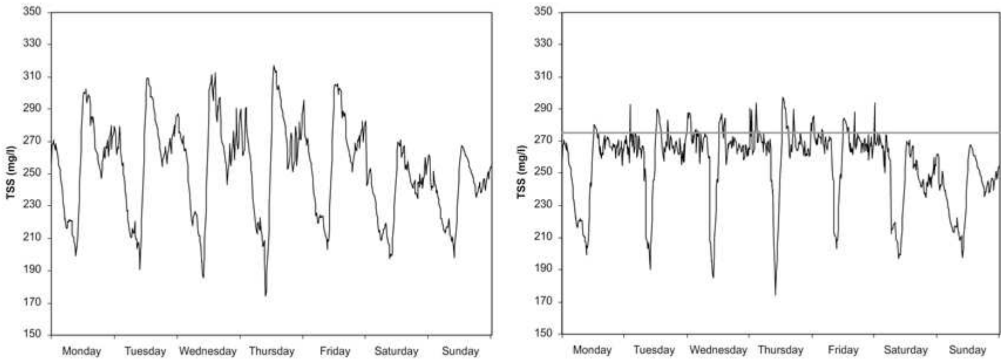

Figure 6.9: TSS without (left) and with (right) the coordination.

Table 6.3: Experimental results obtained in the fourth scenario.

		NO	MFO	VO
Obeying	Without coordination	80.00 (0.00)	9826.00 (0.00)	15213000.00 (0.00)
	Auction-based management	24.00 (0.00)	4996.00 (0.00)	2917420.00 (0.00)
	Fair auction	21.00 (0.00)	4996.00 (0.00)	2544730.00 (0.00)
Disobey	Auction-based management	54.30 (4.31)	14313.35 (1289.01)	9054222.25 (238358.66)
	Fair auction	53.20 (3.11)	14502.90 (1353.67)	8961188.80 (139828.04)

Figure 6.8 shows an example of the incoming flow, without the coordination mechanism at left and with the coordination mechanism and the constraints set R1 (right). We can see how some discharges are distributed in time in order to reduce the overflows. On the other hand Figure 6.9 shows the TSS without and with the coordination with the constraint set R2. In this case the values of the TSS concentration are homogenised.

Then, we have experimentally showed how the auction-based management of discharges improves the WWTP performance. Concretely the constraint set R6 shows the best results. Now here we have added to the auction-based mechanism priorities in order to add fairness to the system. The WWTP has a priority calculated following Equation 3.1 of each agent that is used to clear the auction as in the PA mechanism. Although the environment is combinatorial this mechanism has been used as a first approach.

As the resources auctioned in this domain are uncontrolled, the behaviour of the industries has been simulated allowing them to disobey the WWTP decisions. This disobedience is modelled by a probability function that depends on the tank occupation. The probability that an industry disobey is modelled as follows:

$$pd = \left[\frac{1}{1+e^{-sl(2x-1)}} \cdot (1-min)\right] + min \tag{6.3}$$

Where x is the tank occupation, sl is a parameter indicating the function's slope, and min is the minimum probability value returned by the function. With such function, the probability to disobey increases as the tank occupation level is higher. This function is the same as the bid value, so when the bid value is high the probability of disobey is also high.

Table 6.3 shows the average and standard deviation between brackets of the number of overflows (NO), the maximum flow overflowed (MFO) and the volume overflowed (VO) obtained in 20 simulations.

The table shows the results of the second, third and fourth scenario when all the industries obeys the WWTP decisions. There are 80 overflows of the WWTP hydraulic capacity the system does not use any system for the coordination but when the system uses the auction-based management this number is reduced to 24. Also when priorities are introduced this number is reduced again up to 21. The same happens with MFO and VO, with auctions these values are reduced drastically and with priorities they are reduced a bit more.

Regarding disobedience, Table 6.3 shows the results when the industries disobeys (min = 0 in Equation 6.3). The results show that when industries disobey, obviously the performance in all scenarios is worst but better than the second scenario where there is not any coordination. Regarding priorities, they help to improve the results also in the case of disobedience.

6.4 Summary

This chapter has shown how a fair auction mechanism can be used in a real world problem. The problem, posed by the Laboratory of Chemical and Environmental Engineering (LEQUIA) group of the University of Girona, is the coordination of industrial discharges done in order to improve the performance of a wastewater treatment plant (WWTP).

The use of an auction-based management mechanism has been proposed in order to coordinate the industrial discharges in a simplified UWS. In this auction, the WWTP assumes the role of the auctioneer that is selling its capacity as a resource, and the industries assume the role of bidders that want to buy the WWTP capacity. The auction determines which industries are going to be allowed to discharge to the sewage system and which are not. This process is repeated each time the hydraulic capacity constraint or the pollution constraints would be violated by the discharges in a given time (if they were not coordinated). The results obtained with the IWA/COST simulation show that the auction-based management mechanism using pollution and hydraulic capacity constraint reduces the impact of industrial discharges up to 20.99%. This fact has been possible due to the IQ variability reduction, since it has made the WWTP able to process the pollutants more efficiently.

Then, adding fairness to the auction-based management, the results are improved even more. Also the disobedience of industries to decisions of the WWTP has been modelled since in this domain the resources are uncontrolled and fairness helps to reduce the number of disobediences improving the performance of the WWTP also in the latter case.

Although the simulations do not completely match the treatment system in reality, it is a good starting point for showing to the public authorities and to the industries that the auction-based management approach could help improving both the wastewater management and the water quality.

CHAPTER 7
Manipulations and equilibrium

In the experimentation presented in previous chapters we have assumed that the bidders are honest and they do not try to manipulate the mechanism with strategies or manipulations. They want to obtain the maximum revenue but not to cheat to the auctioneer. In this chapter we discuss some possible strategies that the bidders can follow in order to cheat to the auctioneers and obtain more benefits. Then, a learning bidder agent is designed and the result of experimentation with this kind of agents is presented. The aim of the learning agent is to know the best strategy learnt by bidders and to show the weaknesses of fair mechanism presented in previous chapters.

The chapter is divided in two blocks, in the first one a set of possible manipulations and examples are presented. In the second block the equilibrium of presented fair mechanisms is studied experimentally.

7.1 MANIPULATIONS

Basically we present three families of cheating: the false-name bids, underbidding and overbidding. These kinds are subdivided in different kinds and we present some examples of each one. In order to follow the examples some concepts are defined here. First the *true value* about a package is a private value of each agent and is the maximum price that is willing to pay. In other words the true value is the valuation that the agent makes about the package. Then, the utility obtained in an auction by an agent is defined as the true value of the won package minus the payment done. For example, if an agent won a package and his true value for this package is 5 and the payment done is 3 then, the utility for the agent is 2.

7.1.1 FALSE-NAME BIDS

Bidders can manipulate an auction mechanism creating multiple identities and sending different bids with each identity. There are three different ways to manipulate an auction mechanism with this strategy. The first one is the presented in [70] by Suyama and Yokoo and the other two are introduced in the mechanisms with the priorities. The false-name bidder manipulation can be avoided when the auctioneer can check the identity of bidders but this is not possible in all domains.

Table 7.1: Example of original strategy of false-name bids

truthful strategy				
	package	bid amount	result	payment
B1	$\{r_0, r_1, r_2\}$	2	L	0
B2	$\{r_0, r_1, r_2\}$	3	W	2
untruthful strategy				
	package	bid amount	result	payment
B1	$\{r_0, r_1, r_2\}$	2	L	0
B2a	$\{r_0\}$	1	W	0
B2b	$\{r_1\}$	1	W	0
B2c	$\{r_2\}$	1	W	0

Original False-name bids

The following example is pointed out by [60] and is shown in Table 7.1. Consider a second price auction in which there are two bidders, B1 and B2, and three items, r_0, r_1 and r_2 for sale. B1 values the package $\{r_0, r_1, r_2\}$ at 2€ and B2 values $\{r_0, r_1, r_2\}$ at 3€. Neither B1 nor B2 values any smaller aggregation of items. In the honestly conducted Vickrey auction, B2 will win all three items and pay 2€. However, suppose that bidder 2 decides instead to submit bids under three different names: 2a, 2b and 2c. Suppose that 2a bids 1€ for $\{r_0\}$; 2b bids 1€ for $\{r_1\}$, and 2c bids 1€ for $\{r_2\}$. Now, the three bidders 2a, 2b and 2c each win the item they bid for, but none of them have to make any net payment since there is not any other bid requesting these resources, consequently the second price is 0.

This strategy affects the second-price methods while the first-price methods are not affected. In the previous example with a first price auction B2 will pay 3€ in both situations. The consequence for the auctioneer in a second price auction is a low payment by the resources. Reservation price can slightly reduce the effects of this problem. If the auctioneer adds reservation prices for each item, in the worst case the auctioneer will earn the minimum revenue for each item.

False-name bids and priorities

When priorities are added to an auction, new ways to manipulate the mechanism appear, due to false-name bids. When a bidder wins the resource, his priority is decremented but the bidder could have another bid with a false-name with the same bid amount that have lost. Thus the bidders can win the resource in the following auction because he has a good priority with the false-name bid.

Table 7.2 shows an example in the PGVA auction with 2 bidders and one unit of a resource auctioned. Looking at the agent B2, the agent wins the resource in the first auction and has to pay 2.5 because the second price is fixed by B1 and the original bid of B1 is 5, then 5 multiplied by λ obtaining the 2.5. Consequently the utility of B2 in the first auction following the truthful strategy is 2.5 (the true value (5) minus the payment (2.5)). After 3 auctions, the total utility obtained by B2 following a truthful strategy is $(6-2.5)+(6-2.5)+0=7$. Supposing now that B2 follows the untruthful strategy sending a false-name bid called B2' in each auction, he will obtain a utility of $(6-3)+(6-3)+(6-3)=9$. In this second case, B2 wins the resource in the three auctions since he always obtains a high priority. In

Table 7.2: Example of false-name bids and priorities in PGVA auction

truthful strategy						
auction	bidder	bid	priority	score	result	payment
a_0	B1	5	0.5	$5 \cdot 0.5 = 2.5$	L	0
	B2	6	0.5	$6 \cdot 0.5 = 3.0$	W	2.5
a_1	B1	5	0.6	$5 \cdot 0.6 = 3.0$	L	0
	B2	6	0.5	$6 \cdot 0.5 = 3.0$	W	2.5
a_2	B1	5	0.7	$5 \cdot 0.7 = 3.5$	W	3.0
	B2	6	0.5	$6 \cdot 0.5 = 3.0$	L	0
untruthful strategy						
auction	bidder	bid	priority	score	result	payment
a_0	B1	5	0.5	$5 \cdot 0.5 = 2.5$	L	0
	B2	6	0.5	$6 \cdot 0.5 = 3.0$	W	3.0
	B2'	6	0.5	$6 \cdot 0.5 = 3.0$	L	0
a_1	B1	5	0.6	$5 \cdot 0.6 = 3.0$	L	0
	B2	6	0.5	$6 \cdot 0.5 = 3.0$	L	0
	B2'	6	0.6	$6 \cdot 0.6 = 3.6$	W	3.0
a_2	B1	5	0.7	$5 \cdot 0.7 = 3.5$	L	0
	B2	6	0.6	$6 \cdot 0.6 = 3.6$	W	3.0
	B2'	6	0.5	$6 \cdot 0.5 = 3.0$	L	0

the second price auction (PGVA), a bidder with γ false-name bids could obtain always the higher possible priority in each auction since γ is the number of lost auctions necessary so that the priority arrives to its maximum value.

With this manipulation the PGVA auction is closest to the traditional GVA where richer agents will win the items in all auctions. This manipulation can be done only if bidders are sure that they only win with one of their false-name bids. Regarding to the first-price auctions this strategy can be also used. The agent can always obtain a false-name bidder with the maximum priority and consequently with the maximum score.

Regarding CRPA, DRPA and DRPMUCA the agent could use the same strategy for always obtaining a bid with a low reservation price. In the example shown in Table 7.3 a bidder that wants to send a bid amount of 5 can have a false-name bidder and sent a bid amount

Table 7.3: Example of re-enter in the auction in DRPA

truthful strategy				
auc	bidder	RP	bid	$RP < bid$
a_0	B1	5	5.1	yes
a_1	B1	5.5	5.1	no
a_2	B1	4.95	5.1	yes
untruthful strategy				
a_0	B1	5	5.1	yes
	B1'	5	-	-
a_1	B1	5.5	-	-
	B1'	4.5	5.1	yes
a_2	B1	4.95	5.1	yes
	B1'	4.95	-	-

of 5 alternatively with the two bidder names. With this strategy he will always have the bid amount over the reservation price.

Re-enter in the auction

When priorities are calculated taking into account the number of lost and won auctions, a bidder has a low priority after winning. Then the bidder could leave the auction and re-enter obtaining the initial priority. The consequence of this manipulation is that the bidders that win many times are less penalized. Suppose a priority $p = \frac{lost+1}{total+2}$ as in PA. If the bidder wins an item in the first auction, then his priority in the second is 0.33. Then, the bidder can leave the auction after the first auction and reenter with another identity. In this case the bidder will have the initial priority of 0.5. PMUCA and PGVA avoids this manipulation giving the same priority to agents when they win or when they arrive to the auction.

This strategy can be used to manipulate the dynamic reservation price too. For example, a bidder with a high reservation price could decide to leave the auction and re-enter with a different name in order to obtain a lower reservation price. For instance, in the DRPA mechanism, assume that a bidder with a reservation price of 5.8 sends a bid of 6. At the next auction the reservation price is set to 6 and if he sends a bid amount of 6 again he will lose because of the reservation price. But if the agent, after the first auction, decides to leave the auction and re-enter in the second he will obtain the initial reservation price, for example 5, and he could win with a bid amount of 6.

7.1.2 Underbidding

When bidders know that the mechanism uses priorities and that these are increased when the bidder agent loses an auction, then the bidder can manipulate the mechanism losing some auctions on purpose in order to obtain a higher priority for the future auctions. There are several ways to make this manipulation.

Low bids

Consider an auction where priorities are used to modify the bids amounts and an agent that knows the effects of priorities in the bid amount. Consider a bidder that is not interested in winning the resource in the current auction but he is interested in winning the resource in the following auction. Then, the agent could send a very low bid amount for purposely losing in the current auction on purpose to obtain a higher priority in the next auction. The consequence is less payment for the auctioneer. Consider the following example with PA mechanism. Assume that a dishonest bidder sends a bid amount of 1 in the current auction and that he has a priority of 0.5. Supposing he loses, for the next auction he will have a priority of 0.66 obtaining a score of 5·0.66=3.3. On the other hand if the agent had been honest, he does not participate in the first auction and he participates in the second with a bid amount of 5 and a priority of 0.5 obtaining a score of 2.5, lower than the score obtained with the dishonest behaviour.

DRPMUCA, PMUCA and PVGA avoid this bidder strategy restarting the priority when the bid amount is higher than the previous bid amount for the same package. In the same example in this case the agent has a priority of 0.5 but when in the second auction the bid amount sent is 5, then the priority is restarted and therefore the score is the same for the honest behaviour and the dishonest behaviour.

Regarding the dynamic reservation price, this strategy can be used for obtaining a lower reservation price in CRPA and DRPA. The agent could send low values in the auctions where it is not interested in buying the resource in order to obtain a low reservation price. In the case of DRPMUCA the reservation price is decremented in the same way when the agent sends a low value or when the agent does not participate in the auction, therefore the agent does not have any incentive to use this strategy because he does not obtain any advantage and he is assuming the risk of winning the resource when it is not interested in it.

In order to show that PMUCA mechanism cannot be manipulated by the strategies previously described, let us suppose two consecutive auctions: a_0 and a_1. An agent wants to win a package in the auction a_1 but not in a_0. Suppose the following two situations: an agent that is honest (g_h) and an agent that is not ($g_{\neg h}$). So, g_h in the first auction does not participate and in the second sends a bid $b_{h,1,1}$ for the package with a price $\mathcal{C}(b_{h,1,1})$. While, $g_{\neg h}$ sends a bid in the first auction with a low price $\mathcal{C}(b_{\neg h,0,1})$ with the aim of losing and rise his priority for the package in the next auction. In the second auction $g_{\neg h}$ sends a bid with a price $\mathcal{C}(b_{\neg h,1,1})$, where $\mathcal{C}(b_{\neg h,0,1}) < \mathcal{C}(b_{\neg h,1,1})$. Assume that the price is the same for both agents in the second auction, $\mathcal{C}(b_{\neg h,1,1}) = \mathcal{C}(b_{h,1,1})$. Thus, in order to analyze which agent has more chances to become a winner, we define $pow_x(y)$ as the probability of winning in the auction a_x with a bid price y. Then the probability of winning for the honest agent in the second auction a_1 is $pow_1(\mathcal{C}(b_{h,1,1}) \cdot pr)$ where pr is the priority of agent g_h. Analogously, the probability of winning for $g_{\neg h}$ is $pow_1(\mathcal{C}(b_{\neg h,1,1}) \cdot \lambda)$. Note that $pr \geq \lambda$ since $\mathcal{C}(b_{\neg h,0,1}) < \mathcal{C}(b_{\neg h,1,1})$ and consequently the priority for $g_{\neg h}$ is initialized with the initial value λ. Then the probability of winning for g_h is equal or greater than for $g_{\neg h}$:

$$pow_1(\mathcal{C}(b_{h,1,1}) \cdot pr) \geq pow_1(\mathcal{C}(b_{\neg h,1,1}) \cdot \lambda) \tag{7.1}$$

Regarding the price that the agents have to pay, g_h has an expected value of $pow_1(\mathcal{C}(b_{h,1,1}) \cdot pr) \cdot \mathcal{C}(b_{h,1,1})$. On the other hand $g_{\neg h}$ has an expectation of $pow_1(\mathcal{C}(b_{\neg h,1,1}) \cdot \lambda) \cdot \mathcal{C}(b_{\neg h,1,1}) + pow_0(\mathcal{C}(b_{\neg h,0,1}) \cdot pr) \cdot \mathcal{C}(b_{\neg h,0,1})$. Then, assuming the worst case in which the honest agent was also the initial priority value ($pr = \lambda$), we obtain the results shown in Equation 7.2.

$$\begin{aligned} pow_1(\mathcal{C}(b_{h,1,1}) \cdot \lambda) \cdot \mathcal{C}(b_{h,1,1}) \leq \\ pow_1(\mathcal{C}(b_{\neg h,1,1}) \cdot \lambda) \cdot \mathcal{C}(b_{\neg h,1,1}) + \\ pow_0(\mathcal{C}(b_{\neg h,0,1}) \cdot \lambda) \cdot \mathcal{C}(b_{\neg h,0,1}) \end{aligned} \tag{7.2}$$

As $\mathcal{C}(b_{h,1,1}) = \mathcal{C}(b_{\neg h,1,1})$ we can see that $g_{\neg h}$ has more chances to pay equal or more than g_h supposing that they win the same number of times. Then, the best strategy for a bidder is not to participate in the auction if the agent is not really interested in winning the package.

In order to show that DRPMUCA mechanism cannot be manipulated too, let us suppose the same two situations. In the first situation the agent is honest (g_h) and in the second the agent is not honest ($g_{\neg h}$). g_h in the first auction does not participate and in the second sends a bid $b_{h,1,1}$ for the package with a price $\mathcal{C}(b_{h,1,1})$. In the second case, $g_{\neg h}$ sends a bid in the first auction with a low price $\mathcal{C}(b_{\neg h,0,1})$ with the aim of losing and decrease the reservation price for the package in the next auction. In the second auction $g_{\neg h}$ sends a bid with a price $\mathcal{C}(b_{g_{\neg h},1,1})$, where $\mathcal{C}(b_{g_{\neg h},1,1}) = \mathcal{C}(b_{h,1,1})$. In both cases the reservation price is decremented thus the resulting reservation price are the same and consequently the probability of obtain the package is the same in both situations.

Regarding the payments, analogously to the case of PMUCA, the honest agent has to pay the same or less than $g_{\neg h}$:

$$\begin{aligned} pow_1(\mathcal{C}(b_{h,1,1})) \cdot \mathcal{C}(b_{h,1,1}) \leq pow_1(\mathcal{C}(b_{\neg h,1,1})) \cdot \mathcal{C}(b_{\neg h,1,1}) \\ + pow_0(\mathcal{C}(b_{\neg h,0,1})) \cdot \mathcal{C}(b_{\neg h,0,1}) \end{aligned} \tag{7.3}$$

Low bids waiting

A bidder that wants an item but can wait to obtain it can send a low bid amount in each auction waiting to win thanks to the priorities. The consequence is that bidders with patience can win the resources at a cheaper price. Suppose the PMUCA auction where one resource is auctioned. λ is equal to 0.5 and γ is equal to 1. There are two bidders B1 and B2 with a true value of 5 and 4 respectively. B1 sends a bid amount of 5 and B2 sends a bid amount of 4. B1 wins the resource. In the second auction B1 and B2 have priorities of 0.5 and 1 respectively. In the second auction they send again the same bid amount. Now B2 wins the resource and pays 4. Supposing the same example but now with B2 deciding to send a bid amount of 2.6, the result would be the same: B2 wins the resource in the second auction but in this case the payment is lower than the first situation.

With a second-price payment the agent will pay the same in both situations, thus the agent will not be motivated to do this manipulation, it will be better to send the true value since he will have more probabilities to win and he will pay less. Therefore this problem does not affect PVGA but affects all first-price mechanisms.

Multi-unit manipulation

Consider an auction where the auctioneer has a priority for each bidder and these are used to modify the bid amount. Then consider that the auctioneer avoids the manipulation called ”low bids” taking into account the bids amounts. Then a bidder can lose sending a bid for a large number of units to lose and then in the next auction send the same bid amount for only one unit. Suppose an hypothetic auction mechanism and a bidder agent B1 that tries to lose in the current auction to win a unit of an item in the following auction. He knows the priorities mechanism and he knows that if he sends a low value he will not achieve a better priority for the next auction because the auctioneer resets the priorities when the current bid is greater than the previous. In this case the bidder could send a bid amount of 5 for 1000 units of the resource, supposing that 0.005 is a ridiculous bid amount for the item. He obviously loses in the actual auction and he will achieve a greater priority for the next auction.

The consequence is that the agent can obtain an unfair priority. This problem can be avoided having a different priority for each package and agent, not just a priority per agent. Therefore PMUCA and DRPMUCA avoid this manipulation. This manipulation is not aplicable to PA, CRPA and DRPA since they are designed for non combinatorial scenarios.

Multi-item manipulation

A bidder could send a bid for an item of little value to obtain a high priority and then use the priority to bid for a high value item. For example a bidder could send a bid for a pencil until obtaining a high priority assuming the risk of winning the pencil since the cost of the pencil is low. Then, when the bidder obtains a high priority, he can use the priority to bid for a car. The consequence is that the agent can obtain an unfair priority. This problem can be avoided having a different priority for each package and agent, not just a priority per agent. As in the previous manipulation PMUCA and DRPMUCA avoid this manipulation since the priorities and the reservation prices are different for each package. Also this manipulation is not applicable to PA, CRPA and DRPA.

7.1.3 Overbidding

In the PVGA mechanism the winner bidder has to pay the second price multiplied by λ in order to the paid value not be higher than the bid amount sent by the bidder. The bidder could send a bid amount higher than his true value since he knows that he will pay the same amount of money if he overbids or if he does not overbid in the second price auctions. This problem does not affect the first-price auctions since if a bidder overbids he will have to pay more than his true value and consequently his utility will be negative. Suppose two bidders in a recurrent prioritized second-price auction. Bidder 1 sends a bid of x and knows that his priority is p, and so that his score to win is $x \cdot p$ and if he wins he will pay λ multiplied by the bid amount of the second bidder ($x \cdot \lambda$). If bidder 1 wins, then the score for the second bidder is less than $x \cdot p$. Consequently the bidder knows that he will pay less than $x \cdot p$. Therefore the bidder can overbid up to a bid amount of his true value divided by λ without risk of obtaining a negative utility.

For example, suppose an example with two bidders and a recurrent auction composed by 4 auctions. Bidder 1 and bidder 2 have a true value of 5 but bidder 1 wins the ties. We refer to bidder 1 as the richer agent. The parameters of the mechanism are $\lambda = 0.5$ and $\gamma = 1$. If both bidders send their true values (Table 7.4) both win 2 auctions and obtain a total utility (true value minus the payment) of 5. In Table 7.4 the bid amount of the winners are highlighted in bold.

But suppose that the richer bidder sends a bid amount of 11 with the aim of winning all auctions (Table 7.4). Bidder 2 cannot win if he sends his true value even if he had the maximum priority (5 · 1=5 while 11 · 0.5=5.5). In this case bidder 1 will win all the auctions obtaining a utility of 10 while bidder 2 obtains a utility of 0. In this case the effect of priorities is cancelled and the behaviour of the auction is like the traditional GVA auction. If both bidders overbid more than $5 \cdot \lambda$, the result is negative for both.

Table 7.4: Example of overbidding in PVGA

truthful behaviour					
	a_0	a_1	a_2	a_3	utility
B1	**5**	5	**5**	5	(5-2.5) +0+ (5-2.5) +0 = 5
B2	5	**5**	5	**5**	0 + (5-2.5) +0 + (5-2.5) = 5
B1 overbids					
	a_0	a_1	a_2	a_3	utility
B1	**11**	**11**	**11**	**11**	(5-2.5)+ (5-2.5)+ (5-2.5)+ (5-2.5) = 10
B2	5	5	5	5	0+0+0+0 = 0

7.2 Equilibrium

In this section we make a study of the equilibrium of the presented mechanisms. A Nash equilibrium is a profile of strategies such that each player's strategy is an optimal response to the other players' strategies. The Nash equilibrium is central in game theory, is somehow a minimum condition of individual rationality, since if a combination of strategies is not a Nash equilibrium, there is at least one player who can increase profits by changing his strategy, and therefore it hardly can be considered as a solution of the model [22].

The complexity of the mechanisms and the infinite possibilities of different bidding strategies make the analytical study of the mechanisms very hard. For this reason, we have studied the analytical Nash equilibrium for the mechanism PVGA and the equilibrium for all methods experimentally.

The experimental study has been performed providing bidder agents with a reinforcement learning algorithm, the Q-learning algorithm [75, 76]. Doing this study we will know the behaviour of agents when they are in an auction market with an auctioneer using one of the fair mechanisms.

7.2.1 Reinforcement learning fundamentals

Q-learning is a reinforcement learning technique that works by learning a Q value for each pair state-action that gives the expected utility of taking a given action in a given state. Q-learning is able to compare the expected utility of the available actions without requiring a model of the environment [34].

The agent has a set of states E and a set of actions per state AC. By performing an action ac, the agent can move from state to state. Each state provides the agent a reward (a real or natural number) or punishment (a negative reward). The goal of the agent is to maximize its total reward. It does this by learning which action is optimal for each state. We define $< e, ac, rw, e' >$ as an experience tuple summarizing a single transition in the environment. Here e is the agent's state before the transition, ac is its choice of action, rw the instantaneous reward it receives, and e' its resulting state.

The algorithm learns a quality value for each pair state-action, then the agent uses this Q values to select the action to take in each state. After each action is taken, a new experience tuple is used to update the Q values with the Equation 7.4.

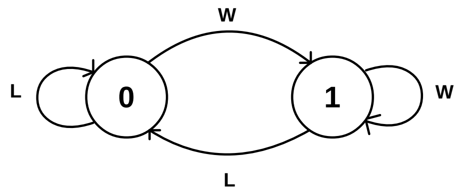

Figure 7.1: Transition between states of the learning modelled agent

$$Q(e, ac) := Q(e, ac) + lrate(rw + dis \cdot max_{ac'} Q(e', ac') - Q(e, ac)) \tag{7.4}$$

Where $lrate$ is the learning rate and dis is the discount factor. The learning rate determines to what extent the newly acquired information will override the old information. A factor of 0 will make the agent not learn anything, while a factor of 1 would make the agent consider only the most recent information. The discount factor determines the importance of future rewards. A factor of 0 will make the agent ”opportunistic” by only considering current rewards, while a factor approaching 1 will make it strive for a long-term high reward. If the discount factor meets or exceeds 1, the Q values will diverge.

Before learning has started, Q returns a fixed value, chosen by the designer. Then, each time the agent is given a reward (the state has changed) new values are calculated. The core of the algorithm is a simple value iteration update. It assumes the old value and makes a correction based on the new information. When the Q values are nearly converged to their optimal values, it is appropriate for the agent to act greedily, taking, in each situation, the action with the highest Q value. During learning, however, there is a difficult exploitation versus exploration trade-off to be made. The Q learning algorithm focuses on the exploitation of the information but does not focus on the way of obtaining new information. In this sense, the agent needs a mechanisms for discovering the unexplored strategies.

Learning agent

For the auction market, the set of possible states is composed by 2 states. The first one is achieved when the agent loses an auction, the second one after winning the auction. Figure 7.1 shows the two states and the transitions between them. Each possible action is to send a bid with a different bid amount. In this trial 20 possible different actions are considered from a bid amount of 1 up to a bid amount of 20 independently of the wealth of the agent. Note then that the agents could overbid.

The values for $lrate$ and dis are 0.3 and 0.2 respectively. In order to deal with the exploration versus exploitation problem we have defined a constant exp that defines a probability of choosing a random action between the actions with non-negative Q values. The actions with negative values are only chosen if there is not any other possibility. This value is set to 0.15. If the action is not chosen for exploration, the action is chosen taking into account the Q value with the probability pq shown in Equation 7.5. The value of Q has been powered[1] to 5 in order to chose the best action with a high probability but sometimes the algorithm can select the other actions.

[1] Only if the value is greater than 1.

		B2			
		5 (true value)		2 (lower value)	
B1	5 (true value)	2.5	0	4	0
	2 (lower value)	0	4	4	0

Figure 7.2: Example of the game described in 7.2.2 composed by one-shot auction in strategic form

$$pq = \frac{Q(e,ac)^5}{\sum_{ac \in AC} max(Q(e,ac),0)} \tag{7.5}$$

7.2.2 Analytical equilibrium for PGVA

Before using the learning agent to experimentally study the equilibrium, we show a simplified example auction in order to show the Nash equilibrium of PGVA analytically. In this example we assume that bidders can chose between two different actions assuming that they cannot overbid. Then, in the experimental analysis of the equilibrium we allow bidders to overbid.

Suppose an example with 2 bidders: B1 and B2. In the auction there is one item auctioned. Both bidders have a true value of 5 for the item. The parameters of the mechanism are $\lambda = 0.5$ and $\gamma = 1$. If there is a draw, B1 wins because we define a precedence between bidders to decide the winners when their scores are the same. Let's see this auction in a strategic form. A game in strategic form has three elements: the set of players (in this case B1 and B2), the pure-strategy space for each player and the payoff function. In this example the bidders can choose between two actions: to bid his true value (5) or to bid a low value (2). Regarding the payoff, they are the utility for the agents with the outcome of the auction. Then, the game for a one-shot auction in strategic form is shown in Figure 7.2. For example, when both bidders send their true value, the winner is B1 and the first cell shows the utility for both bidders with this outcome. For B1 the utility is 2.5 (5-2.5) since his true value is 5 and he wins and pays 2.5. Regarding B2, his utility is 0 since he does not win the resource. The best response for B1 to all possible moves of B2 is to bid the true value. But for B2, knowing that B1 will send the true value is the same to send the true value or a low value. Then, this game has two Nash equilibriums (2.5, 0) and (4, 0). In both situations B1 wins the resource.

The game for a recurrent auction composed by two one-shot auctions in extensive form is shown in Figure 7.3. The extensive form of a game contains the following main information: the set of players, the order of move (i.e. who moves and when), the players' choices are when they move and what each player knows when he makes his. The players are B1 and B2. In this case both players move in the first auction at the same time without knowing the movement of the other player. Then, in the second auction they move again without knowing the movement of the other player but they know the outcome of the first auction. Figure 7.3 shows a tree where each branch means a possible action that the players can choose. The number in each branch means the bid amount. The information shared is noted in Figure 7.3 with the absence of the double dashed line. The double dashed line means that the player has to choose in both cases the same action because he does not

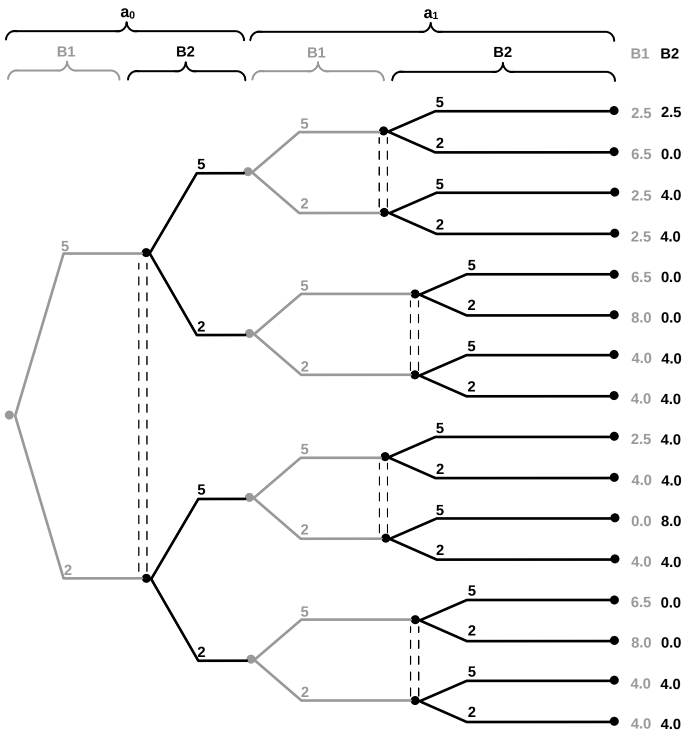

Figure 7.3: Example of the game described in 7.2.2 composed by two auctions in extensive form

know the action chosen by the other player. The final numbers that appear in the last node are the total utility achieved by players if they choose the corresponding sequence of actions.

The game has one Nash equilibrium that is (4,4) and it is achieved when the bidder agents alternate their bid amounts. That is when B1 sends a bid amount of 2 in the first auction and B2 sends 5 obtaining the resource and paying only 1. Then in the second B1 sends 5 and B2 sends 2, obtaining B1 the resource and paying 1. In this case the utility for both bidders is 4. This has a bad consequence for the auctioneer since the bidders will pay the minimum possible amount of money. The mechanism could be modified in order to obtain the Nash equilibrium when bidders sent their true value in this example but anyway the problem of overbidding will be present since this example is assuming that there are no overbidding.

7.2.3 Case study for experimental equilibrium

The example used for the simulations is the following. There are 8 learning bidder agents competing for the resources. There are two agents of a wealth of 6 (his true value for the resource is 6), these are the richer agents, two agents of a wealth of 5, two with a wealth of 4 and the last two have a wealth of 3. The TCL of agents is set to ∞ to avoid the bidder drop problem in the simulations. The aim is of these simulations is that agents learn the bidding policy according to the environment. The bidder drop problem could provoke the leave of some bidder agents and consequently the situation in the auction is different and consequently the agents have to adapt to the new situation and learn again. For this reason

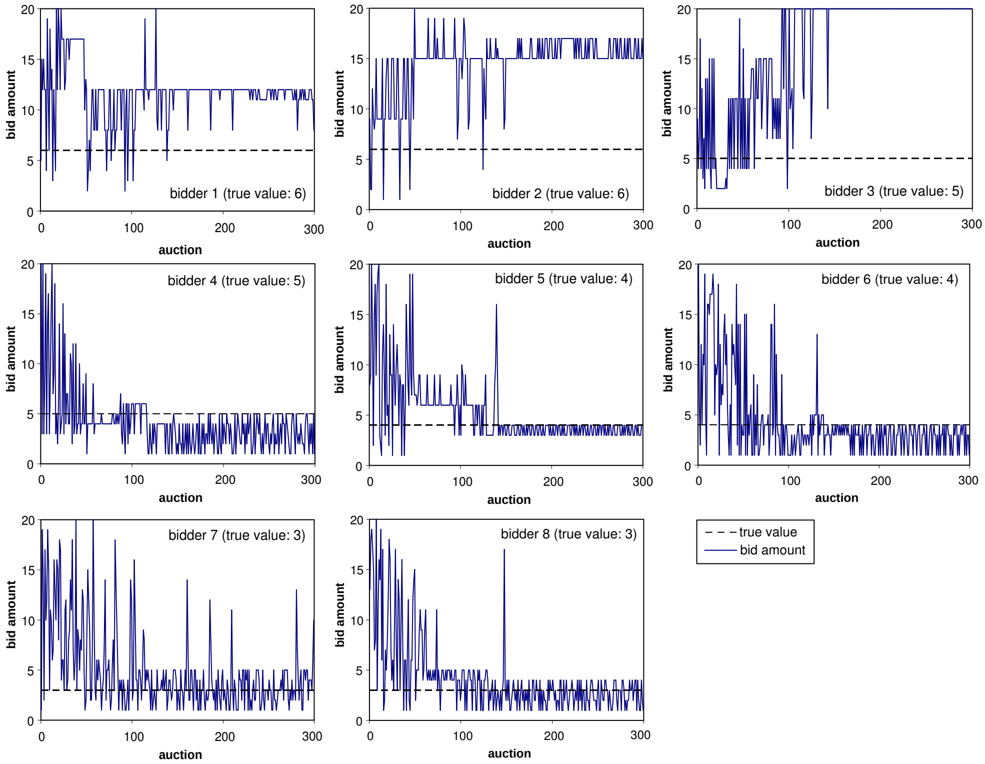

Figure 7.4: Bid amounts sent by the learning bidder agents in a simulation of PVGA

the bidder drop problem in disabled in these simulations but we have done simulations with different ratios between the available resources and the number of bidders. There is 1 resource auctioned and different quantities of units of the resource. The simulations have been done with 3, 4, 5 and 6 units of the resource representing that there are resources for the 37% of the bidder agents, the 50%, the 62% and the 75% respectively. The recurrent auction is composed by 300 one-shot auctions. There is assumed that the auctioneer can check the identity of bidders.

7.2.4 Experimental equilibrium for PVGA

Figure 7.4 shows the results obtained by the learning bidder agents in the example shown in Section 7.2.3. Figure 7.4 shows the bid amount sent by the 8 bidder agents during a simulation where 3 resources are auctioned in each one-shot auction. At the beginning all bidders try to overbid but when the equilibrium is achieved only 3 bidders can overbid: bidder 1, bidder 2 and bidder 4 in the showed simulation. These bidders learn that overbidding wins the resources and pay a price lower than their true value fixed by the group of bidders that do not overbid. The second group cannot overbid since if they do it they pay the price of the loser of the first group, consequently they will pay a high price, higher than his true value.

In the general case, the equilibrium is achieved when the q_0 richer bidders overbid a bit more than λ multiplied by the true value, where q_0 is the number of resources and the rest of bidders send a bid amount lower than their true value.

Therefore the behaviour of the PGVA is the same as the GVA when the equilibrium is achieved. The winners are always the richer bids. This fact will provoke the drop of the poor bidders and if all poor bidders disappear, the richer bidder will pay a price of 0 for the resources. The behavior is the same with more resources auctioned, for the bidders of the "overbidding" group they overbid the same bid amount independently of the other since they will pay the second price.

7.2.5 Equilibrium for the first price mechanisms

In this section the results obtained by the learning agents are shown in the case study explained in Section 7.2.3. The results show the equilibrium achieved empirically with the first-price mechanisms. First we show the equilibrium of the traditional or first-price sealed bid auction (TA) to have a reference, and then for the more representative fair mechanisms described in this thesis: CRPA, PMUCA and DRPMUCA.

In general, the bidders in the first price auction learn that overbiding is not a good strategy, since they pay the bid amount sent, when they do it and win, being this payment higher than the true value obtaining a negative utility. They overbid at the beginning of the simulation due to the exploration but they learn quickly that is not good for them.

TA

Figure 7.5 shows the bids sent by bidders in TA. The bidders are learning about the outcomes received from the mechanism. On the one hand, a bidder wants the minimum value necessary to win in order to obtain a higher utility in each won auction. On the other hand a bidder wants to win the greater number of auctions possible. Note that a lost auction has a utility of zero for the bidder agent. Then, a bidder is trying to find a value, lower than his true value but a value that achieves the best utility in the long term, that is, a trade-off between number of winnings and utility achieved in each won auction. Then, the competence existent in the market will have a big influence in the value chosen by bidders. If the agent does not have competence, he will chose a very low value, but if there is a lot of competence with a low value he will won few times, and so he needs to bid a higher value.

Figure 7.5 shows that the richer bidders found a value, approximately 4 in this example, that is the best value for them. These bidders will be the winners in the greater part of the auctions. The loser bidders have a high variability in their bid amounts since it is difficult to win and consequently it is also difficult to learn a concrete value.

Figure 7.6 at top left shows the results for TA as the average bid amount sent by the bidders classified by their true value. There results are different from the simulations where there are different quantities of the resource. Looking at the bid amount sent by richer bidders (true value equal to 6), we can see how they decrease their bid amount when the supply is large. When there are a lot of resources they have no incentive to maintain the bid amounts at a higher level and they sent low bids.

In these simulations there is no bidder drop problem but there are 4 different situations with different ratios between supply and demand. Note that when a bidder drops of the auction the ratio between supply and demand increases, lowering the competence since there is

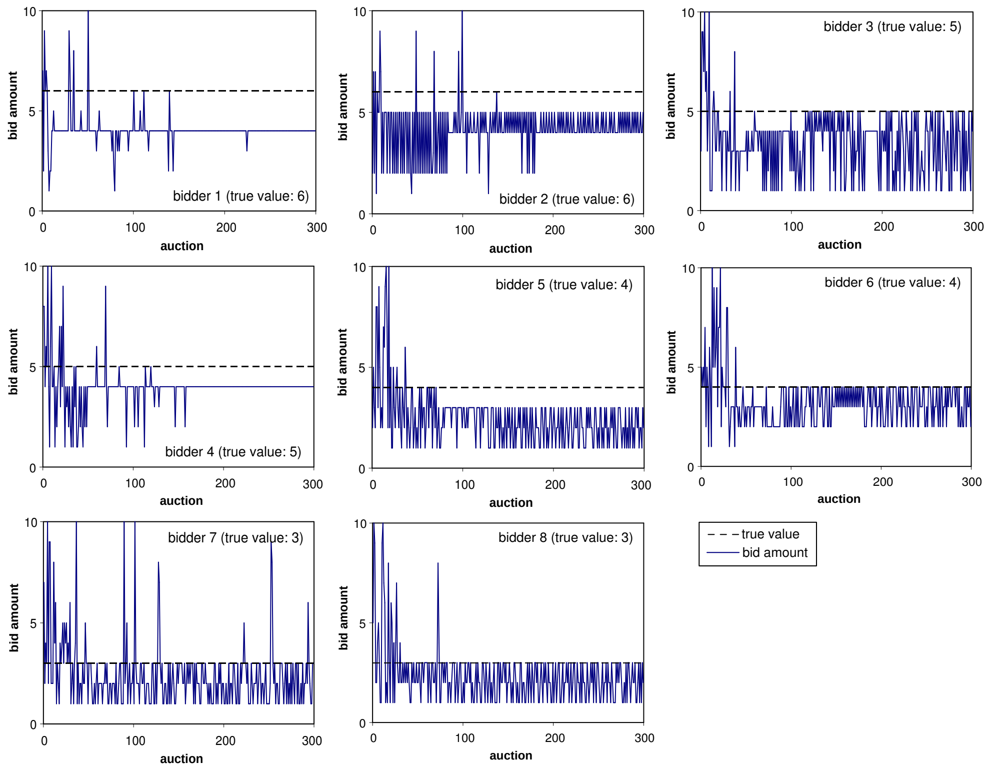

Figure 7.5: Bid amounts sent by the learning bidder agents in a simulation of TA

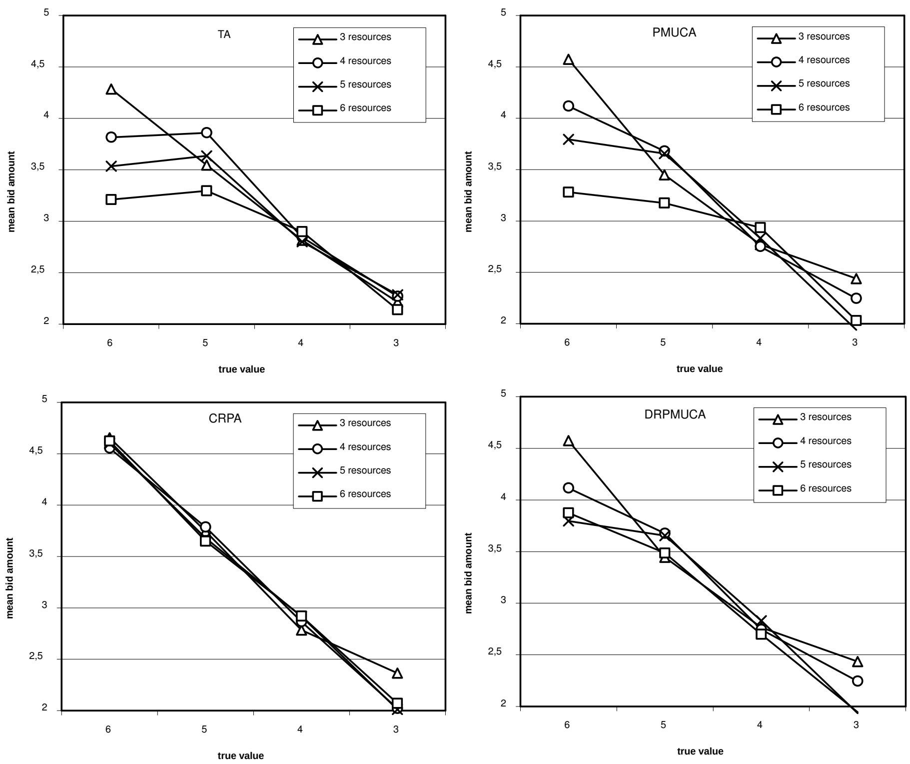

Figure 7.6: Average bid amount in the 4 simulations classified by the true value of the agent

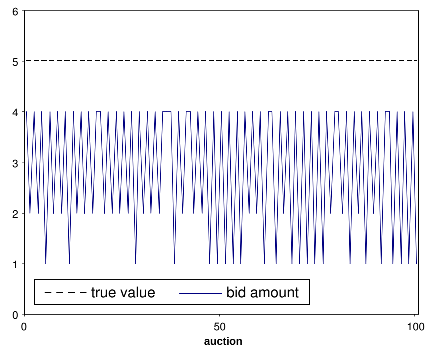

Figure 7.7: Behaviour of an agent whose strategy is to alternate high bid amounts with low bid amounts (called ”low bids”)

less demand. Therefore we can suppose that in a long term simulation with the bidder drop problem the ratio between supply and demand decreases.

CRPA

Figure 7.6 shows that CRPA is the mechanism less sensitive to the different supply and demand ratios. In all simulations (3, 4, 5 or 6 resources auctioned) the average price is similar. But there are some agents that sometimes learn the strategy of sending a low bid to decrease the reservation price and in the next auction send a high bid amount. To win the resource, after winning the resource they send a low value again to lose on pourpose since the bidders have learnt that their expected utility is greater sending a low value after a win. Figure 7.7 shows an example of this behaviour, called ”low bids” in the previous section, extracted from the simulation. The agent sends a value of 4 in order to win the resources but after a win he sends a low bid amount in order to obtain a lower reservation price in the future.

PMUCA

The behaviour learnt by agents with PMUCA (Figure 7.8) is very similar to the behaviour learnt for the TA mechanism (See 7.6). The rich bidders have to maintain the bid amount a bit higher than in TA, the competence has been increased due to the fact that poor bidders can win the resources. But when the supply is high, as in TA, the rich bidders are not motivated to maintain the bid amount at the high levels.

DRPMUCA

The behaviour learnt in this case (Figure 7.9) is a midpoint between PMUCA and CRPA. The mechanism is more sensitive to changes in the supply than CRPA but less than PMUCA. Regarding the strategies learnt, the agents found a value as in the other mechanisms and sometimes it is affected by the behaviour of alternating high and low values.

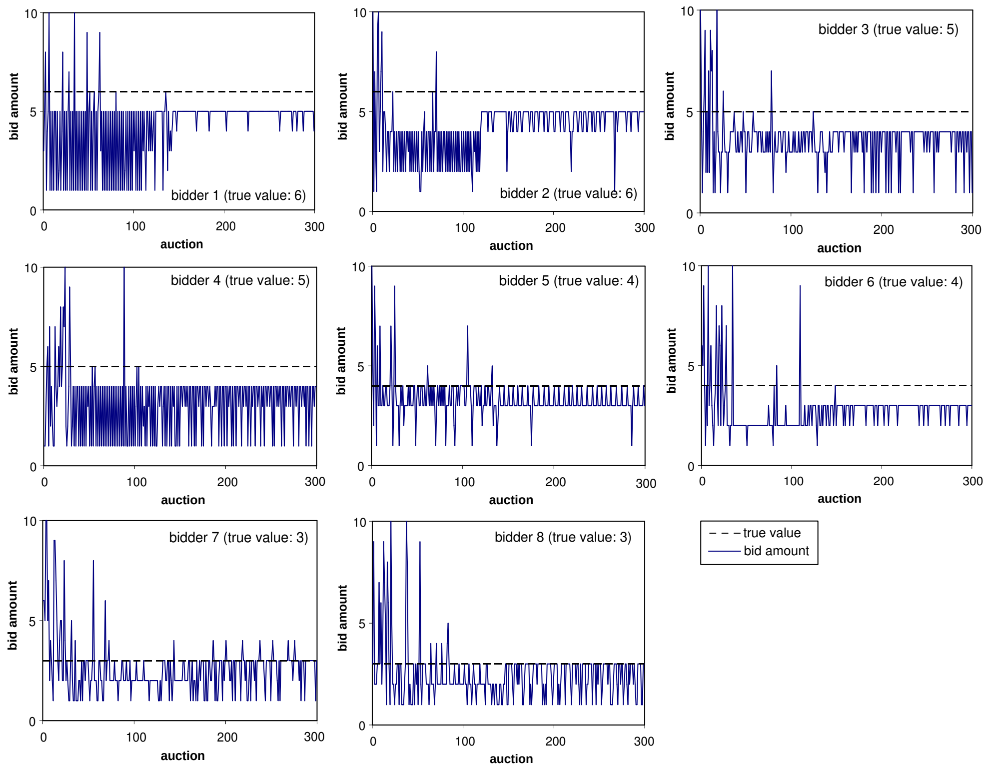

Figure 7.8: Bid amounts sent by the learning bidder agents in a simulation of PMUCA

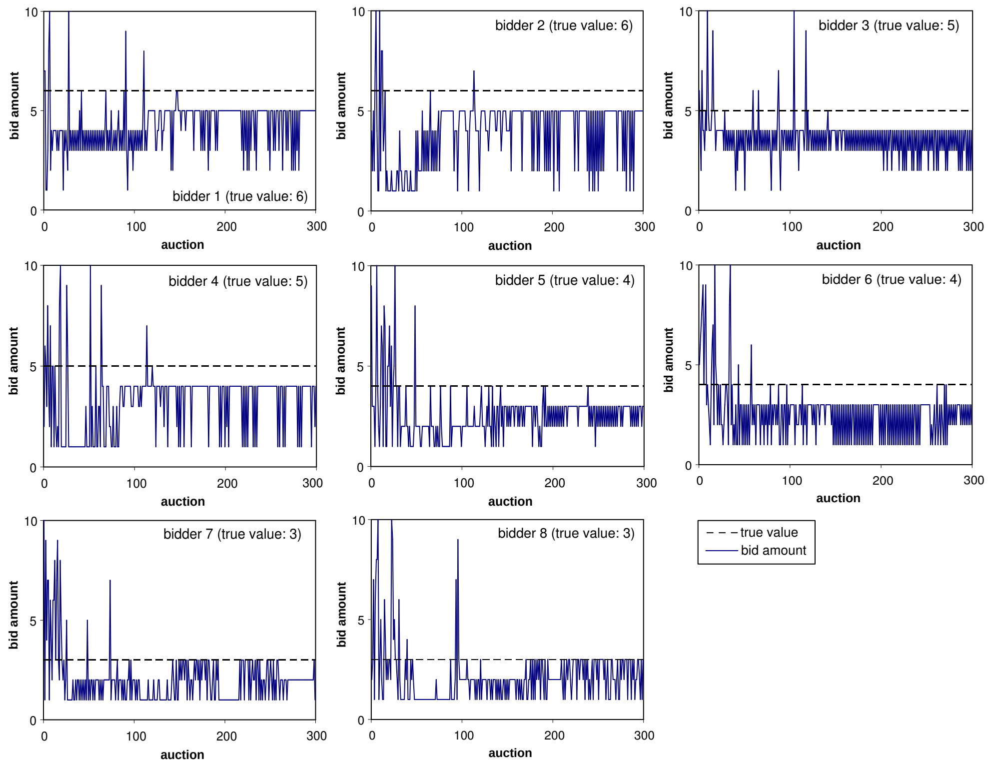

Figure 7.9: Bid amounts sent by the learning bidder agents in a simulation of DRPMUCA

Table 7.5: Table of manipulations

			False-name bids			Underbidding				Overbidding
			□	◇	△	⋆	⊕	⋈	■	
MUA	FP	PA	✓	✗	✗	✗	✗	-	-	✓
		CRPA	✓	✗	✗	✗	✗	-	-	✓
		DRPA	✓	✗	✗	✗	✗	-	-	✓
MUCA	FP	DRPMUCA	✓	✗	✗	✓	✗	✓	✓	✓
		PMUCA	✓	✗	✓	✓	✗	✓	✓	✓
	SP	PGVA	✗	✗	✓	✓	✓	✓	✓	✗

✓: not affected	□: False-name bids
✗: affected	◇: False-name bids and priorities
- : not applicable	△: Re-enter in the auction
⋆: Low bids	⋈: Multi-unit manipulation
⊕: Low bids waiting	■: Multi-item manipulation

7.3 Summary

The mechanisms presented in the previous chapters have shown that fairness helps to minimize the effects of bidder drop problem but under the assumption that agents are honest. When the agents try to manipulate the mechanisms some problems appear. Table 7.5 summarizes the possible manipulations that bidders can perform and whether the mechanisms are affected by them.

When applying fair mechanisms, the auctioneer has to avoid the problem of false-name bids. This problem affects all presented mechanisms and the consequence is the cancellation of the effects of fairness. Without the effects of fairness the mechanisms behaviour is as the First price auction (TA) and the bidder drop problem could provoke the collapse of the auction.

A second problem is the occasional underbidding. This problem is not as serious as the previous problem for first price mechanisms. When a rich bidder is sending low bids, he is giving chances to poor bidders to win the resources. Selfish agents are showing a fair behaviour and the low bids do not have a great impact to the revenue for the auctioneer, since the low bids do not affect the high values sent in the other occasions.

A way of avoiding underbidding is to use a second price mechanism. For this reason the mechanism PGVA is shown. This mechanism is not affected by underbidding, but it is affected by overbidding due to the parameter λ that multiplies the price paid by the winners. Then, this method is not incentive compatible and overbidding makes the mechanism sensible to the bidder drop problem.

In domains where the auctioneer is not able to check the real identity of bidders there is not a best method since bidders could cheat to the auctioneer transforming the fair auction mechanism in the traditional first-price sealed bid auction (TA or TMUCA) with the corresponding problems. Assuming that the auctioneer is able to check the identity, and consequently is able to avoid the false-name bids, the mechanisms less affected by manipulations are PMUCA and DRPMUCA since they are only affected by underbidding. Regarding PGVA, it is the only mechanism that avoids underbidding completely. However, it is affected seriously by the overbidding, transforming the mechanism into the same as the traditional auction.

CHAPTER 8
Conclusions

This chapter summarizes the main contributions of this thesis and analyses the needed future work for the presented fair auction mechanisms. Finally the publications done during the development of this thesis are listed.

8.1 CONTRIBUTIONS

Several basic fair mechanisms based on priorities and reservation prices for recurrent multi-unit auctions have been designed (Chapter 3). These mechanisms have been tested experimentally showing that fairness minimizes the effects of the problems that appear in recurrent auctions when the resources are perishable and the wealth of bidders is unevenly distributed. On the one hand the priorities help to fairly share the resources between all bidders incentivising the participation in the auction process and minimizing the bidder drop problem and helping to reduce the resource waste. On the other hand the dynamic reservation prices help to maintain the equilibrium of the negotiation power, maintaining the prices at an acceptable level for the auctioneer.

The presented mechanisms have been extended in order to deal with combinatorial auctions (Chapter 4). In the combinatorial scenarios bidders can bid for any combination of items giving them the possibility of better expressing their preferences. In the same way that their non-combinatorial predecessors, the presented mechanisms have avoided the problems of recurrent auctions, but in these case in combinatorial scenarios.

The fair mechanisms have been studied both in static and dynamic scenarios. This latter experimentation is new regarding previous work, and it considers more real-word problems such as changes in the supply of the auctioneer.

Moreover, the proposed fair mechanisms have been tested in open and closed markets, giving bidders in the latter case the possibility of entering and dropping out from the auction (Chapter 5). Also the bidders have been improved with a trust model about the available auctioneers in the market.

A simulator has been designed in order to perform the needed experiments for obtaining the results of this thesis. The simulator is described in Appendix A.

In order to analyze the degree of fairness of the proposed mechanism, a metric has been defined (Chapter 5). This metric is based on the standard deviation of the mean satisfaction of bidders. There were other metrics in the literature, but they did not take into account the recurrent nature of this work and they were measured from the point of view of the auctioneer agent.

The proposed fair mechanisms have been experimentally analysed comparing their performance with the performance of other fair mechanisms existing in the literature and with other unfair mechanisms. The results of the experimental analysis show that assuming that the agents are honest, the fair mechanisms obtain higher long term benefits since they maintain the interest of bidders in remaining in the auction and consequently they minimize the effect of the bidder drop problem. We have also experimentally shown how the use of reservation prices can be mixed with priorities in order to obtain mechanisms able to maintain the negotiation power of the auctioneer. However there are some dynamic situations where the fair mechanism needs also a method to avoid that rich bidders obtain the resources at a cheaper price. We have called this mechanism control of fair resources. The combination of these three components: priorities, reservation prices and control of rich bidders bring two of the proposed mechanisms to obtain the best performance under all simulated situations.

One of the proposed fair mechanisms has been adapted to a real-world application, concretely to a Waste Water Treatment Plant (WWTP) coordination scenario (Chapter 6). In this domain the WWTP has to coordinate the industries discharges in order to avoid that the pollutants overpass the WWTP capacity. For this problem an auction based mechanism that uses priorities is proposed, in order to avoid the starvation of certain industries and improving the performance of the WWTP.

Finally the weaknesses of the proposed mechanisms have been analysed (Chapter 7). The bidders participating in fair auctions can try to manipulate the mechanisms. The more significant ways to manipulate the mechanism have been pointed out, indicating to which mechanisms they affect. Then, a new agent has been designed with a reinforcement learning algorithm in order to learn the best strategy for the bidders and experimentally find the equilibrium with the mechanisms. Discovering these weak points of the mechanisms gives us the possibility of treating them in the future work.

8.2 FUTURE WORK

In Chapter 7 the weaknesses of the fair mechanisms presented are pointed out. An auctioneer has to take into account these manipulations in order to avoid them. For example, checking the identity of the participants in the recurrent auction. However, this is not the most desirable situation. In the future work we plan to design new mechanisms or adapt the presented ones in order to achieve an incentive compatible mechanism that avoids the false-name bids or demonstrate that it is not possible to have an incentive compatible mechanism that uses priorities. If this desirable mechanism is found the bidders may not be able to manipulate the mechanisms and their best strategy will be to send the true value in each auction. It is not an easy work because of the correlating equilibrium. Although the Nash equilibrium was good for the auctioneer the bidders can observe that the same sequence of winners is repeated over time. This observation can be understood by bidders as a signal and they can start lowering prices as they can think that the others bids will start to lower prices too. Bidders could think that if the sequence of winning is the same independently of the bid amounts, all bidders will start to decrease the bids. This is known as the correlated equilibrium. The idea is that each player chooses his action according to his observation of the value of the same public signal [22]. In the case of fair auctions the public signal is the repeated sequence of winnings. On the other hand there are other ways to design fair mechanisms; the priorities are not the unique way. For example CRPA is fair and is based on dynamic reservation prices, not on priorities. This and another new ways should be explored.

Fair mechanisms need a method to avoid rich bidders obtaining the resources shared fairly. This fact has been pointed out in the experimentation and the proposed method has been called “control of fair resources”. DRPA and DRPMUCA implement the control of fair resources with the parameter $minimumPriority$. This method needs more attention in the future work. On the one hand a study of the value of $minimumPriority$ is needed in order to properly fix it or study if the value can be fixed in each one-shot auction. On the other hand other mechanisms can be tested in order to learn who the richer bidders are. Once the richer bidders are detected, they can be labelled and the mechanism can avoid giving them the fair resources at low price.

In Chapter 2 we show the 4 most used ways by researchers to solve the combinatorial auctions. We have used a linear programming tool for this pourpose. It is a good solution when the size of problems is not large, but with large problems the execution time of these tools could be too high. A solution to this problem is to constraint the possible combinations of resources that the bidders can bid for, in order to have a problem solvable in a polynomial time. Although this solution limits the capacity of bidders of expressing their preferences, in some domains it can be useful. We should further study this possibility. It is a very important issue to take into account when resources are perishable since the auction has to be cleared before the perish of resources.

Another interesting issue is to experiment with the fair mechanism in other domains as the vehicle routing optimization. In this domain some authors have used one-shot auctions to solve the allocation of drivers to services where a service is to transport people from one point to another. In this domain it seems interesting to use fair recurrent auctions in order to take into account the outcome of the previous allocations and the effect of fair allocations. For example, if the auctions are solved individually, some drivers could work more hours than others and this fact could provoke problems for the company. In this sense the fair solutions could help to fairly share the work hours between drivers. In the same way, the fair allocations can be used to have an equal use of the vehicles avoiding the overuse of some of them as a measure to prevent repairs.

During the experimentation the mechanisms have used several parameters arbitrarily set (See Appendix E). The criterion followed has been giving the more similar values to all mechanisms in order to compare them. We should verify in a future whether the mechanisms behave differently when using other values for the parameters. Thus, some kind of sensibility analysis should be performed in order to assess the effect of each parameter on the behaviour of the mechanisms.

8.3 Publications

The publications directly related with this thesis that have been published are listed below. There are 2 papers published in journals, 6 papers published in international conferences, 2 of them obtaining awards and 1 paper published in a national conference. Also there is another paper submitted to a journal in process of review.

- Journals:
  - **Javier Murillo**, Beatriz López, Víctor Muñoz and Dídac Busquets. Fairness in Recurrent Auctions with Competing Markets and Supply Fluctuations. *Computational Intelligence. To appear.* **Impact Factor (2009): 5.378. Computer Science, Artificial Intelligence 1/102.**

  - **Javier Murillo**, Dídac Busquets, Jordi Dalmau, Beatriz López, Víctor Muñoz and Ignasi Rodríguez-Roda. Improving urban wastewater management through an auction-based management of discharges. *Environmental Modelling and Software*. Submitted. First revision. **Impact Factor (2009): 3.085. Computer Science, Interdisciplinary Applications 7/95.**
  - **Javier Murillo**, Víctor Muñoz, Dídac Busquets and Beatriz López. Schedule Coordination through Egalitarian Recurrent Multi-unit Combinatorial Auctions. *Applied Intelligence, Springer, 2009.* **Impact Factor (2009): 0.988. Computer Science, Artificial Intelligence 71/102.**

- International conferences:

  - **Javier Murillo** and Beatriz López. Fair Mechanisms for Recurrent Multi Unit Combinatorial Auctions. *European Conference on Artificial Intelligence (ECAI 2010)*. Short Paper.
  - **Javier Murillo** and Beatriz López. Fair Mechanisms for Recurrent Multi Unit Combinatorial Auctions. *European Starting AI Researcher Symposium (STAIRS 2010). Lisbon, Portugal. August 16-20, 2010.*
  - **Javier Murillo**, Víctor Muñoz, Beatriz López and Dídac Busquets. A Fair Mechanism for Recurrent Multiunit Auctions. *Sixth German conference on Multi-Agent System Technologies MATES. Kaiserslautern, Germany. September 23-26, 2008. **Awarded as the Best Paper Award**.*
  - **Javier Murillo**, Dídac Busquets, Jordi Dalmau, Beatriz López and Víctor Muñoz. Improving waste water treatment quality through an auction-based management of discharges. *Proceedings of the iEMSs Fourth Biennial Meeting: International Congress on Environmental Modelling and Software (iEMSs 2008), pp. 1370-1377. 2008. **Awarded as the Best Student Paper**. Barcelona, Spain, July 7-10, 2008.*
  - Víctor Muñoz , **Javier Murillo**, Dídac Busquets and Beatriz López. Improving Water Quality by Coordinating Industries Schedules and Treatment Plants. *AAMAS Workshop on Coordinating Agent Plans and Schedules (CAPS). Honolulu, Hawaii, USA. May 16-18, 2007.*
  - **Javier Murillo**, Víctor Muñoz, Beatriz López and Dídac Busquets. Dynamic Configurable Auctions for Coordinating Industrial Waste Discharges. *Lecture Notes in Artificial Intelligence (Proceedings of MATES 2007), Vol. 4687, pp. 109-120, Springer, 2007. Fifth German conference on Multi-Agent System Technologies MATES. Leipzig, Germany. September 24-26, 2007.*

- National conferences:

  - **Javier Murillo**, Víctor Muñoz, Dídac Busquets and Beatriz López. Coordinating Agents Schedules through Auction Mechanisms. *Workshop on Planning, Scheduling and Constraint Satisfaction, The Conference of the Spanish Association for Artificial Intelligence (CAEPIA). Salamanca, Spain, November 12-16, 2007.*

Although the thesis is focuses on fairness another papers related in a minor way have been published. The listed below are about multi-agent modelling and trust modelling.

- Journals:

  - Víctor Muñoz and **Javier Murillo**. Agent UNO: Winner in the 2nd Spanish ART competition. *Inteligencia Artificial Vol. 12, 39 (2008), pp. 19-27. ISSN: 1137-3601. AEPIA (http://erevista.aepia.org/).* Not in the JCR list.

- International conferences:
  - Víctor Muñoz, **Javier Murillo**, Beatriz López and Dídac Busquets. Strategies for Exploiting Trust Models in Competitive Multiagent Systems. *Seventh German conference on Multi-Agent System Technologies (MATES). Hamburg, Germany. September 9-11, 2009.*

- National conferences:
  - **Javier Murillo**, Víctor Muñoz, Beatriz López and Dídac Busquets. Developing strategies for the ART Domain. *The Conference of the Spanish Association for Artificial Intelligence (CAEPIA). Sevilla, Spain. November 9-13, 2009.*
  - **Javier Murillo** and Víctor Muñoz. Agent UNO: Winner in the 2007 Spanish ART Testbed competition. *Workshop on Competitive agents in Agent Reputation and Trust Testbed, The Conference of the Spanish Association for Artificial Intelligence (CAEPIA). Salamanca, Spain, November 12-16, 2007.*

Finally also other related publications about solving auctions with specialized algorithms and with liner programming techniques have been published.

- Journals:
  - Beatriz López, Víctor Muñoz, **Javier Murillo**, Federico Barber, Miguel A. Salido, Montserrat Abril, Mariamar Cervantes, Luis F. Caro and Mateu Villaret. Experimental analysis of optimization techniques on the road passenger transportation problem. *Engineering Application of Artificial Intelligence 22, pp. 374-388, (Ed. Elsevier Science), ISSN: 0952-1976, 2009.* **Impact Factor (2009): 1.444. Computer Science, Artificial Intelligence 46/102.**

- International conferences:
  - **Javier Murillo** and Beatriz López. An Empirical Study of Planning and Scheduling Interactions in the Road Passenger Transportation Domain. *Proceedings of The 25th Workshop of the UK PLANNING AND SCHEDULING Special Interest Group (PlanSIG2006), Rong Qu (ed.), 14th-15th December 2006. Nottingham, UK. ISSN 1368-5708.*

- National conferences:
  - Víctor Muñoz and **Javier Murillo**. CABRO: Winner Determination Algorithm for Single-unit Combinatorial Auctions. *Artificial Intelligence Research and Development. (Proceedings of CCIA 2008). Sant Martí d'Empúries, Spain. October 22-24, 2008.*
  - **Javier Murillo** and Beatriz López. An Efficient Estimation Function for the Crew Scheduling Problem. *Frontiers in Artificial Intelligence and Applications AI Research and Development (Proceedings of CCIA 2007), pp. 11-18, IOS Press, 2007. Sant Julià de Llòria, Andorra, October 25-26, 2007.*

APPENDIX A
Recurrent auction simulator

In order to have a tool for performing the simulations needed in this thesis, a simulator for recurrent auctions has been developed. The simulator has been designed using the object oriented paradigm and implemented in Java. The core of the simulator is composed by an object that controls the simulation and two interfaces, one for the bidder agent and one for the auctioneer agent. The aim of these interfaces is that the objects that implement the interfaces fulfil the auction protocol of the recurrent auctions.

A.1 SIMULATOR CORE

The core of the simulator has a simple structure composed by one class for the simulator itself, one interface for the auctioneers and one interface for the bidder agents. The simulator class is in charge of creating and initializing the objects of the bidder agents and auctioneer agents participating in the auction, it controls the timing of the simulation and collects the necessary data for the results of the simulation. The interfaces assure that the implementation of bidder and auctioneer agents that participate in a simulation follows the protocol of the recurrent auction. They force bidders and auctioneers agents to implement the needed methods to fulfil the recurrent auction protocol.

A.2 AGENTS

To perform a simulation the needed auctioneer and bidder agents must be implemented following the interfaces. The interface for auctioneers forces to implement the following methods:

- $Enter\_msg$: A bidder calls this auctioneer's method to inform the auctioneer that he wants to enter in the auctioneer's recurrent auction.
- $Auction\_start\_msg$: Allows the simulator object to inform the auctioneers about when they could start a one shot-auction. Only when the auctioneer receives this message he can start the auction process.
- Bid_msg: This method allows bidders to send their bids to the auctioneer.
- $No\_participate\_msg$: This method is used by bidders in order to inform the auctioneer that they do not want to participate in the current one-shot auction.
- $Payment\_msg$: Allows bidders to send the payment for the resources.
- $Drop\_msg$: Allows a bidder to inform the auctioneer that he drops of the recurrent auction.

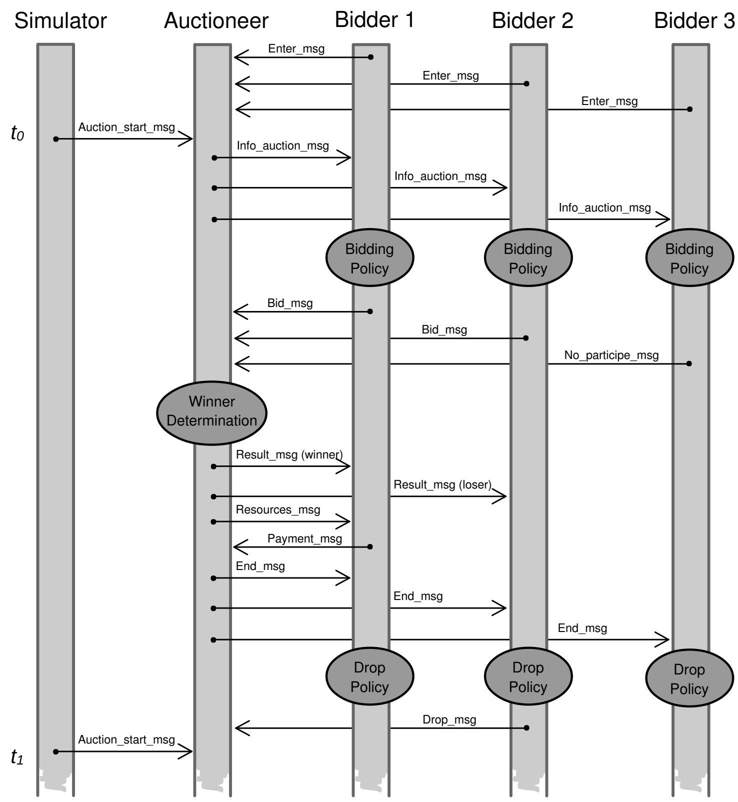

Figure A.1: Protocol of a recurrent auction

These methods allows the communication between the bidder, the simulator object and the auctioneer, but the auctioneer also has to implement the mechanisms for the winner determination. Regarding the bidders, the bidder interface forces them to implement:

- $Info\_auction\_msg$: Allows the auctioneer to inform the bidders about the resources that will be auctioned in the current one-shot auction.
- $Result\_msg$: Allows the auctioneer to inform the bidder about the result of the auction. This message will contain whether the bidder has resulted winner or loser, and in case of winner, the bidder will be informed about which bid is the winner.
- $Resources\_msg$: Allows the auctioneer to deliver the resources to the bidder.
- End_msg: Allows the auctioneer to inform to bidders about the end of the current one-shot auction.

Bidders have to implement their own bidding policies in order to decide which bid to send in each auction and other methods as the drop policy or the selection of new auctioneers.

A.3 Recurrent Auction Protocol

The agents can participate in one and only one recurrent auction at the same time. To enter, a bidder has to send to the auctioneer a message. Figure A.1 shows an example of the pass of messages between the simulator object, the auctioneer and the bidders following the recurrent auction protocol. The main function of the simulator object is sending a message to all auctioneers of the simulation in each time step. This message notifies to auctioneers that they can start a one-shot auction. If there are several auctioneers in the same recurrent auction, they perform the auction in parallel. Then each auctioneer can decide to start an auction or not. For example in the bandwidth allocation domain the auctioneer performs a one-shot auction in each time step but in the WWTP domain the auction only takes place if the level of pollutants exceeds the WWTP capacity. In Figure A.1 we can see that the simulator object sends to each of the auctioneers (in this case only one) one message in time step t_0 and another message in time step t_1. If the auctioneer agent decides to start an auction, he sends to each bidder agent that is currently participating in the recurrent auction a message to inform that a new one-shot auction starts, the resources that will be auctioned and the units of each resource. For this reason the auctioneer agent has to maintain a list, or another structure, about the current bidders participating in the recurrent auction. In Figure A.1 the auctioneer informs three bidders about the start of an auction.

Then, the bidders have to send back to the auctioneer a message containing the bid for participating in the auction or a message indicating that the agent does not want to participate in the current one-shot auction. Although the agent sent the no participation message he remains in the recurrent auction. In Figure A.1 bidder 1 and bidder 2 decide to participate and they send their bids to the auctioneer. On the contrary bidder 3 decides not to participate.

After the auctioneer has received all the messages, he has to select the winners using a WDP solving mechanism. After selecting the winners of the one-shot auction the auctioneer sends a message to the winner bidders indicating the winner bid and the payment. Also he sends a message to the loser agents to inform them that they have not won the resources. Then the auctioneer agent sends the bidders a message that represents the delivery of the resources to the winner agents and the winner agents send back to the auctioneer a message that represents the payment. In Figure A.1 only bidder 1 has resulted as winner and consequently only him receives the resources and has to pay.

Finally, the auctioneer sends the bidders a message indicating that the one-shot auction has ended. Bidders could now update their structures taking into account the result of the auction.

After a one-shot auction has ended, bidders could decide to leave the recurrent auction following their drop policy. In this case the bidder agent sends the auctioneer a message indicating about his dropping from the auction. Then the auctioneer will update his list of bidders. In the Figure A.1 bidder 2 decides to drop from the recurrent auction. Then the auctioneer in the next one-shot auction will not send the message informing about the new auction to this bidder.

Note that this protocol is independent of the kind of one-shot auction. The particular implementations of the auctioneer and bidder agents should take this fact into account.

APPENDIX B
Glossary

Auction. It is a mechanism used to match supply with demand allowing buyers and sellers to agree on a price of a resource following a set of rules and procedures well defined. Firstly, the auctioneer starts the auction and offers to bidders the resources that will be auctioned. Secondly the bidders send back to the auctioneer their bids if they are interested in buying the resources. A bid is usually composed by the resources desired by the bidder agent and the bid amount that is the maximum price that the bidder is willing to pay for the requested resources. The auctioneer collects the bids and then, closes the auction. This means that the auctioneer stops receiving bids. The next step for the auctioneer is selecting the winners. Finally the auctioneer distributes the resources to the winners and collects the payments.

Bidding policy. It is the method used by bidder agents to decide which resources to bid for and the price they are willing to pay for them.

Combinatorial auction. A combinatorial auction is an auction where bidders can bid for combination of resources called packages.

Closed market. The term closed makes reference to the fact that bidders can not enter in the recurrent auction when it has started.

CPLEX. Mixed integer programming software from IBM ILOG.

Fair solution. In the recurrent auction mechanism a fair solution means that at long term, all of the participants accomplish their goals in the same degree or in the more equal possible degree, independently of their wealth.

First-price auction. In the the first price auctions the bidder agent have to pay the bid amount sent in the bid if the bid results as winner.

Free disposal condition. With the free disposal condition the auctioneer can keep some of the units being auctioned if doing so its revenue is higher. Otherwise when there is not the free disposal condition, the auctioneer must sell all the units auctioned.

One-shot auction. We will use the term one-shot to differentiate the auction that take place and ends from the process that involves sequences of auctions with relationships between the results of different auctions. When we refer to an auction we will refer to a one-shot auction, while when we refer to an auction composed by several auction, we will refer to a recurrent auction.

Open market. In open markets the bidders when they leave a market they joins to another one.

Package. A package is formed by a set of tuples indicating the items required by the agent and the number of units of each item (i.e. $\{\langle bandwidth, 2\rangle, \langle memory, 5\rangle\}$).

Perishable resource. A resource is perishable if it vanishes or loses its value when held over an extended period of time.

Pricing mechanism. It determines how the auctioneer decides the price to be paid by the winners. Typically there are two principal families of payment schemes. The first one is the first price auctions where the bidder agent have to pay the bid amount sent in the bid if the bid results as winner. Conversely in the second-price auctions the price paid for the winners bidder agents is the highest bid amount of the loser agents.

Recurrent Auction. Sequence of one-shot auctions of any kind where the result of one auction may influence the following one.

Reservation Price. A *reservation price* fixes the minimum requirements of the auctioneer. The reservation prices can be fixed for units of resources, for packages of resources or for all the resources auctioned. This value is known only by the auctioneer and is used to decide the winners. For example an auctioneer can fix a reservation price for a resource r_0. This means that the resource r_0 will not be sold with a price lower than the reservation price.

Sealed bid auction. In sealed-bid auctions the bid amount offered by other bidders is private, only the auctioneer knows all bids sent by bidders.

Second-price auction. In the second-price auctions, also known as Vickrey auctions [11, 28], the price paid for the winners bidder agents is the highest bid amount of the loser agents.

True value. The true value about a package is a private value of each agent and is the maximum price that is willing to pay for the package. In the scenario of non combinatorial auctions is equivalent to wealth.

Utility. The utility obtained in an auction by an agent is defined as the true value of the won package minus the payment done. For example, if an agent won a package and his true value for this package is 5 and the payment done is 3 then, the utility for the agent is 2.

Wealth. Regarding bidder agents, a high wealth means that the bidder agent is rich and is able to send high bid amount and pay high prices for the resources.

Winner determination mechanism. It is the mechanism with which the auctioneer decides which are the winning bids (i.e. how the resources are allocated to the agents). Depends on the kind of auction, the Winner Determination Problem (WDP) can be an $\mathcal{NP}$ optimization problem.

XOR Bidding language. [16] With this bidding language bidders express their preferences with XOR bids.

APPENDIX C
Acronyms

ASM1: Activated Sludge Model N1.

BOD: Biochemical Oxygen Demand.

BSM1: Benchmark Simulation Model N1.

CA: Cancellable Auction.

CABOB: Combinatorial Auction Branch On Bids.

CASS: Combinatorial Auction Structured Search.

CAMUS: Combinatorial Auction Multi-Unit Search.

CMUCA: Cancellable Multi-Unit Combinatorial Auction.

COD: Chemical Oxygen Demand.

CRPA: Customizable Reservation Price Auction.

CRPAP: Customizable Reservation Price Auction with Priorities.

DP-ORA: Discriminatory Price Optimal Recurring Auction.

DP-ORMUCA: Discriminatory Price Optimal Recurring Multi-Unit Combinatorial Auction.

DRPA: Dynamic Reservation Price Auction.

DRPMUCA: Dynamic Reservation Price Multi-Unit Combinatorial Auction.

EQ: Effluent Quality.

GCS: Grid Computing Services.

GLPK:GNU Linear Programming Kit.

GVA: Generalized Vickrey Auction.

IDR: Index of Desirable Resources.

IQ: Influent Quality.

MK: Minimum Knowledge.

MUA: Multi-Unit Auction.

MUCA: Multi-Unit Combinatorial Auction.

LEQUIA: Laboratory of Chemical and Environmental Engineering group of the university of Girona

LP: Linear Programming.

PA: Prioritized Auction.

PGVA: Prioritized Generalized Vickrey Auction.

PI-ORA: Participation Incentive Optimal Recurring Auction.

PI-GVA: Participation Incentive Generalized Vickrey Auction.

PMUCA: Prioritized Multi-Unit Combinatorial Auction.

QoS: Quality of Service.

RA: Recurrent Auction.

RMUA: Recurrent Multi-Unit Auction.

RMUCA: Recurrent Multi-Unit Combinatorial Auction.

RPA: Reservation Price Auction.

RPMUCA: Reservation Price Multi-Unit Combinatorial Auction.

TA: Traditional Auction (first-price sealed bid auction).

TCL: Tolerance to Consecutive Loses.

TKN: Total Kjeldhal Nitrogen.

TMUCA: Traditional Multi-Unit Combinatorial Auction.

TSS: Total Suspended Solids.

UWS: Urban Wastewater Systems.

VLLF-BDC: Valuable Last Loser First Bidder Drop Control.

WDP: Winner Determination Problem.

WWTP: WasteWater Treatment Plant.

Appendix D
Notation

A: Recurrent auction. $A = \{a_0, ..., a_{|A|-1}\}$.

a_j: j-th one-shot auction.

b: Bid.

$b_{i,j}$: Bid of bidder agent g_i in the auction a_j when they only can send one bid.

$b_{i,j,x}$: x-th bid of bidder agent g_i in the auction a_j.

$\mathcal{C}(b_{i,j,x})$: Function to know the bid amount in bid $b_{i,j,x}$.

C: Set of components (COD, BOD, TKN and TSS).

c: Component.

$conc_{i,c,ts}$: Concentration of component c produced by the industry i or the influent at time step ts.

$flow_{i,ts}$: Flow discharged by industry or influent i at time step ts.

G: Set of bidder agents. $G = \{g_0, ..., g_{|G|-1}\}$

g_i: Agent i-th.

K_i: Set of the bid amounts sent by agent g_i in the first auction of the current cycle of each package sent by g_i. $K_i = \{k_{i,0}, ..., k_{i,|\mathbb{S}_i|-1}\}$.

$k_{i,m}$: Bid amount sent in the first auction of current cycle of agent g_i about package $S_{i,m}$.

L_i: Set of counters of lost auctions of bidder g_i. $L_i = \{l_{i,0}, ..., l_{i,|\mathbb{S}_i|-1}\}$.

$l_{i,m}$: Counter of lost auctions for agent g_i about package $S_{i,m}$.

LT: Length of the time window.

MF: Maximum flow.

MC_c: Maximum concentration threshold for component c.

p_i: Priority of agent g_i.

$p_{i,m}$: Priority of agent g_i about the package $S_{i,m}$.

$P(A,i)$: Set of auctions belonging to A where agent g_i has participated.

pd: Probability of disobey.

pq: Probability of choosing an action in the Q-learning algorithm.

q_x: Available units of resource x-th.

R_j: Resource set auctioned in the auction a_j. $R_i = \{\langle r_0, q_0\rangle, ..., \langle r_{|R_i|-1}, q_{|R_i|-1}\rangle\}$

r_x: Resource x-th.

RP_i: Set of all reservation prices of agent g_i. $RP_i = \{rp_{i,0}, ..., rp_{i,|\mathbb{S}_i|-1}\}$.

rp_{ORA}: Reservation price in DP-ORA mechanism.

rp_i: Reservation price of agent g_i.

$rp_{i,m}$: Reservation price of agent g_i about package $S_{i,m}$.

$S_{i,m}$: m-th different package sent by agent g_i in a recurrent auction.

$\mathcal{S}(b_{i,j,x})$: Function to know the package required in bid $b_{i,j,x}$.

$\mathbb{S}_i$: Set of all different packages sent by agent g_i during a recurrent auction. $\mathbb{S}_i = \{S_{i,0}, ..., S_{i,|\mathbb{S}|-1}\}$

T: Set of time steps where the one-shot auctions corresponding to a recurrent auction happens. $T = \{t_0, ..., t_{|A|-1}\}$.

t_i: Time step of the a_j auction.

TS: Final time of a simulation.

v_i: Bid amount sent by agent g_i.

v_i': Bid amount modified or score.

$V_{i,j}$: Set of bids sent by g_i in the auction a_j.

w_i: Wealth of agent g_i.

$w_{i,m}$: Wealth of agent g_i about package $S_{i,m}$.

$x_{i,j}$: Outcome of agent g_i in the auction a_j. $x_{i,j} = 0$ if g_i its a loser and $x_{i,j} = 1$ if its a winner.

$z_{i,m}$: Current bid amount of bidder g_i about package $S_{i,m}$.

Appendix E
Parameters

α: Factor of increment of the bid amount in DP-ORA.

β: Factor of decrease of the bid amount in DP-ORA.

δ: Minimum percentage of increment or decrement of reservation prices. Is used by CRPA, CRPAP, DRPA and DRPMUCA.

dis: Discount factor in the Q-learning algorithm.

exp: Probability of choosing an action for exploration in the Q-learning algorithm.

γ: Number of lost auctions necessary so that the priorities arrives to his maximum value (1.0). Is used by PMUCA, DRPMUCA and PGVA.

$minimumKnowledge(MK)$: Minimum number of auctions needed to determine if a bidder agent knows his auctioneer. Used by agents with trust model.

$minimumPriority$: Minimum priority necessary in order to achieve fair resources. Used by DRPA and DRPMUCA.

min: Minimum probability value returned by the probability of disobey function.

λ: Initial priority value. Used by PMUCA, DRPMUCA and PGVA.

$lrate$: Learning rate in the Q-learning algorithm.

sl: Slope of the probability of disobey function.

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