A STUDY ON SEQUENTIAL INTERNET AUCTIONS USING AGENT-BASED MODELING APPROACH

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Yıldız Akkaya

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A Study on Sequential Internet Auctions Using Agent-Based Modeling Approach

The thesis of Yıldız Akkaya

has been approved by

Assist. Prof. Bertan Badur ______________________
(Thesis Advisor)

Assoc. Prof. Osman N. Darcan ______________________
(Thesis Advisor)

Assist. Prof. Sona Mardikyan ______________________

Assoc. Prof. Eyüp Çetin ______________________

Assoc. Prof. Ünsal Tekir ______________________

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Thesis Abstract

Yıldız Akkaya, "A Study on Sequential Internet Auctions Using Agent-Based Modeling Approach"

With widespread use of the Internet, Internet auctions (e-auctions) become more popular in order to trade increasing number of goods as Internet provides both almost perfect market information and an infrastructure for executing auctions at lower administrative costs. The sequential auctions are the most widely used auction format.

The aim of this study is to present a dynamic model of an e-auction so as to investigate how the welfare of buyers is affected by different bidding strategies. This problem has been studied in economics by conducting laboratory and field experiments and theoretically in various static auction mechanisms where perfect rationality of participants is assumed. On the other hand, observing the biding strategies of individuals is almost impossible in laboratory or field experiments. To overcome the limitations of these approaches, the new agent-based modeling methodology in which researchers use simulations to investigate the behavior and interactions of autonomous, heterogeneous, boundedly rational adaptive population of agents in the social and economical environments, has been emerged. In the study, the bottom-up agent-based modeling and simulation methodology is adapted to investigate the behavior of participants in electronic markets.

A simulation model is developed to understand the effects of different bidding and bid increment strategies on the welfare of the bidder. To some extend sensitivity of the auction outcome on auction rules and market design parameters are also investigated.

Tez Özeti

Yıldız Akkaya, “Eyleyici Tabanlı Simülasyon ve Modelleme Yaklaşımı ile Internet üzerinden Ardışık Müzayede Çalışması”

Internetin yaygın kullanımı ile birlikte, internet üzerinden malların ticareti icin yapılan müzayedeler daha çok kullanılmaya başlanmıştır. Bunun nedeni, Internet sayesinde bu müzayedelerde pazara yönelik bilginin neredeyse tam bir şekilde elde edilebilir olması ve müzayedelerin düşük idari maliyetle gerçekleştirilebilir olmasıdır. Günümüzde web sitelerinde ürünler en çok ardışık müzayedeler ile satılmaktadır.

Bu çalışmanın amacı, ardışık müzayelerdeki teklif stratejilerinin, katılımcıların refah seviyeleri üzeindeki etkilerini araştırmak ve dinamik bir Internet müzayede modeli sunmaktır. Teklif verme stratejisinin refah üzerine etkisi, ekonomi biliminde, katılımcıların tamamen rasyonel olduğu varsayımı altında pek çok durağan müzayede için teorik olarak çalışılmıştır. Ayrıca, bu problem laboratuar ve alan çalışmalarında ele alınmış fakat bu çalışmalarda kişilerin strateji bilgilerine ulaşmak neredeyse imkansız olduğu için, istenilen sonuçlar alınamamıştır. Bu yaklaşımların sınırlamalarından kurtulmak için araştırmacılar, sosyal ve ekonomik ortamlardaki kendi kendini idare eden, heterojen, rasyonelliği sınırlı ve davranışları uyarlanabilen eyleyicilerin davranışlarını ve kendi aralarındaki ilişkilerini anlamak için, eyleyici tabanlı modelleme ve simülasyon (ETMS) yaklaşımını kullanmaktadırlar.

Çalışmada, Internet müzayedelerine katılan kişilerin davranışlarını incelemek için aşağıdan yukarıya ETMS yaklaşımı kullanımıştır. Simülasyon deneylerinde katılımcıların teklif miktarlarını ve bir müzayede süresince tekliflerini ne şekilde arttıracaklarına yönelik verdikleri kararları içeren iki grup strateji sınanmıştır. Ayrıca sonuçlar üzerinde müzayede kurallarının ve tasarımının etkisini anlamak amacıyla çeşitli duyarlılık analizleri yapılmıştır.

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INTRODUCTION

> There is some strategic bidding behavior in the way bidders advance their bids. Bidders consider the way the auction progresses which implies that a bidders' strategy includes not only the stopping point along the bidding path but also the precise nature of the path that led there (Raviv, 2008).

Auction mechanisms have been used throughout the human history for the efficient allocation of goods and price determinations (McMillan, 2002). Individuals discovered that auctions are profitable way to trade used items and firms applied auctions in procurement in expectation of lower prices. Since the rapid development of the internet, goods are being traded using on-line versions of auctions, called e-auctions. Buyers and sellers use e-auction as a mechanism to accomplish price discovery, winner determination and payment mechanism (Dang & Jennings, 2003).

As the business world and people become more closely integrated with the tools of internet, the integration of classical and new auction mechanisms became commonly used (Turban & King, 2002). Today, the most commonly used internet sites are eBay (www.ebay.com) and Amazon (www.amazon.com).

In auctions and e-auctions, the bidding behavior of participants will be different due to the variety of auction protocols, which means that there is no general optimal bidding strategy that can be used in all types of auctions. In order to get profitable outcomes from auctions bidding strategies should be tailored to the type of the auction in which they are intended to be used (Ma & Leung, 2008). For this purpose, researchers conduct theoretical studies and field experiments. In the former method, the strategic behavior of the bidder cannot be explained and in the latter method, it is very costly to conduct experiments with human subjects. In order to bridge the gap between theory and experimental work with human subjects, agent-based simulation approach, where auction mechanism and actors are modeled in predetermined software platforms, is being used by researchers (Duffy, 2006). The most important feature of using simulation is that, it enables to study markets with controlled environmental parameters. On the other hand, building the right model in the simulation is intense and difficult. Many researchers used agent-based models to investigate the behavior of boundedly rational, heterogeneous and autonomous adaptive agents in different trading environment (Tesfatsion, 2006).

In this study, agent-based modeling and simulation (ABMS) approach is used to address several research questions regarding the behavior of the agents in e-auctions. The effect of different bidding strategies played by heterogeneous agents in different multi-unit auction settings on the winner's payoff, is investigated. The agent-based model involves bidders, who have independent private values, demanding at least an item from a single seller offering multi-unit item. The items are sold sequentially and only one item is being sold at a time. The bidders, who are the only active players in our model, play strategies against one another repeatedly in multi-period auctions. A limited set of sensitivity analysis is performed to examine how the outcome of different strategies is affected from different market parameters set by the auction designer.

The remainder of this thesis is organized as follows. In Chapter 2 the background information about auction mechanisms and ABMS is given. Chapter 3 states the definition of the problem, agent strategies and the simulation model design. Chapter 4 presents the experimental set-ups and the results of the simulation experiments in detail. Finally, Chapter 5 concludes the study with a summary of the findings and gives suggestions for the further research directions.

CHAPTER 2

LITERATURE REVIEW

This chapter presents background information about auctions, different auction mechanisms and various research methodologies about auction studies. Also agent-based simulation and modeling methodology is explained in details referring to the previous studies about auctions.

Auctions and e-Auctions

An auction is a market mechanism for resource allocation with predetermined set of rules and for price determination based on the bids of participants (McAfee & McMillan, 1987). Currently, auctions are mainly used for their efficiency on resource allocation, simplicity and ability to generate high revenues to the seller (Krishna, 2002). Also, auctions can minimize communication within a system, and generate near-optimal solutions that maximize the overall value of all agents (Parkes & Ungar, 2000). In addition auctions are more flexible than a fixed price sale and perhaps less time-consuming than negotiating a price (Menezes and Monteiro, 2005).

Since the rapid development of the internet, goods are being traded using on-line versions of auctions, called e-auctions. Sellers and buyers prefers trading via e-auctions instead of trading in a physical market place. When a seller or a buyer decide to use e-auctions as a channel to sell or buy some items, they must make several important strategic decisions. As it can be seen in Figure 1, in order to make such decisions, sellers and buyers usually complete four processes: Searching and comparing, getting started at an auction, bidding, and conducting post-auction activities (Turban & King, 2002).

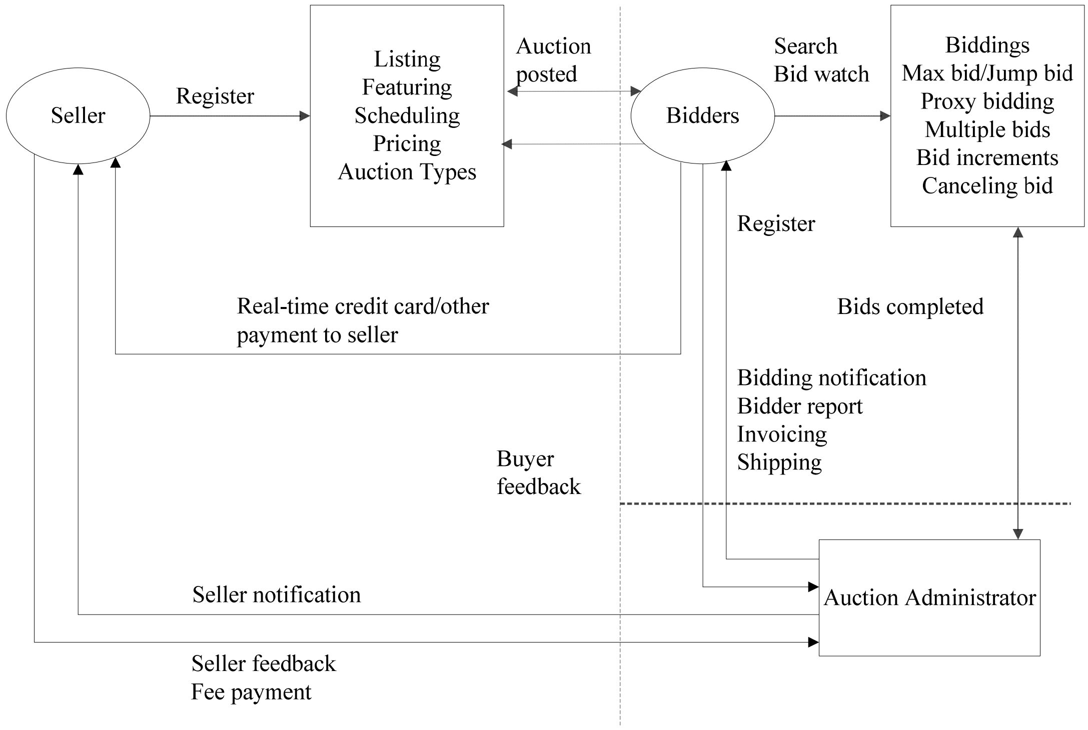

Fig. 1 The e-auction process

Since there are hundreds of e-auction web sites, buyers and sellers need to execute extensive searches and comparisons to select desirable auction locations. After making the decision of which auction to enter then in order to participate it, buyers and sellers need to register at the selected site. In the bidding phase, buyers can submit bids themselves or can use proxy bidding which place bids on behalf of them. Post-auction activities like bidding notifications and end-of-auction notices, take place once an e-auction is completed (Turban & King, 2002).

Traditional auctions provide benefit over e-auction in allowing the bidders to see and touch the item, however e-auctions do provide significant benefits for both buyers, and sellers (Turban & King, 2002).

<u>Benefits to buyers</u>

Some of the benefits that is provided by e-auctions to the buyer are explored below (Turban & King, 2002).

1. *Lower Prices:* One of the key benefits of e-auctions is that, the users do not have to spend money and time travelling to the auction venue. Also buyers can use bidding mechanism to reduce prices instead of buying the item in a fixed price.

2. *Convenience:* e-Auctions are convenient as it allows users to trade from anywhere via internet.

3. *More bidding opportunities:* The buyers can place bids over a number of days rather than minutes as it would be the case in traditional auctions. This allows the individuals to spend more time comparing the items in terms of quality and price against similar items across the website.

4. *Anonymity:* In traditional auctions the anonymity was very difficult for buyers. However, in e-auctions, there is no direct relationship between the buyers and seller, so the anonymity is easier to obtain.

5. *Entertainment:* e-Auctions could provide the user entertainment associated with participating in an auction. Not only the competitive environments, but also the interaction between the buyers and sellers may create positive feelings.

Benefits to sellers

e-Auctions also have benefits for sellers. Some of these benefits are explained in below (Turban & King, 2002).

1. *Lower cost of sale:* Compared with traditional auctions, e-auctions offer lower transaction costs. Also it provides substantial cost savings through auction being online and instantaneous .

2. *Less time required to sell the item:* Sellers are able to liquidate the items that they want to sell, very quickly.

3. *Increased Revenues:* Since e-auctions enable sellers to reach a large number of buyers, they can sell more items at a price equals to buyer valuation of the product.

Sellers can gain revenue by offering items directly to the buyers instead of going through expensive intermediaries.

4. *Better customer relationships:* As in e-auctions almost no intermediary is used, the sellers have a possibility to find out the buyers thoughts and critics about the item directly. In addition, buyers and sellers have more chances to interact with each other, thus creating a sense of loyalty.

According to Bajari and Hortaçsu's (2004) study, the most important reasons of common usage of e-auctions can be summarized to two important factors as: (i) it is convenient and (ii) it is fun. e-Auctions removes borders so that the people in different cities of the same country or even the people from different countries are able to buy what they want and sell their goods to others. Second factor of the popularity of e-auctions is, many bidders obviously enjoy considering the refinement of strategic offering and sharing their views with the others.

Classification of Auctions

Auctions can be classified according to several distinct criteria as the termination rule of the auction, the number of objects on sale and the order of conducted auctions. Despite this classification, there are four classical mechanisms of actions as: the ascending bid auction, the descending bid auction, the first-price sealed-bid auction, and the second-price sealed-bid auction (see Fig. 2). Most of the other auction mechanisms are the variations of these four classical type by changing the number of sellers (one or many), the number of units to be traded and applying different termination rules (Dinther, 2007).

Auctions
- The ascending bid auction
- The descending bid auction
- The First-Price Sealed-Bid auction
- The Second-Price Sealed-Bid auction

Fig. 2 Classical auction mechanisms

The ascending bid auction: The price of the item on sale is increased by the bidders until the termination of the auction. The bidder with the highest bid wins the object at the final price (Klemperer, 2004). Once aparticipant leaves in the course of the auction he/she is not allowed to back in. This format, which is also known as English Auction, is commonly used in art auctions.

The descending bid auction: In this type of an auction the price of an item starts at a high level and is decreased by the auctioneer. The first bidder who accepts to pay the announced amount gets the item by paying that amount. This format is known as Dutch Auction and is usually used for the items which are need to be sold out quickly like flowers, fishes etc.

The first-price sealed-bid auction: The bidders submits their bids independently and without knowing what the other bidders bid. The item is sold to the highest bidder who pays the winning bid (Klemperer, 2004).

The most substantial reason for this mechanism to be used is; it is the most popular mechanism for purchasing items on the Internet. Also in first price auctions, the bidders do not change bids according to their beliefs about the other agents. In addition, this auction mechanism is the most appropriate and preferred protocol if the agents have difficulty on item valuation (Cramton, 1988).

The second-price sealed-bid auction: In this format of an auction, the bidders submit their bids independently, without knowing what the other bidders bid. The item is sold to the highest bidder with the second highest bidders' bid value. This auction format was first suggested by Vickrey (1961). Second price auction protocol is implemented due to several reasons. Firstly, it is communication efficient. Secondly, for the sealed-bid single-auction case, the optimal strategy is to bid the true value and thus requires no computation (Vickrey, 1961).

As the business world and people become more closely integrated with the tools of internet, the integration of classical and new auction mechanisms became commonly used (Turban & King, 2002). The most commonly used classification of e-auctions according to different rules are shown in Fig. 3. For instance different formats of auctions due to the termination rules (hard-close and soft-close) are being implemented on e-auction websites. In hard-close auction format, the duration of the auction is set before the auction starts and when the time comes the auction closes. Besides, in the soft-close auction format duration depends on the last bid's time. If a bidder bids in the scheduled time interval right before the closing time, the duration of the auction is extended for a fixed period of time (Duffy & Unver, 2008).

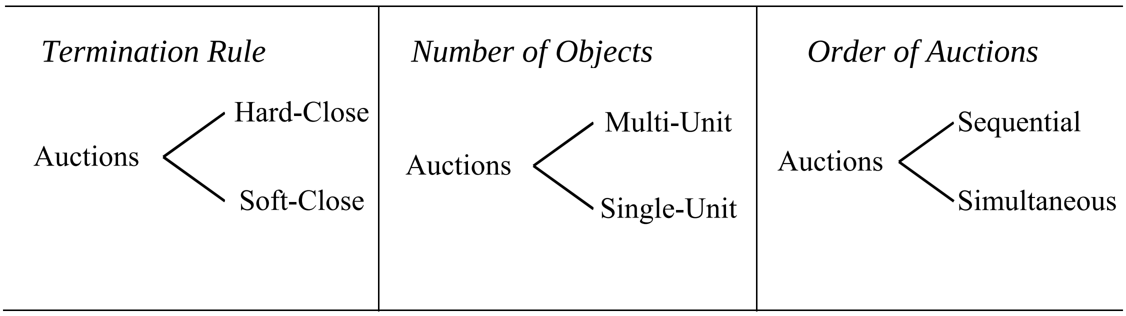

Fig. 3 Different auction classifications

The early theoretical studies; Vickrey (1961), Milgrom and Weber (1982), and McAfee and McMillan (1987), just like a large proportion of their followers, made their auction studies considering the case where there is only one unit of an indivisible good on sale or when buyers are assumed to desire at most one unit from multi-units on sale (see Weber, 1982, McAfee and Vincent, 1997). On the other hand, since middle 90s the multi-unit auctions with multi-unit demand have drown intense interest of the researchers.

In multi-unit settings, the auctions can be simultaneous or sequential. In simultaneous auctions, items are sold in auctions which are running concurrently. According to their market design, simultaneous auctions could run in parallel with different starting and ending times. Besides, bids to be submitted in these acutions have to be computed simultaneously (Ausubel, 2004).

Sequential auctions are auctions for the identical goods, ordered in time, and are commonly observed on e-auction websites such as eBay (Kaiser & Kaiser, 1999). The items are sold one at a time, with separate bidding on each item. The main disadvantage of sequential auction is that when the total number of units on sale is large, it could be time consuming to sell all items one by one. However, the bidders are able to collect data regarding the past auctions and this allows the bidders to bid in multiple sequential auctions and to assess their likelihood of winning a future auction (Arora, Xu, Padman, & Vogt, 2003). In practice there are two main reasons which explain the use of sequential auction procedures such as; the units may not be available at the same time and they may be perishable and would then have to be sold separately (Mezzetti, Pekec, & Tsetli, 2008).

Sequential auctions are mostly used for selling groups of similar or identical items like wine, fish, flower, satellite broadcast (Gale & Stegeman, 2001). Hausch (1986) finds that instead of simultaneous auctions, sellers prefer sequential auctions in order to sell multiple objects because bidding behavior provides information about buyers' private values. McAfee and Vincent (1997) studied on sequential sale of 120 identical cases of wine at Christie's of Chicago in 1990 whereas Lambson and Thurston (2006) studied on sequential sale of pelts in Seattle Fur exchange. In sequential auctions even though there is only one object on sale at a time, the biding behavior of the participants strongly depends on the auctions that are yet to be conducted (Elmaghraby, 2003).

Although sequential auctions are old, most of the literature study is done after the observation of Ashenfelter (1989) regarding "declining price anomaly", i.e. the observation that prices for identical products which are sold sequentially often follow a decreasing pattern. Some theoretical studies (Scoones & Bernhardt, 1994; Gale and Hausch, 1994; Pezanis-Christou, 1996; Katzman, 1999) also confirmed this anomaly in sequential auctions as a consequence of supply and demand uncertainty. Also Neugebauer and Pezanis-Christou (2007) showed that the greater the uncertainty of the supply, the more the expected prices decline because the bidders are in tendency to discount their future profits and they are impatient to acquire their units. On the other hand Neugebauer and Pezanis-Christou (2007) also found that in longer sessions, involving 100 sequential auctions, as the bidders have gained some experience in the environment the price declines vanish. Arora et al. (2003) showed that in two-period sequential auctions, the volatility in the number of bidders in the second period lowers the first period bid.

In addition to the formats described above, e-auction sites mostly implement a hybrid of ascending-bid auction and the second-price sealed bid auction (Duffy and Ünver, 2008). For instance the most popular e-auctions sites eBay and Amazon implement this hybrid format with one difference; eBay uses Hard-Close format while Amazon conducts Soft-Close format. At all major Internet auction websites, it is common to observe sequential auctions for the same type of good. In fact, in Vakrat and Seidmann (2000), the results of extensive field data collection on online auctions show that about 85% of the goods auctioned at a popular business-to-consumer auction site were offered repeatedly.

Despite the differences of these auction mechanisms, some features of auctions may still be common. For instance, in all of these auctions bidders may adopt different “attitudes towards risk” such as risk neutral, risk averse and risk taker. In the bulk vast of the literature however, the agents are assumed to be risk neutral which is not the typical case in practice. Another common factor is “agent’s value towards the item” on sale in the auction. The agents may be certain or uncertain about their private value. Also the value of an item may be unknown for all agents. In most of the literature the agents have independent private valuations, however, in practice, the agents are not quite sure whether their valuations is precise and correct. One other common factor is the spending limit of the agent, in other terms “budget constraint”. Especially in auctions when agents demand more than one-unit of an item the budget constraint has to be taken into consideration. Finally, in most of the auction settings a minimum transaction cost, “reserve price”, is set in order to increase the revenue of the seller. However, the effects of the reservation price in the total revenue of the auction is still an open end question in which the answer depends on the auction parameters.

All these types of auction mechanisms have aroused the attention of the researchers for several years. For instance Gandal (1997) has studied a sequential auction of multiple independent objects in the context of area cable television licenses in Israel. Chanel et. al, (1996) examined the cause and measurements of decreasing prices in sequential auctions of multiple objects. Donald, Paarsch and Robert (1997) constructed and estimated a theoretical model of participation and bidding at a sequential, ascending-price auction with multi-unit demand. Katzman

(1999), assuming that bidders are symmetrically informed, has shown that when only two objects are sold, the sequence of second price auctions achieve an efficient allocation.

New theoretical and empirical literature is formed by the recent development of new auction mechanisms especially those used by e-auction sites. Most of the researchers have studied the market design of auction mechanisms, while others made their studies on finding the most profitable strategies to implement for bidders and sellers in different auction designs (Ausubel, 2004; Bajari & Hortaçsu, 2004).

Different Research Methodologies about Auction Studies

The researchers used different methods for their studies on auction theory and market design. Mehlenbacher (2007), names these methodologies as: mathematical theory, econometric models, laboratory experiments, computational models (like dynamic programming), and simulation.

Mathematical approach uses a developed mathematical machinery as optimization, order statistics, etc. In this approach some restricted and simplifying assumptions, which cause fragile conclusions, are made and theorems are used in order to prove the results (Milgrom, 1989). However, the theoretical results are not easily applicable to the real-world auctions (Mehlenbacher, 2007). Theoretical studies of auctions have been conducted mainly in the field of microeconomics for perfectly rational agents and static environments. The study of Vickrey (1961), is one of the cornerstones in the auction literature which leads more researchers to conduct studies about auction theory (Riley & Samuelson, 1981; Myerson & Satterthwaite, 1983). In a static standard sealed-bid second-price auction it is well established fact that, bidders with independent private valuations have a weakly dominant strategy of submitting a bid equal to their own valuation (Vickrey, 1961). In addition, Said

(2009) considered a theoretical model of second-price auction in which buyers and sellers arrive randomly to the auction. He examined the equilibrium behavior of bidders in response to these arrivals, as well as to changes in market conditions. He found that in equilibrium bidders do not bid their true value instead, they shade their bids down by their option value of participating in future auctions, which depends on the number of randomly arriving participants.

In econometric methods, the data from real auctions have used to conduct analysis. For instance, Lucking-Riley et al. (2006) gathered data from e-Bay auctions for one-cent coins which took place during July and August 1999. They presented an exploratory analysis of the determinants of prices in online auctions. They found that a seller's feedback have a measurable effect on her auction prices, minimum bids and reserve prices tend to have positive effects on the final auction price and auction price on average is significantly increase when the duration of the auction is longer. In addition, some researchers apply regression analysis to the data (De Silva, Dunne, & Kosmopoulou, 2002; Athey & Levin, 2001; Iledare, Pulsipher, Olatubi, & Mesyanzhinov, 2004), while others have used structural models which assume a Bayesian Nash equilibrium bidding strategy for the bidders (Li & Vuong, 2000; Li & Perrigne, 2003; Haile, Hong, & Shum, 2003). The major disadvantage of using econometric methods is the difficulty to obtain the data.

Third approach for dealing the limitation of auction theory is to conduct laboratory experiments by using human subjects, mostly economics undergraduate students (Kagel & Levin, 2002). The main advantage of this approach is, it allows the researchers to observe the effects of human reasoning and feeling (Meclenbacher, 2007). The results of these experiments reveal that some of the observed outcomes such as late bidding behavior in e-auctions, cannot be successfully explained with these microeconomic theories (Kim, 2007; Mizuta & Steiglitz, 2000). Also experimental studies (Keser & Olson, 1996; Kagel & Levin, 2002; Alsemgeest, Noussair, & Oslon, 1998; Manelli, Sefton, & Wilner, 2006) have explored the various designs for multi-unit demand auctions.

Février et al (2004) studied two-unit sequential auctions and investigated the the role of the buyer's option by conducting laboratory experiment. They assume that the two units are sold to two risk-neutral buyers who desire both units, and their demand for the items is either decreasing, flat, or increasing (implying that the value of the second unit exceeds the value of the first unit). In their setting four main auction mechanisms as: ascending bid, descending bid, first-price sealed-bid and second-price sealed-bid are considered. The results of their study indicate that the revenue-ranking of the four auction mechanisms is the same as the one found in the single-unit experimental literature. In addition, important deviations between the Nash equilibrium strategies and the observed bidding strategies is found in the auctions for the first unit.

Even though, the result of these experiments provides useful benchmarks in other methodologies, the experiments are expensive, time consuming and not adaptable enough with changes (Duffy & Unver, 2008).

Fourth approach is to use a computational method that is not agent-based (Meclenbacher, 2007). In order to determine optimal bidding strategies for bidders dynamic programming (DP) methods have been used. DP methods are useful for the researchers (such as: Tesauro and Bredin, 2001, Attaviriyanupap et al., 2005) when there is huge amount of data exists as it produces an optimized bidding strategy based on the real-world data. However, the datasets can not be obtained easily from auctions

Fifth approach that has been used by researchers is the simulation in which the auction mechanism and behaviors of sellers and buyers are simulated in order to predict actual behavior. According to Ostrom (1988) social science theory cannot be expressed neither by formalized expressions of mathematics, nor by verbal explanations. For this reason, in spite of deduction and induction methods, in social sciences the alternative way of doing researches is the simulation (Neumann, 2004).

In spite of the large amount of theoretical and experimental works that have been done by researches, there is still a lack of explanation of the types of biddings strategies that are being used in different e-auction formats. Although economic theory provides some insights into some structural properties of bidder strategies, it is difficult to compare the different format when the bidder population is heterogeneous (Hailu & Thoyer, 2007) and when bidder marginal values are not constant (Ausubel & Cramton, 1998). Besides, both in the laboratory experiments and field studies only the bid amounts of the agents are observable but not the strategy of the bidders. As Duffy and Unver mentioned, in the field study, the sensitivity on any change in auction rules, environmental parameters or other design features are difficult to assess because these parameters are out of control of the researcher. Further in the laboratory, it is costly to make such kind of changes because any variation means extra session with paid human subjects (Duffy and Unver, 2008).

Agent-based modeling and simulation (ABMS) approach is used by the researchers in order to bridge the gap between experimental work with human subjects and theory.

Agent-Based Modeling and Simulation

An agent is a software entity that is autonomous, communicating, and adaptive (Wooldridge, 2009). Agents are driven by their own objectives, are capable of recording information about their environments and can choose how to react to the environment. All these features together mean autonomy. Agents are also communicating software entities which means that they directly communicate with other agents by passing messages. In addition, agents are adaptive and they endeavor to improve their states (Meclenbacher, 2007).

ABMS is a new approach for modeling systems, comprised of interacting autonomous agents, in predetermined software platforms (Duffy, 2006; Tesfatsion, 2006). During the last decade the use of software agents for simulating problems of social science became more and more popular due to several reasons. For example, ABMS can relax the classical assumptions of standard microeconomic theory such as (Meclenbacher, 2007):

1. Economic agents are rational and they are able to optimize their behaviors in accordance with their well-defined objectives.
2. Economic agents are homogenous which means the agents have identical taste
3. There are decreasing returns of scale from economic processes
4. The long-run equilibrium state of the system is the primary information set

Firstly, there is a huge amount of theoretical literature considering the optimal strategies of rational agents in different types of auctions, however, agents participating in auctions are rarely fully rational. Also, agents not always try to optimize their behavior instead they are "*satisficing*[1]" their attitudes (Simon, 2001). Secondly, in the real world agents are heterogeneous and this causes real complexity. Thirdly, according to Arthur et al.(1997), the underlying dynamic processes of rapid exponential growth in economics is the increasing returns and positive feedback loops. Fourthly, as Axtell (2000) has shown, not all the systems come to an equilibrium which is also not the only results of interests.

Tesfatsion (2002) coined the term "Agent-based Computational Economics" (ACE) and provided an introduction to the use of ABMS in economics. ACE is a methodological approach to study dynamic economic systems of numerous independent components. The system behavior results from the interaction of these components. The field of ACE has grown up around the application of ABMS to economic systems (Tesfatsion, 2002).

The most important feature of using ABMS in economic mechanisms as auctions is that it enables to study markets in a controlled environmental parameters and thus able to isolate effects through variation of these parameters. ABMS gives opportunity to explore the possibilities of the model (Banks, 1998; Dinther, 2007). However, building the right model in ABMS is intense and difficult (Tesfatsion, 2006) .

For the last 10 years, there has been an interest in designing agents that represents participants when bidding in online auctions (Bajari & Hortaçsu, 2004). While designing the behaviors of bidding agents for auctions, game theory is used as a useful tool.

Cliff et al. (1998), and Preist et al. (1998) are the first examples of work which brought techniques from experimental economics to analyze the dynamics of

[1] (a portmanteau of "satisfy" and "suffice") is a decision-making strategy that attempts to meet criteria for adequacy, rather than to identify an optimal solution.

agent-based systems in order to present adaptive agents that able to effectively bid in many to many marketplace.

In order to build an agent-based model, one should apply same steps as building any type of model or simulation such as, identification of the model's purpose; identification of components and the interaction between components and so on. However, developing an agent-based simulation model is a part of more general software and model development process. ABMS requires one to fulfill extra tasks in addition to the standard model building (Macal & North, 2005). These tasks can be summarized as:

1. Identification of the agents and definition of the behavior of the agents based on a theory
2. Identification of the agents' relationships and definition of the interaction of the agents based on a theory
3. Identification of ABMS platforms and ABMS model development strategy
4. Obtaining the requisite agent-related data
5. Validation of the agent behavior models in addition to the model as a whole.
6. Running the model and analyzing the output from the standpoint of linking the micro-scale behaviors of the agents to the macro-scale behaviors of the systems.

However, there is no systematic software engineering framework available for designing strategies for trading agents.

Agent-Based Modeling and Simulation Studies about Auctions

Many researchers investigate the behavior of boundedly rational, heterogeneous and autonomous adaptive agents in different e-auction mechanisms by using agent-based models (Byde A. , 2001; Fatima, Wooldridge, & Jennings, 2005; Jiang & Leyton-Brown, 2007; Boutilier, Goldszmidt, & Sabata, 1999; Greenwald & Boyan, 2004; Arora, Xu, Padman, & Vogt, 2003; Cai & Wurman, 2005; Akkaya, Badur, & Darcan, 2009).

Arora et al. (2003) , designed an e-market simulation environment, IBIZA, that allows researchers to make experiments in different market mechanisms with various e-auction mechanisms.

Gerding et al. (2007) derived utility-maximising strategies for bidding in multiple, simultaneous second-price auctions. They first analysed the case where a single global bidder who bids in all auctions, whereas all other bidders are local who bid in a single auction. Second they investigated a setting with multiple global bidders by combining analytical solutions with simulation approach. They compared the efficiency of a market with multiple concurrent auctions with and without a global bidder. They showed that, if the bidder can accurately predict the number of local bidders in each auction, the efficiency slightly increases. In contrast, if there is much uncertainty, the efficiency significantly diminishes as the number of auctions increases due to the increased probability that a global bidder wins more than two items.

Byde (2001), examined three bidding algorithms, namely Greedy, Historian and Dynamic Progamming (DP), of increasing sophistication and computational complexity capable of bidding in sequences of overlapping English auctions for purchasing similar goods, and tested these algorithms by competing them one against the other by simulation experiments. The agent adopting Greedy strategy always bids in the auction with the currently lowest price; Historian agent bids in the auction with lowest expected price and DP constructs a Markov Decision Process and solves it with Dynamic Programming. They found that DP outperforms both Greedy and Hıstorian, even when its beliefs are very crude and often wrong.

Hailu and Thoyer (2004), constructed an agent-based model to examine the performance of different formats for multi-unit auctions. In their mechanism the auctions are repeated and bidders use reinforcement learning in order to update their individual bid functions so they will be able to increase their payoff (Hailu & Thoyer, 2007).

Neugebauer (2004), worked on bidding strategies in sequential auctions with experienced experimental subjects who are asked to formulate profit maximizing strategies that are used to run an auction simulation. He found that risk-neutral Nash equilibrium strategy cannot be recommended as a profit maximizing strategy for the simulations.

Fatima et al. (2005), have analyzed sequential auctions for objects with private and common values in an information setting. They found that for each auction in a sequence, efficiency decrease with uncertainty and the efficiency of auctions in an agent-based setting is higher than that in an all-human setting due to the huge number of bidders.

Pardoe and Stone (2005), have created a self adapting mechanism in sequential auctions that adjusts auction parameters in response to past auction results. They found that straightforward adaptive method performs better than more sophisticated ones.

Airiau et al. (2002), have developed a strategic bidding agent that uses a user valuation function for different quantities of an item and the knowledge of valuations of other bidders in auctions to be held in the near future. The simulation results have shown that strategic agents with longer look ahead perform better than agents with shorter look ahead (Airiau, Sen, & Richard, 2002) .

CHAPTER 3

METHODOLOGY

This chapter initially states the definition of the problem followed by the explanation of the bidding strategies of the agents. Finally the simulation model is presented.

Problem Definition

The aim of this study is to analyze the effects of the auction environment and the bidding strategies on the agents' payoff on multi-unit sequential auctions by using agent-based modeling and simulation approach.

Multi-item auctions have become a subject of intense interest of economic theorists and experimentalists due to academic interest and growing use of multi-item auctions in reality. Although a considerable research effort has been devoted to the problem, still the strategic behavior of the bidders in each individual auction cannot be fully analyzed.

There are several factors in an e-auction that affect the payoff of the bidders such as; auction type, duration of the auction, number of bidders, newly arriving bidders, number of item that a bidder demands, private value of the bidders, and minimum bid increment amount. In different studies, researchers look individually to all these parameters' effects on bidder's payoff. For instance, Said (2009),work on the effects of randomly arriving buyers to the equilibrium price in sequential auctions. Lucking-Riley et al.(2006), have worked on the analysis of price determinants such as minimum bid increments, reserve price and seller's feedback ratings in e-auctions. Arora et al. (2003), have worked on the effects of the auction duration to the final price and the bidders payoff. In this thesis, however, all of the parameters mentioned above, are taken into consideration in order to conduct a more general strategy analysis.

In particular we investigate the effect of different strategies played by heterogeneous agents in different multi-unit auction settings on the winner's payoff. The agent-based model involves bidders, who have independent private values, demanding one or more items from a single seller offering multi-unit item. The items are sold sequentially and only one item is being sold at one time. The bidders, who are the only active players in our model, play strategies against one another repeatedly in multi-period auctions.

Methodology

As a consequence of widespread use of auctions the interest in theoretical and empirical studies related to auctions has increased in the recent years. Theoretical studies of auctions have been conducted mainly in the field of microeconomics for perfectly rational and risk neutral agents and static environments (Lucking-Reiley, et.al, 2006; Milgrom & Weber, 1982).

In addition to theoretical work researchers also conduct laboratory experiments and field study to investigate the validity of the theories and restrictive assumptions that these theories based on (Ockenfels & Roth, 2005). The results of laboratory experiments reveal that some of the observed outcomes such as late bidding behavior in e-auctions cannot be successfully explained with these microeconomic theories. Also in the field studies, the real world data which is collected from e-auction web sites are analyzed.

Despite the large amount of theoretical and experimental works that have been done by researches, the bidding strategies of bidders that are being used in different e-auction formats cannot be completely determined. Not only in the field but also in the laboratories, it is not the bidders' strategy but the bid amount is to be observed. As Duffy and Unver mentioned (2004), in the field studies, the sensitivity on any change in auction rules, environmental parameters or other design features are difficult to assess because these parameters are out of control of the researcher. Further in the laboratory, it is costly to make such kind of changes because any variation means extra session with paid human subjects.

In order to bridge the gap between experimental work with human subjects and theory, agent-based simulation approach, where auction mechanism and actors are modeled in predetermined software platforms, is being used by researchers (Duffy, 2006).

In this study, due to the complexity of the problem, we use agent-based modeling and simulation (ABMS) approach to address several research questions regarding the behavior of agent in e-auctions.

The Model for Developed e-Auction

In the model, there is a single seller offering multi-unit identical objects to potential risk-neutral buyers (bidders) in sequential auctions. Each bidder demands at least one unit of an item. The number of bidders exceed the number of items on auction so that some of the bidders will not be able to meet their demand while some others will be able to meet their demands fully or partially. The number of agents who demand one unit of item is more than the number of agents who demand more than one unit of item. The information about the outcome of the auction becomes available after the termination of the auction. The flowchart of the auction mechanism is shown in Figure 4.

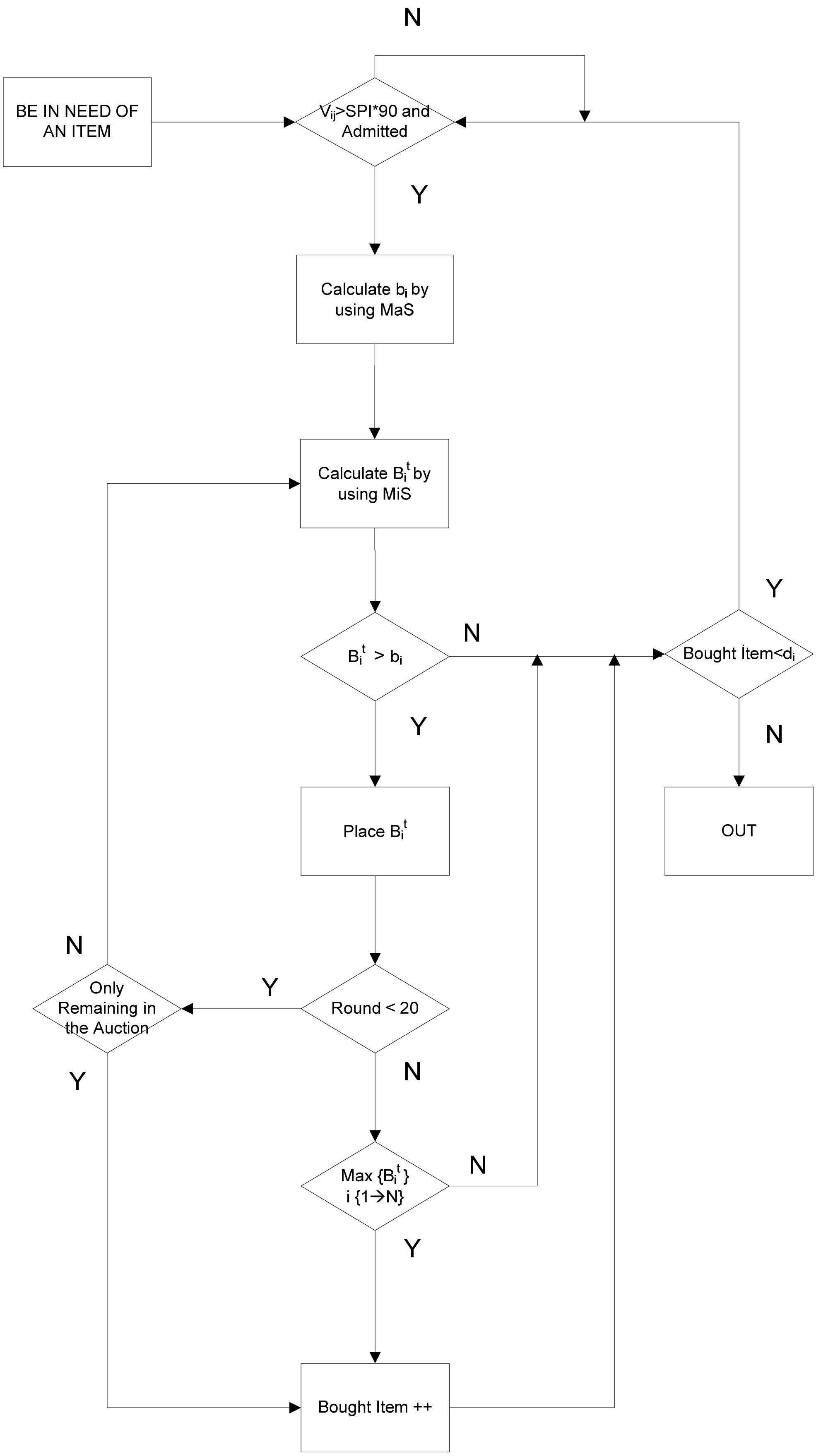

Fig. 4 Sequential auction system flowchart

In brief, the system starts with an agent demanding one or many items and she intends to enter an auction in order to meet her demand. If her private value for the demanded items (v_{ij}) is 90% more than the selling price of the previous auction (SPI) and is admitted to the auction, she calculates her maximum bid amount (b_i) by using her macro level strategy (MaS). Once determined in the beginning the auction the agent's b_i does not change throughout the auction. Next, she calculates her bid increment amount by using her micro level strategy (MiS) and she continues to bid until the end of the auction (i.e. until the round number is 20) as far as her bid amount (B_i^t) is smaller than b_i. If she has the maximum bid amount within the participants in the auction (N) or she is the only one left in the auction then she buys the item. In addition, if she wants to buy more of that item (i.e. the item she bought is less than her demand amount (d_i)) then, as long as she fulfills the entering criteria and chosen to be a participant in the auction, she will enter another auction in the sequence. She could leave the auction when her all demand is met. On the other hand, if the agent does not have the maximum bid amount or the bid placed in the auction by her opponents exceeds her b_i than she leaves that auction. She is able to enter another auctions in the sequence if she is determined to buy another item. Otherwise, she will leave the system.

Buyers have private values which are independently drawn from a uniform distribution. The private values are randomly assigned to the bidders. Also, for some bidders we assume decreasing marginal utility which means the valuation of agent i for the j^{th} good is lower than $(j-1)^{th}$ and higher than $(j+1)^{th}$ good.

The bidders in the current auction are not obliged to enter all of the auctions in the sequence until their demand is met ,instead, they are able to choose to which auction to enter or not. In practice it is a characteristic of online auctions that bidders arrive according to a random process, so, in the system new buyers can arrive to the auctions. In order to make the setting more realistic, the arrival process also depends on the observed selling price of the item in the previous auction. If there is remarkable difference between the agent's reservation price and the selling price of the item, then she does not enter to the next auction. Hence, the number of bidders can increase, decrease or stay the same from one auction to the next.

Each auction proceeds in T discrete consecutive rounds indexed by t, ranging from 1 to T. Each agent submits one bid in each round. This bid is accepted as a valid bid by the auctioneer if and only if it is a certain increment above the current maximum bid. During the course of auction the bidders cannot lower their own previous submitted price. In that case, she will be considered to have dropped out of the auction.

The auctions end exactly at a pre-specified time which means that the auctions are operated under the hard-close rule. No other bid will be accepted after the deadline. The auction will terminate before the predetermined time when there is only one bidder remained in the auction.

The model has been studied in the context of two standard types of auction formats; the first price ascending bid auction with continuous bidding format (FP) and the second price ascending bid auction with continuous bidding format (SP).

In the FP auction setting each bidder is announced the highest winning price at the end of each round however, in the SP setting the bidders are announced to highest loosing price. In both setting at the end of each auction all of the bidders' highest submitted price and the identity of the winner is declared.

The winner of the auction pays the current bid, which is the highest bid amount in the FP setting and the second highest amount submitted in SP setting, to the seller at the end of each auction in order to purchase the item.

The surplus of each bidder i, is the difference between her reservation price for the j^{th} item (also called private value), v_{ij}, and the amount she pays for the item. The cost of entering the auction is zero. The calculation of a bidder's surplus differs with the implemented auction protocol. In the FP auction setting the payoff of the winning agent is given by the difference between her private value and bid value (b_i) as:

$$The\ payoff\ of\ agent\ in\ FP = v_{ij} - \ b_i\ .$$

However, in the SP auction setting the payoff of the winning agent is the difference between her reservation value and the highest loosing bid, $b^{2nd}\ as$:

$$The\ payoff\ of\ agent\ in\ SP = v_{ij} - \ b^{2nd}.$$

The value of these functions cannot be negative as a rational agent never bids above her private value. Since each agent is willing to maximize their surplus, she tries to get the item at a price as low as possible and she is indifferent between not winning the auction and winning it with a price equals to her reservation value for the j^{th} item, v_{ij}.

Strategies

In this study, two types of strategies are developed. First one is, called macro-level strategy (MaS) in which the maximum bid amount (b_i) that an agent should submit in each auction is calculated. In the beginning of each auction, the agent analyses the market environment with the available information and update her b_i in accordance with her MaS. On the other hand, the second type of the strategy is called micro-level strategy (MiS) in which the amount of bid increment that an agent should add to her bid value in the course of an auction, is calculated. Once determined in the beginning of the auction, the MaS and MiS will not change during the sequence of auctions.

Macro-Level Strategies

There are 5 Macro-Level Strategies namely MaS-1, MaS-2, MaS-3, MaS-4, and MaS-5. In each of these strategies, the agents' maximum bid amount cannot be higher than their reservation price.

MaS-1

The strategy is based on the model developed by Février et al., (2004). These authors, however, considered the case where there are two bidders desiring two units of a good. However, in the setting, the number of bidders and the number of units demanded are not restricted into two items.

Let $b_i^1(v_{ij})$ denote the maximum bid amount for the bidders in the first auction and $b_i^t(v_{ij})$ denote the maximum bid amount for the following auction that the bidder participate after the first auction.

Each bidder i is assumed to demand d_i units of an item and for each unit she calculates b_i . In this strategy, on the first auction the agent starts with bidding the value for the second unit of the item and continues to bid the value of the next desired item as long as she wins in the auction. If she loses in the course of the auction sequences then she bids the last bid value that makes her win the auction. Besides, if she loses in the first auction that she enters then she increases her bid value, auction by auction so as to converge to her reservation price v_{ij}. This strategy is extended for $d_i$desired units as shown below. For the first auction that the bidder participate the maximum bid amount is calculated as:

$$b_i^1(v_{ij}) = k.v_{ij}$$

where the parameter k can take any value between the interval [0, 1]. Once determined in the beginning, the value of k will not change throughtout the sequence of auctions .

For the second auction that the bidder participates, the maximum bid amount depends on the result of the first auction that she entered.

$$b_i^t(v_{ij}) = \begin{cases} k.b_i^{t-1}(v_{ij}) & \mathit{If\ the\ agent\ wins\ the\ previous\ auction} \\ b_i^{t-1}(v_{ij}) + (v_{ij} - k.v_{ij}).l & \mathit{If\ the\ agent\ loses\ the\ previous\ auction} \end{cases}$$

where l represents the proportion of the amount of increase that will be made in convergence to reservation price of the bidder and is calculated as follows:

$$l = \frac{W}{z + (z-1) + (z-2) + \cdots + 1} \ .$$

W , represents the weight of the z auctions in which the amount of increase is rated. W , starts from the z value and decreases one by one as the bidder continues to lose the auctions in the sequence.

The calculation of z is formulated below :

$$z = \frac{\#\ of\ remaining\ auction}{\#\ of\ demand} \ .$$

z is calculated for the first time the bidder lose an auction in the sequence and as she continues losing the auctions, the same z value is used. On the other hand if the bidder has won an auction but lost in the next auction, a new z is calculated.

MaS-2

The strategy represented here is based on the bidding strategy developed by Gerding et al. (2007). In this strategy the agents' b_i is calculated according to the probability of not winning any auction. Since an agent demands one or more items, then the probability of not winning any auction to meet her demand is crucial. So, b_i of the agent is calculated by multiplying her reservation price with the probability of not winning at least one item as:

$$b_i(v_{ij}) = v_{ij}.p$$

$$p = \frac{NE-1}{NE} .$$

$NE,$ is the estimated number of bidders who will participate to the next auction.

MaS-3

In this strategy the bidders bid their reservation price (v_{ij}). In the setting this strategy is called the flat strategy and is assumed to be the weakly dominant strategy for the sealed-bid SP auctions which is proved by Vickrey (1961). This strategy's formulation is shown as:

$$b_i(v_{ij}) = v_{ij} .$$

MaS-4

In the fourth strategy the bidders consider the previous auctions' selling price in order to calculate b_i. The aim of the bidders adopting this strategy is to find a trend in the announced selling prices at the end of each auction in order to estimate the next auctions selling price in advance. For this reason, when bidders obtain sufficient information set in order to calculate the standard deviation, they bid accordingly but the required information set cannot be gathered until the fifth auction. So, until fifth auction the bidders calculate their b_i as follows:

In the first auction that the bidders, the bidder bids her reservation value (v_{ij})

$$b_i^1\ (v_{ij}) = v_{ij}\ \ .$$

In the second auction the bid value of the agent is calculated as the average value of the selling price of the item in the first auction (SPI_1) and the bidder's reservation price as:

$$b_i^2\ (v_{ij}) = \frac{SPI_1 + v_{ij}}{2}\ .$$

When it comes to calculating the bid value for the third auction, the bidder takes the average of the selling price of the items in the previous auctions (SPI_1, SPI_2) and her reservation price(v_{ij}) as:

$$b_i^3(v_{ij}) = \frac{SPI_1 +\ SPI_2 + v_{ij}}{3}\quad .$$

In the fourth auction, the bidder calculates the change amounts (ΔSPI), of the selling prices as:

$$\Delta SPI_1\ = SPI_1 -\ SPI_2$$
$$\Delta SPI_2\ = SPI_2 -\ SPI_3\ .$$

Then the bid value is chosen randomly from a uniform distribution $[SPI_3 + \min(\Delta SPI_1, \Delta SPI_2)\,,\ SPI_3 + \max(\Delta SPI_1, \Delta SPI_2)]$ as:

$$b_i^4(v_i) = U[SPI_3 + \min(\Delta SPI_1, \Delta SPI_2)\,,\ SPI_3 + \max(\Delta SPI_1, \Delta SPI_2)]\ .$$

In the fifth auction the bid value calculation is similar to the one in the fourth auction, however, this time standard deviation of the selling price change amounts is taken into consideration. The moving average of three changes in the selling price, which is representing with μ_4, is calculated as:

$$\mu_4 = \frac{\Delta SPI_1 + \Delta SPI_2 + \Delta SPI_3}{3} \quad .$$

Then, μ_4 is added to the selling price in the fourth auction (SPI_4). The standard deviation value of the changes in the last three auctions (σ_4) which is calculated as:

$$\sigma_4 = \sqrt{\frac{1}{3}\sum_{i=1}^{3}(\Delta SPI_i - \mu_4)^2} \quad .$$

is used in order to form the uniform distribution from which the bid value for the fifth auction is chosen as

$$b_i^t(v_i) = U\,[SPI_{t-1} + \mu_{t-1} + \sigma_{t-1},\, SPI_{t-1} + \mu_{t-1} - \sigma_{t-1}]\ .$$

The bid values after the fifth auction is calculated just in the same way as the fifth auction.

MaS-5

In this strategy the bidders analyse the results of the previous two auctions. If there is a decrease in the price then the agents simply reduces the selling price by 10% and if there is an increase in the selling price then they raise it by 10%. For the first two auctions, however, the agent place her reservation price as her bid value. The formulation of this strategy is shown as:

$$b_i(v_{ij}) = \begin{cases} 1{,}1.SPI^{t-1}, & SPI^{t-2} < SPI^{t-1} \\ 0{,}9.SPI^{t-1}, & SPI^{t-2} \geq SPI^{t-1} \end{cases} .$$

Micro-Level Strategies

There are 6 micro-level strategies that bidders can adopt during the course of each auction. The bid amount which will be incremented for the next round is the announced price at the end of each round. For all the strategies, an initial bid increment value, $\Delta_{\mathrm{i}}^{\mathrm{t}}$ is computed. If this increment is less than the minimum bid increment, it is updated to Δ_{min} which is shown as:

$$B_i^t = \begin{cases} B_i^{t-1} + \Delta_{min}, & \Delta_i^t < \Delta_{min} \\ B_i^{t-1} + \Delta_i^t, & \Delta_i^t \geq \Delta_{min} \end{cases} .$$

The agent keeps implementing one of these 6 strategies provided that B_i^t is less then or equal to the b_i. If the agent's bid value is greater than b_i, then she bids the maximum bid amount. If the current bid is higher than the agent's b_i then she outbids.

Each of these strategies that can be formulated as a simple rule, are explained as follows:

MiS-1. Constant Minimum Increment Strategy

In this strategy, the bidder determines a constant bid increment which is set at the beginning of the auction and bids continuously by this amount, (Δ_i). A bidder with this strategy computes a random increment amount as generating a random number from a uniform distribution U[0,1]. This random number is then multiplied with the minimum increment (Δ_{min}) value and the result is added to Δ_{min}. The calculated number is of the used as the upper limit bid increment value (Δ^u) as:

$$\Delta^u = c.\Delta_{min} + \Delta_{min}$$

where c is a constant within the interval [0,1].

The bid increment amount is chosen randomly between the interval limit by the Δ_{min} and Δ^u as:

$$\Delta_i = U[\Delta_{min}, \Delta^u]$$

Once determined in the beginning of the auction Δ_i does not change through out the course of auction.

MiS-2. Variable Random Increment Strategy

In this strategy, the interval of the minimum increment value is calculated in the same way as MiS-1, however, the difference is that the randomly chosen increment amount is recalculated at each round.

$$\Delta_i^t = U\ [\Delta_{min}, \Delta^u]$$

MiS-3. Rate Based Increment Strategy

In MiS-3, the increment values for each agent *i*, at each period *t* is proportional to the difference between the maximum bid amount of agent *i*, b_i and the latest bid, ${B_i}^{t-1}$.

$$\Delta_i^t = \left(b_i - {B_i}^{t-1}\right).r$$

where *r* is rate or proportionality constant, chosen from the interval [0,1] at the beginning of the auction.

MiS-4. Time Based Increment Strategy

In this strategy the bid increment is proportional to the difference between the agent's b_i and the latest bid. The proportionality rate increases with the number of periods remaining in the auction.

$$\Delta_i^t = \frac{1}{T-t+1} \cdot (b_i - {B_i}^{t-1})$$

MiS-5. Weighted Moving Average Strategy

In this strategy the bid increment is the weighted average of the three bid value differences in previous rounds. The weight of previous lags decreases monotonically. In the first four auction however, the agents incremented their bid values by Δ_{min}.

$$\Delta_i^t = \begin{cases} \Delta_{min}, & t \leq 4 \\ \dfrac{x(B_i^{t-1} - B_i^{t-2}) + y(B_i^{t-2} - B_i^{t-3}) + z(B_i^{t-3} - B_i^{t-4})}{x + y + z}, & t > 4 \end{cases}$$

x, y, z are the weights of the increment values from round to round where $x > y > z$.

MiS-6. Minimum Computed Increment Strategy

The bid increment is calculated by dividing the b_i , to the number of periods as:

$$\Delta_i^t = \frac{1}{T} . b_i \quad .$$

Simulation Environment

In the simulation two different auction mechanism settings are being implemented; a first price ascending bid auction format with continuous bidding (FP) and a second-price ascending bid auction format with continuous bidding (SP). In both settings, there is a single seller offering *G*>0 perfectly substitute (identical) items to PN>*G* potential buyers in sequential auctions without any reserve price.

7 aspects of the simulation environment namely; The quantity of demanded item, Submitting bid, The number of bidders, Reservation price, Duration of auction, Outputs, and Pseudo code, is explained as follows..

The quantity of demanded item

Each bidder demands d_i units of same item which is ranging from 1 to D. In the model the number of agents who seek to buy many units are less than the number of agents with single unit demand. The number of agents that demand j items is determined probabilistically as follows:

$$P(d = j) = \frac{\mathrm{D} - \mathrm{j} + 1}{\sum_{\mathrm{i}=1}^{\mathrm{D}} \mathrm{i}}$$

The number of agents who demands j items are calculated by multiplying the probability with PN.

Submitting Bid

The bidders may or may not submit bids at every auction stage $g \in \{1,2, \dots G\}$ as long as their demand is not met. Thus, bidders do not have to enter every auction in a sequence. They can choose to which auction they should place their bids or not according to comparison of the SPI and their reservation price. In the mechanism, all of the agents are created in a pool (PN) where their characteristics such as reservation price, number of demanded item, and the strategies are assigned to them. In the first auction, N_g agents are chosen randomly from the pool. If the bidder meets all her demand in an auction then she does not go back to pool, but if she is not able to meet all her demand, she returns to the pool in order to participate to upcoming auctions. In the setting, the selling price that the item sold in the previous auction is multiplied with parameter Φ which is chosen from the uniform distribution U[0,1] in the beginning of the auction. This number is the lower limit of the reservation price of an agent who wants to participate to the next auction. The agents whose reservation price exceed this limit are able to participate to next auction. The agents who leave the auction is also chosen in the same manner, but this time the agents whose reservation price is less than the lower limit, will leave the auction. The number of agents who participates to the next auction or leaves the auction is defined by γ. Once set in the beginning of the auction, the value of γ does not change. From the agents who fulfill the entrance and leaving criteria only $\gamma.N_g$ number of agents, that are chosen randomly, are allow to leave the auction or participate to the next auction in the sequence. Nevertheless, if there exists no agent that fulfills the leaving criteria then no agent will leave the system. This is also the case where there exists no agent in order to participate to the next auction. This procedure is repeated for each auction until the end of sequence of auctions.

<u>The Estimated Number of Bidders</u>

As it is mentioned earlier, the number of bidders is announced after the termination of each auction. However, the number of participants for the upcoming auction after the randomly arriving and leaving bidders is not known. The bidders who are adopting MaS-2 should calculate the estimated number of bidders, NE, for the next auction.

In the first four auctions, for each individual auction ε is randomly drawn from a uniform distribution U[0, 1]. This parameter is then used to randomly draw the NE from a uniform distribution on the interval $[N_{g-1} - N_{g-1}\varepsilon, N_{g-1} + N_{g-1}\varepsilon]$.

After the fourth auction the agent calculates the change in the number of the bidders in the previous auctions.

$$\Delta N_1 = N_{g-1} - N_{g-2}$$

$$\Delta N_2 = N_{g-2} - N_{g-3}$$

$$\Delta N_3 = N_{g-3} - N_{g-4}$$

The average of changes in the previous four auctions, which is calculated as;

$$\Delta N_g = \frac{\Delta N_1 + \Delta N_2 + \Delta N_3}{3}$$

is then multiplied with Ɛ in order to generate the interval $[N_{g-1} - \Delta N_g . Ɛ,\ N_{g-1} + \Delta N_g . Ɛ]$. NE for the next auction is randomly drawn from a uniform distribution on the calculated interval.

$$NE_g = \begin{cases} U\,[N_{g-1} - N_{g-1}.Ɛ,\ N_{g-1} + N_{g-1}.Ɛ], & g \leq 4 \\ U[N_{g-1} - \Delta N_g.Ɛ,\ N_{g-1} + \Delta N_g.Ɛ], & g > 4 \end{cases}$$

Reservation Price

At the beginning of every auction each buyer receives a uniformly drawn independent private value for the first item (v_{i1}) from the interval [A, B]. The valuation of the items take the form of a vector

$$v_{ij} = \{v_{i,1}, v_{i,2}, \dots, v_{i,d_i}\}$$

where v_{ij} denotes the valuation of jth item for ith agent. For some agents we assume decreasing marginal utility, so that $v_{i,1} \geq v_{i,2} \geq \cdots \geq v_{i,d_i}$ and for others the valuations do not differ with the number of demanded item. In the pool, the number of agents who have decreasing marginal utility is defined by δ which is chosen from a uniform distribution U[0,1]. δ.PN number of the agents are determined to have decreasing marginal utility where the rest of the agents have the same private value for all units of item. In the case where the agents have decreasing marginal utility valuations, the relationship between the valuations can be formulized as follows:

$$v_{ij} = (1-\alpha)^{j-1}.v_{i1}$$

where α is marginal decreasing utility parameter whose value is between (0,1). Once set in the beginning, the value of α does not change throughout the sequences of auctions.

Duration of Auction

Each auction consists of T consecutive bidding periods, indexed by t ranging from 1 to T. If and only if the bidders' private valuations are lower than the submitted bid in the last period before the T, then the item is sold to the highest bidder without waiting for the T^{th} round.

In any period t the bidder i, decides her bidding value B_i^t, based on the information set available to her as of that period. The auctioneer gets the bids from the agents and determines the current bid in each round t, where each of the bidders can submit a single bid at most. The current bid, which is the highest amount bid in the FP auction and the second highest amount bid in the SP auction to date, and the identity of the highest bidder are announced to each participant by the auctioneer.

The summary of the parameters in the model are given in Table 1.

Table 1 The summary of the parameters in the setting

The parameters that are given and maintain the same value throughout the simulation are:

a)

Parameter Name	*Symbol*
Supply Quantity	G
Number of Agents in the Pool	PN
Maximum Demand Quantity	D
The percent of agents with Decreasing Marginal Utility	δ
The percent of Decreasing Marginal Utility	α
Number of Agents in g^{nd} Auction	N_g
The percent of getting in and out of auction	γ
The lower limit identifier	Φ
Minimum Bid Increment	Δ_{min}

The parameters that change in the simulation settings are:

b)

Parameter Name
Minimum Reservation Price
Maximum Reservation Price
Number of Rounds
Auction Type
The distribution of MaS among bidders
The distribution of MiS among bidders

<u>Outputs</u>

The outputs of the simulation are the average payoff of the agents playing with the same MaS and/or MiS and the demand satisfaction rate of the participants. In order to compute the average payoff, the total payoff of all the agents playing with the same strategy throughout the simulation runs are divided to the number of bidders who play with the strategy. The average payoff will give information regarding the performance of the strategy. Besides, the demand satisfaction rate is the ratio of the quantity demanded by the agents and the number of items that they were able to obtain from the auction. It can be said that the higher the demand satisfaction rate, the better the strategy performs.

Pseudo-Code

The e-auction simulation model is programmed in JAVA. In Figure 5, the algorithm of the model is shown.

```
Pseudo-Code Level 1 - Auction

set simulation parameters
for each run
        define new auction setting
        create agents
        select agents for the first auction
        for each auction
                get agents in to the auction
                update strategy parameters
                calculate max offer value for agents
                run round
                calculate payoff
                decrease demand of the winner
                get agents out of the auction
                calculate statistics and report auction output

Pseudo-Code Level 2 – Create Agents

for each agent
        set agent id
        set agent demand quantity
        set decreasing marginal utility
        for each demand
                set reservation price
        set agent micro level strategy
        set agent macro level strategy

Pseudo-Code Level 2 – Run Round

while remaining participants greater than 2 and round is less than T
                for each agent
                        update strategy parameters
                        give bid
                count valid bids
                find winner of the round based on the auction type
                find winner of the auction
```

Fig. 5 Pseudo Algorithm of e-auction simulation model

The full source-code of the program is available upon request.

CHAPTER 4

SIMULATION EXPERIMENTS AND FINDINGS

This chaptes aims to explain the experimental set-ups and the results of the experiments.

Experimental Settings and Results of the Experiments

In order to investigated the effects of different bidding strategies played by the agents on the winner's payoff, different multi-unit auction settings are examined. There are two benchmark simulation set-ups and ten other experimental set-ups which are intended to measure the effects of different parameters as bidding strategies among agents, reservation price, and the duration of the auction, on the payoff of the winner.

The simulations were conducted using 16 computers. 15 of the computers are 32-bit Operating System, Intel Pentium D, 2.80 GHz CPU, 2.00 GB RAM PCs and one of the computers is a 32-bit Operating System, Intel Core 2 Duo, 2.00 GHz CPU, 4.00 GB RAM Notebook. Each experiment took an average time of 2 hours to be run in computers with the configurations stated above, and as a whole, experiments were carried out in a period of one week.

As it is defined in Chapter 3, the main criterion to evaluate the performance of a bidding strategy is the payoff of the agents. The payoff of the bidder is the difference between her reservation price and the amount she pays for the item. The results of the simulation set-ups will be analyzed based on this measure.

The agents have two strategy types: Macro Level Strategy (MaS) which is used for calculating the maximum bid amount and Micro Level Strategy (MiS) that is used for calculating the bid increment amount within an auction. As explained in Chapter 3 there are 5 MaSs and 6 MiSs that can be used by an agent.

There are two benchmark simulations which are differentiated basically according to the implemented auction format; first-price ascending bid auction format with continuous bidding (FP) and second-price ascending bid auction format with continuous bidding (SP). The first benchmark simulation is defined for the FP auctions and the second benchmark simulation is conducted for the SP auctions. The details of these settings are given in the following subsections.

The First Benchmark Simulation Set-up

The first benchmark simulation setting is aimed to measure the profitability of the strategies. In the setting, there are 15 identical goods auctioned one by one in 15 sequential auctions. There are 120 agents created in a pool, and the demands of each agent range from 1 to 3. The strategies are assigned to each agent with the same probability according to the procedure described in Chapter 3. For the first auction, 30 (N_1=30) agents are chosen randomly from the pool and in all of the upcoming auctions, new agents who are chosen from the pool arrive to the auction. If the agent meets all her demand, which is assigned to her in the pool, then she leaves the system. Otherwise, according to difference between the selling price in the previous auction and the agent's reservation, the agent will participate to the next auction or she will go back to pool so as to participate to the upcoming auctions.In this setting the Φ parameter which is the lower limit identifier is set to 0.90 which means if the reservation price of the auction participant is higher than the 90% percent of the selling price then she will participate to the next auction, otherwise she leaves. 20% of the agents whose reservation price is more than 90% of the selling price in the previous auction, is chosen randomly from the pool to participate to the next auction.

Each bidder has a uniformly distributed independent private value form U[1000, 2000]. Also, 40% of the agents participating in the auction has reservation price with decreasing marginal utility and the α parameter, which defines the amount of the decrease, is taken 0.20 for these agents.

The auction is repeated over 20 consecutive bidding periods (T=20) and Δ_{min} is set to 20 for these rounds.

The summary of the parameters and their values in the simulation are given in Table 2.

Table 2 The Summary of the Parameters and Their Values for the First Benchmark Simulation

Parameter Name	Symbol	Value
Supply Quantity	G	15
Number of Agents in the Pool	PN	120
Maximum Demand Quantity	D	3
The percent of agents with Decreasing Marginal Utility	δ	0.4
The percent of Decreasing Marginal Utility	α	0.2
Number of Agents in the g^{nd} Auction	N_g	30
The percent of getting in and out of auction	γ	0.2
The lower limit identifier	Φ	0.9
Minimum Bid Increment	Δ_{min}	20
Minimum Reservation Price		1000
Maximum Reservation Price		2000
The distribution of Reservation Price among bidders		Uniformly
Number of Rounds	T	20
Auction Type		FP
The distribution of MaS among bidders		Evenly
The distribution of MiS among bidders		Evenly

For profitability comparison, the average payoff made by the bidders using each MaS and MiS is presented. The result of this simulation experiment is shown in Table 3.

Table 3 Experiment Results for the First Benchmark Simulation

		Number of Agents	Average Payoff
MaS-1		35963	10.746
	MiS-1	6508	11.912
	MiS-2	6167	12.147
	MiS-3	5900	11.552
	MiS-4	5622	6.931
	MiS-5	5953	9.556
	MiS-6	5813	12.048
MaS-2		36177	12.648
	MiS-1	6030	14.143
	MiS-2	6202	14.302
	MiS-3	6310	14.985
	MiS-4	5950	8.170
	MiS-5	5841	10.997
	MiS-6	5844	13.035
MaS-3		36131	7.704
	MiS-1	5839	8.313
	MiS-2	6082	7.696
	MiS-3	6106	5.740
	MiS-4	6399	7.362
	MiS-5	5883	7.140
	MiS-6	5822	10.103
MaS-4		35894	9.433
	MiS-1	5784	10.489
	MiS-2	5846	10.854
	MiS-3	5909	9.982
	MiS-4	6064	6.426
	MiS-5	6260	8.538
	MiS-6	6031	10.455
MaS-5		35964	7.571
	MiS-1	5909	7.833
	MiS-2	5792	7.646
	MiS-3	5900	5.829
	MiS-4	6002	7.080
	MiS-5	5977	7.053
	MiS-6	6384	9.815
Total		180129	9.622

In Table 3, Number of Agents represents the total number of agents that participate in the auctions over the 3000 runs, Average payoff stands for the average surpluses of the strategies that the agents adopt in the auctions.

The sample data generated in simulation is tested in order to investigate whether the distribution of the data is normal or not. For this purpose Kolmogorov-Smirnov goodness-of-fit test (K-S) is performed for all settings. The results of the Kolmogorov-Smirnov normality test for the first benchmark simulation is given in Table 4.

Table 4 K-S Test Result for the First Benchmark Simulation

One-Sample Kolmogorov-Smirnov Test		
		MaS
N		9000
Normal Parameters	Mean	42.5548
	Std. Deviation	36.80560
Most Extreme Differences	Absolute	0.134
	Positive	0.134
	Negative	-0.124
Kolmogrov-Smirnov Z		12.69
Asymp. Sig. (2-tailed)		0.00

Since two-tailed asymptotic significance of the test statistic is very small (.000), it can be said that, the data is not coming from a normal distribution with the given mean and standard deviation. So, in order to analyse the significance difference of the strategies a non-parametric test, Kruskal-Wallis, should be used.

The test results are presented in Table 5.

Table 5 Kruskal-Wallis Test Statistic and Ranks of Strategies in the First Benchmark Simulation

a) Test Statistics

	MaS
Chi-Square	2823.02
Df	4
Asymp. Sig	0.000

b)

Ranks			
	MaS No	N	Mean Rank
MaS	1	1932	5474.35
	2	1160	7544.69
	3	2110	3220.55
	4	1768	4358.37
	5	2030	3288.31
	Total	9000	

The figures in Table 5 indicates that, tests results at the 0.05 significance level shows a significant difference between groups as the Asymptotic Significance is smaller than .05 (0.00<0.05). It can be seen that the agents playing with MaS-2 outperforms other strategies since its Mean Rank, which represents the mean rank values of the average payoffs, is the highest among all others (7544.69). An explanation for this result is as follows. The agents adopting MaS-2 are able to adjust their bid amounts depending on their estimated number of bidders which brings variability to their b_i and at the same time cause a profitable deviation. For this reason the agents adopting this strategy are able to adjust their bid amounts more precisely and they could get high payoffs.

The figures in Table 5 indicates that the second highest profitable strategy is MaS-1 in which the agents reduces their maximum bid amount values as they win in auctions. As the agents adopting this strategy keep winning in the auctions, their profit margin gets higher which leads to high average payoffs.

Table 6 represents the demand satisfaction ratio of the agents according to their Macro Level Strategies in the first benchmark simulation.

Table 6 Demand Satisfaction Rate for the First Benchmark Simulation

Demand Satisfaction		Meet Demand			
		0	1	2	3
Number of demands within stratgies	1	0.78217	0.21783		
	MaS-1	0.76601	0.23399		
	MaS-2	0.87052	0.12948		
	MaS-3	0.74599	0.25401		
	MaS-4	0.7869	0.2131		
	MaS-5	0.74207	0.25793		
	2	0.78904	0.15159	0.059	
	MaS-1	0.80515	0.14826	0.047	
	MaS-2	0.87492	0.09256	0.033	
	MaS-3	0.73019	0.18811	0.082	
	MaS-4	0.79285	0.15161	0.056	
	MaS-5	0.74267	0.17717	0.080	
	3	0.80205	0.13564	0.017	0.045
	MaS-1	0.85896	0.09328	0.034	0.013
	MaS-2	0.87149	0.09164	0.010	0.027
	MaS-3	0.75052	0.16792	0.010	0.072
	MaS-4	0.7829	0.15365	0.018	0.046
	MaS-5	0.74363	0.17349	0.012	0.071
	Total	0.7878	0.18244	0.022	0.008

Table 6 displays the percentage of demand satisfied. Number of Demanded Items within strategies which is the number of items that an agent demands and the Meet Demand which represents the number of items that a bidder obtained after the auctions.

The Total row at the end of Table 6 gives the overall ratios of the agents' satisfied and unsatisfied demands. From the Total row it can be concluded that 78% of the agents were not able to buy any product from the auctions, whereas 18% of the agents were able buy one product. On the other hand, .2% of the agents bought two products where .08% of the agents bought three products. If the demand amounts of the agents are taken into consideration, it can be seen that 78% of the agents with single-unit demand were not able to meet their demand while 22% of the agents have satisfied their demands. The most successful MaS for obtaining goods for the agents who demanded single-unit of item is MaS-5 since almost 26% of the agents playing with this strategy were able to satisfy all their demands. In addition 78% of the agents with two-unit demand could not get any product from the auctions, however 15% of those agents have partially met their demand as they bought one product. Finally, only .59% of the agents with two-unit demand were able to meet all their demands. In this case the most successful MaS is MaS-3 since the agents playing this strategy has the highest ratio (.82%) for obtaining two units of goods. If the agents who demands three units of item are taken into account, 74% of the agents were not able to buy any product, while 17% of them were able to buy one unit of the item. Also .12% of the agents were able to get two units of items where only .17% of the agents achieved the success to meet all of their demand. The agents playing with MaS-3 and MaS-5 has the highest ratio of satisfying all their demands which are .72%, and .71% respectively.

One important point in the figures of Table 6 is that, the demand satisfaction rate of the most profitale strategy (MaS-2) is the lowest. The reason for this result will be the variability of the maximum bid amount which occurs due to the NE. The agents adopting MaS-2 are winning the auctions with high profit, so despite the low rate of demand satisfaction, the strategy becomes the most profitable strategy.

The Second Benchmark Simulation Set-up

In the second benchmark simulation the settings in the first benchmark simulation is preserved and the payoff of the strategies are analysed in the SP auction format. The result of this simulation experiment is shown in Table 7.

Table 7 Experiment Results for the Second Benchmark Simulation

		Number of agents	Average payoff
MaS-1		35783	14.312
	MiS-1	5879	14.719
	MiS-2	6151	14.403
	MiS-3	5880	16.272
	MiS-4	5804	8.466
	MiS-5	5784	13.780
	MiS-6	6285	17.899
MaS-2		35873	14.125
	MiS-1	6327	16.105
	MiS-2	6075	14.936
	MiS-3	5921	15.667
	MiS-4	5946	9.481
	MiS-5	5839	14.271
	MiS-6	5765	14.157
MaS-3		35907	12.109
	MiS-1	6029	10.439
	MiS-2	6060	11.213
	MiS-3	6068	12.731
	MiS-4	5941	7.798
	MiS-5	5932	12.313
	MiS-6	5877	18.257
MaS-4		35618	11.273
	MiS-1	5834	11.979
	MiS-2	5820	12.442
	MiS-3	6053	13.821
	MiS-4	6041	7.824
	MiS-5	6017	10.422
	MiS-6	5853	11.209
MaS-5		35792	11.979
	MiS-1	5950	10.649
	MiS-2	5914	10.181
	MiS-3	5798	12.293
	MiS-4	6045	7.994
	MiS-5	6167	12.681
	MiS-6	5918	18.146
Total		178973	12.761

As shown in Table 8, the results of the Kruskal-Wallis test, at the 0.05 significance level, show a significant difference between groups as the Asymptotic Significance is smaller than 0.05 (0.000<0.05).

Table 8 Kruskal-Wallis Test Statistic and Ranks of Strategies in the Second Benchmark Simulation

a) Test Statistics

	MaS
Chi-Square	2349.52
df	4
Asymp. Sig	0.000

b)

Ranks			
	MaS No	N	Mean Rank
MaS	1	1943	5362.33
	2	1243	7145.87
	3	2129	3311.85
	4	1589	4469.73
	5	2096	3363.47
	Total	9000	

Figures in Table 8 indicates that the agents playing with MaS-2 outperforms other agents as its Mean Rank is the highest among all others with the score of 7145.87. The reasons for this result are same with the arguments described in the first benchmark simulation experiment.

Table 9 represents the demand satisfaction ratio of the agents according to their Macro Level Strategies in the second benchmark simulation.

Table 9 Demand Satisfaction Rate for the Second Benchmark Simulation

Demand Satisfaction		Meet Demand			
		0	1	2	3
Number of demands within stratgies	1	0.793	0.207		
	MaS-1	0.779	0.221		
	MaS-2	0.880	0.120		
	MaS-3	0.744	0.256		
	MaS-4	0.812	0.188		
	MaS-5	0.752	0.248		
	2	0.797	0.103	0.100	
	MaS-1	0.806	0.108	0.086	
	MaS-2	0.875	0.068	0.057	
	MaS-3	0.747	0.110	0.143	
	MaS-4	0.810	0.114	0.076	
	MaS-5	0.746	0.114	0.140	
	3	0.809	0.136	0.016	0.039
	MaS-1	0.859	0.090	0.032	0.018
	MaS-2	0.875	0.093	0.010	0.021
	MaS-3	0.752	0.172	0.009	0.068
	MaS-4	0.811	0.149	0.015	0.025
	MaS-5	0.745	0.177	0.013	0.065
	Total	0.797	0.161	0.035	0.007

Examining the demand satisfaction figures in Table 9, from the Total row it can be seen that 79% of the agents who participate to an auction, were not able to meet any of their demand, 16% of the agents bought only one item whereas .35% bought two items and only .07% of the agents bought three items. In addition, only 20% of the agents with single unit demand, have met their demands where 10% of the agents with two-unit demand achieve this success and only .39% of the agents with three-unit demand were able to meet their whole demand. When MaSs are taken into consideration, it can be seen that the agents with single unit demand and playing with MaS-3 are more successful than the other agents with single unit demand in terms of the demand satisfaction ratio (24.8% of the agents met their demands which is the highest ratio of the single-item demand column). On the other hand, the agents who are playing with MaS- 3 and need two units of item are more likely to meet their whole demand than other agents because the demand satisfaction ratio, 14,3% is the highest among others. Furthermore, the agents demanding three units of item and playing with MaS-3 outperforms other agents (.68% of the agents, which is the highest demand among the other strategies, meet their all demands).

The low demand satisafaction rate of MaS-2 is also observed here, due to the reasons described in the first benchmark simulation experiment.

When the results of first and second benchmark simulation are compared it can be seen that the Total Average profit of the agents is higher in the SP auctions than in the FP auctions. This finding coincides with the theoretical findings in the auction literature (Vickrey, 1961).

Experimental Set-up 3

In the third experimental set-up, the aim is to compare the MaSs under the same circumstances for the FP auctions and find out the more profitable MaS. For this purpose, in each set-up only a single MaS is taken into consideration at one time and MiSs are distributed evenly to all the agents for all experiments. In this set-up, all of the other settings are kept the same as the first benchmark simulation.

The result of simulation experiments are shown in Table 10.

Table 10 Experiment Results for the 3rd Experiment Set-up

Strategies	Number of Agents	Average Payoff
MaS-1	205,206	21.037
MaS-2	188,575	19.867
MaS-3	172,977	4.652
MaS-4	222,037	12.768
MaS-5	172,731	4.592

Examining figures in Table 10, it can be conluded that, in a FP auction, the agents playing with MaS-1 and MaS-2 outperforms agents playing with other strategies as their Average payoff values, 21.037 and 19.867 are the highest among others.

An explanation for this result is the following. The MaS-1 is sensitive to the outcomes of the previous auctions more than other strategies. For this reason the agents adopting this strategy are able to adjust their bid amounts more accurately. Furthermore, as it is mentioned in the previous experiment set-up, in MaS-2 the variability of the bid amount which is due to the variability of the estimated N create an environment which the bidders can gain more profit.

Experimental Set-up 4

In the fourth experimental set-up, all of the settings in the third simulation experiment are preserved and the payoff of the strategies are analysed in the SP auction format.

The result of this experiment is shown in Table 11.

Table 11 Experiment Results for the 4^{th} Experiment Set-up

Strategies	Number of Agents	Average Payoff
MaS-1	201,514	23.892
MaS-2	187,324	22.247
MaS-3	171,761	7.124
MaS-4	229,773	16.188
MaS-5	179,696	9.124

When the intersection of the Average payoff column is taken into consideration, one can easily observe that the agents playing with MaS-1 get the highest average payoff (23.892), followed by MaS-2 (22.247) due to the same reasons explained in the previous set-up.

For the last two experiments it can be concluded that the strategies MaS-1, MaS-2, are winning strategies in terms of Average payoff both in SP and FP settings. However, Average payoff obtained in the SP auction is higher than the one that is obtained in the FP auction.

Experimental Set-up 5

In the fifth experimental set-up, the aim is to compare the MiSs under the same conditions for the FP auctions and find out the MiS which provides the highest payoff. For this purpose in each set-up only one MiS is taken into consideration and MaSs are distributed equally to all the agents. In this experiment all other settings of the first benchmark simulation is preserved.

Results of these experiments are shown in Table 12.

Table 12 Experiment Results for the 5th Experiment Set-up

Strategies	Number of Agents	Average Payoff
MiS-1	360,000	126.611
MiS-2	360,000	126.876
MiS-3	177,151	7.971
MiS-4	171,206	4.048
MiS-5	360,000	126.894
MiS-6	197,853	25.911

The figures in Table 12 show that, the strategies MiS-1, MiS-2 and MiS-5, have the highest Average payoffs. The number of agents in these strategies are the highest. If the participating and leaving conditions of an auction are taken into consideration, it can be concluded that in these experiments, if all the agents play with one of these three MiSs then there is a point of time in the sequence of auctions that all the agents fulfill the condition of participating an auction. As a result the Number of agents in these experiments are highest among all other experiments in the setting. One reason for that is, in the MiS-1 and MiS-2, the bid increment value remains small in comparison to the agents maximum bid amount which prohibits reaching the b_i value at the end of the auctions. The same situation occurs for the MiS-5 as the agents in the first four auctions only raise their bid values by minimum increment value. So, when all the agents apply this strategy, the moving average of the bid increments will be equal to the minimum bid increment. For this reason, the item is sold to a low price at the end of the auction. There are two practical consequences of this situation; first one is that, when the auction terminates there remains a huge difference between the selling price and the agent's b_i which leads to high profit margins for the bidders. The second one is while there are agents who fulfill the auction entrance criteria so as to participate to the next auction in sequence, there is no agent to leave the auction as the selling price of the item is low enough to keep them in the auction. For this reason the number of agents are increasing dramatically.

Experimental Set-up 6

In the sixth experimental set-up, the settings in the fifth simulation experiment are preserved and the effects of strategies on payoff are analysed for the SP auction format.

Table 13 summarizes the results of these experiment.

Table 13 Experiment Results for the 6^{th} Experiment Set-up

Strategies	Number of Agents	Average Payoff
MiS-1	360,000	126.935
MiS-2	360,000	126.909
MiS-3	175,362	11.026
MiS-4	171,784	8.640
MiS-5	360,000	128.941
MiS-6	186,959	13.148

Figures in Table 13 indicate that, MiS-5 outperforms other strategies and followed by MiS-1 and MiS-2. Furthermore, the number of agents participating in the auctions and the average payoff amount is similar to the 5^{th} experiment set-up outcomes, according to the same reasons described in the 5^{th} experiment.

Besides, when the results of Experiment Set-up 5 and 6 are compared, it can be seen that the Average payoff obtained in the SP auction is higher than the one that is obtained in the FP auction.

Experimental Set-up 7

In this experiment, the agents are assigned equally to the top winning two MaSs in the FP auction format.

The results of the experiments can be seen from Table 14.

Table 14 Experiment Results for the 7th Experiment Set-up

	Number of agents	Average payoff
MaS-1	93509	15.482
MiS-1	15851	16.938
MiS-2	15679	17.421
MiS-3	15237	17.603
MiS-4	15313	9.239
MiS-5	15602	14.162
MiS-6	15827	17.406
MaS-2	93940	20.267
MiS-1	15382	22.110
MiS-2	15744	21.513
MiS-3	15831	23.152
MiS-4	15919	12.493
MiS-5	15630	20.105
MiS-6	15434	22.384
Total	187449	17.880

In order to determine a significant difference between the results of the strategies Kruskal-Wallis Test is applied to the data. The result of the test is shown in Table 15.

Table 15 Kruskal-Wallis Test Statistic and Ranks of Strategies in the 7th Experiment Set-up

a) Test Statistics

	MaS
Chi-Square	642.507
Df	1
Asymp. Sig	0.000

b) Ranks

	MaS No	N	Mean Rank
MaS	1	4652	3829.35
	2	4348	5218.57
	Total	9000	

Figures in Table 15 indicate that there is a significant difference between the two strategies' payoffs since the Asymptotic Significance value is smaller than .05 (.000 < .05). So it can be said that, if all of the agents are playing with only the two top winning strategies the agents playing with MaS-2 gets the highest average payoffs. Results of this experiment can be analysed according to the results of Kruskal-Wallis test. Figures in Table 14 present that the average payoff of the agents playing with MaS-1 is 15.482 where the average payoff of the agents playing with MaS-2 is 20.267. So, MaS-2 is the most profitable strategy for the FP auctions.

As compared to the first benchmark simulation outcomes, the results of the experiment show that when all of the agents adopt the strategies which are proven to be the more profitable strategies, the average payoffs of the agents become higher.

In addition the demand satisfaction ratio of the agents according to their Macro Level Strategies is shown in Table 16.

Table 16 Demand Satisfaction Rate for the 7th Experiment Set-up

Demand Satisfaction		Meet Demand			
		0	1	2	3
Number of demands within stratgies	1	0.799	0.201		
	MaS-1	0.776	0.224		
	MaS-2	0.822	0.178		
	2	0.805	0.119	0.076	
	MaS-1	0.788	0.139	0.073	
	MaS-2	0.822	0.099	0.079	
	3	0.807	0.128	0.027	0.037
	MaS-1	0.802	0.129	0.040	0.029
	MaS-2	0.813	0.128	0.015	0.045
	Total	0.802	0.161	0.030	0.006

The figures in Table 16 indicates that 80% of all agents were not able to buy any product from the auctions, whereas 16% of the agents were able buy one product. In addition, .3% of the agents bought two products where .06% of the agents bought three products. If the demand amounts of the agents are taken into consideration, it can be seen that 79% of the agents with single-unit demand were not able meet their demand while 21% of the agents have satisfied their demands. Also, 80% of the agents with two-unit demand got nothing from the auctions, however, 11% of the agents of this kind were able to obtain single item and .76% of the agents have met all their demands. When it comes to the agents who demand 3 units of item, the success rate of obtaining three units of good is .37%.

When the performance of two top winning strategies are compared, it can be seen that the agents adopting MaS-1 meet more of their demands but due to the reasons described in the first benchmark simulation experiment results the agents adopting MaS-2 win the items with more profit margins.

Experimental Set-up 8

In the eighth experimental set-up, all of the settings in the seventh simulation experiment are preserved and analyzed in the SP auction format.

Table 17 summarizes the results of the experiment.

Table 17 Experiment Results for the 8th Experiment Set-up

	Number of agents	Average payoff
MaS-1	93288	19.137
MiS-1	15630	19.859
MiS-2	15770	19.672
MiS-3	15325	20.073
MiS-4	15358	11.485
MiS-5	15444	19.742
MiS-6	15761	23.837
MaS-2	93466	23.072
MiS-1	15441	24.172
MiS-2	15287	23.728
MiS-3	15868	25.748
MiS-4	15811	14.655
MiS-5	15538	24.147
MiS-6	15521	26.096
Total	186754	21.106

In order to analyse the significant difference between two strategies, Kruskal-Wallis Test is used and the result of the test is shown in Table 18.

Table 18 Kruskal-Wallis Test Statistic and Ranks of Strategies in the 8th Experiment Set-up

a) Test Statistics

	MaS
Chi-Square	531.363
Df	1
Asymp. Sig	0.000

b) Ranks

	MaS No	N	Mean Rank
MaS	1	4634	3887.71
	2	4366	5150.91
	Total	9000	

The Asymp. Sig value is smaller than .05 so that there is significant difference between the payoff's of the two strategies. Ranks table indicates that MaS-2 performs better than MaS-1 as the average payoff of the agents playing with MaS-1 and MaS-2 are 19.137 and 23.072 respectively.

Table 19 Demand Satisfaction Rate for the 8th Experiment Set-up

Demand Satisfaction		Meet Demand			
		0	1	2	3
Number of demands within stratgies	1	0.797	0.203		
	MaS-1	0.770	0.230		
	MaS-2	0.824	0.176		
	2	0.804	0.120	0.076	
	MaS-1	0.787	0.139	0.074	
	MaS-2	0.821	0.101	0.078	
	3	0.808	0.129	0.027	0.036
	MaS-1	0.797	0.133	0.040	0.030
	MaS-2	0.819	0.124	0.014	0.043
	Total	0.801	0.163	0.030	0.006

Examining figures in Table 19, it can be concluded that only the 20% of the agents who demands single unit of the item have achieved to meet their demands. This success ratio reduces to .76% and .36% for the agents who demands two units of item and three units of item respectively. If the Total row is taken into consideration 80% of the agents in the auctions were not able to buy anything from the auction while 16% of the agents have bought only a single item, .3% of the agents have bought 2 units of the item and finally only .06% of the agents habe bought three units of the item.

In addition, when the profitability and the demand satisfaction rates of two strategies are compared, it can be observed that MaS-2 outperforms MaS-1 due to the same reasons described in the second benchmark simulation experiment results.

Comparing the payoff figures in Table 14 and Table 17, it can be said that the agents have higher profits in the SP auction than in the FP auctions. On the other hand, when the demand satisfaction ratios are taken into consideration there is no significant difference between the ratios regarding the auction format.

Experimental Set-up 9

In this set-up the effect of variability of reservation price to the bidder's payoff will be tested for FP auction format. All of the settings in the first benchmark simulation will be preserved but the reservation price interval which is set to [1000, 2000] initially, will decrease gradually.

The result of the simulation experiments are shown in Table 20.

Table 20 Experiment Results for the 9th Experiment Set-up

	Average Payoff					
	Reservation Price Intervals					
	1000-2000	1100-1900	1200-1800	1300-1700	1400-1600	1500-1501
MaS-1	10.746	8.493	5.800	3.565	1.256	0.380
MaS-2	12.648	9.944	7.045	4.579	1.923	0.388
MaS-3	7.704	6.365	5.423	3.959	2.111	1.408
MaS-4	9.433	7.747	6.043	4.085	1.852	1.000
MaS-5	7.571	6.579	5.310	3.970	2.116	1.386
Total	9.622	7.825	5.924	4.031	1.852	0.913

As it can be seen from Table 20, if the interval of the reservation price reduces the Average Payoff of the agents decrease for each MaS and in total. This is meaningful when we consider the case, when all of the agents have the same reservation price then the selling price will be close to that value, as they will increase their bid values till the same value. So, the average payoff will reduce as the reservation values of the agents become close to each other.

In other words, as the homogenity of the agents increase, the theoretical findings of Vickrey (1961) regarding the best bidding strategy is verified. MaS-3 in which the agnets bid their reservation value becomes the most profitable strategy.

As the reservation price interval becomes narrow, the average payoff of the MaS-2 and MaS-1 decreases dramatically and these strategies lose their profitability. The reason of MaS-2's losing advantage will be explained due to the variability of NE which also leads variability in the b_i. On the other hand, MaS-1 is losing its advantage because the agents adopting this strategy is reducing their b_i values as they win the auction. When the reservation price values of the agents become similar, while the agents adopting MaS-1 reduces their bid, other agents keep their b_i values in the same level. For this reason, MaS-1 adopters lose the auctions and get the lowest average payoffs.

<u>Experimental Set-up 10</u>

In the tenth experimental set-up, all of the settings in the ninth simulation experiment are preserved and the payoff of the strategies are analysed in the SP auction format.

Results of these experiments are shown in Table 21.

Table 21 Experiment Results for the 10^{th} Experiment Set-up

	Average Payoff					
	Reservation Price Intervals					
	1000-2000	1100-1900	1200-1800	1300-1700	1400-1600	1500-1501
MaS-1	14.312	12.940	7.787	4.638	1.584	0.414
MaS-2	14.125	13.447	7.817	4.892	2.209	0.131
MaS-3	12.109	9.991	8.722	6.470	3.424	1.907
MaS-4	11.273	10.863	7.236	4.850	2.189	0.962
MaS-5	11.979	10.094	8.512	6.170	3.127	1.660
Total	12.761	11.470	8.014	5.405	2.507	1.015

Figures in Table 21 present that, as the reservation price of the agents becomes similar, the Total Average Payoff decreases. In the 10^{th} experiement results the MaS-1 and MaS-2 also becomes the less profitable strategies due to the reasons described in the 9^{th} experiment set-up.

When the results of experiment set-up 9 and 10 are compared it can be seen that the Total Average profit of the agents is higher in the SP auctions than in the FP auctions.

Experimental Set-up 11

In this set-up the effect of auction duration on the bidder's payoff will be analyzed for FP auction format. All of the settings in the first benchmark simulation setting will be preserved but the number of rounds will be increased to 50, 100, 250, 500 and 1000 respectively.

Table 22 presents the result of the simulation.

Table 22 Experiment Results for the 11th Experiment Set-up

	Average Payoff					
	T=20	T=50	T=100	T=250	T=500	T=1000
MiS-1	10.585	9.657	9.911	9.752	9.977	9.759
MiS-2	10.574	10.219	9.838	10.093	9.893	10.079
MiS-3	9.664	9.397	9.026	9.014	8.850	9.036
MiS-4	7.196	6.171	7.332	7.357	7.300	7.116
MiS-5	8.649	8.787	9.059	8.970	9.360	8.930
MiS-6	11.064	10.929	7.579	7.278	7.255	7.883
Total	9.622	9.196	8.788	8.744	8.772	8.799

It can be observed from Table 22 that, as the number of rounds increase the average payoff of the agents decrease up to a certain point around T=100 and then stays in the same levels (around 8.75). This shows that the duration of the auction has effect on the payoff of the bidders until a specified period and from that point on the duration of the auction has no significant effect on the outcome.

Another important finding is that, the average payoff of the agents adopting MiS-4 is the lowest among all others because in MiS-4 the bid increment amount is proportional to the number of periods left in the auction. This proportionality causes the bid increments to be so low that the agents adopting this strategy could not able to win the auction.

Experimental Set-up 12

In the twelfth experimental set-up, all of the settings in the eleventh simulation experiment, are analyzed in the SP auction format.

The results of the experiments are shown in Table 23.

Table 23 Experiment Results for the 12th Experiment Set-up

	Average Payoff					
	T=20	T=50	T=100	T=250	T=500	T=1000
MiS-1	12.812	12.189	11.720	11.805	11.625	11.739
MiS-2	12.655	11.770	11.629	11.572	11.875	11.658
MiS-3	14.153	12.830	12.166	11.879	11.894	11.648
MiS-4	8.309	6.842	7.420	7.561	7.662	7.758
MiS-5	12.676	12.249	11.709	11.778	11.688	11.799
MiS-6	15.974	12.970	7.732	7.796	7.610	7.691
Total	12.761	11.470	10.397	10.399	10.401	10.385

Table 23 indicates that as the duration of the auction increase, the Average Payoff in total decreases until a certain point which coincides around T=100 and from that point on the affect of the duration to the outcome of the auction becomes ambiguous.

In addition, the average payoff of the agents adopting MiS-4 is lower than the others due to the reasons explained in the previous set-up.

Finally, if the results of the experiment 11 and 12 are compared, it can be seen that the total payoff of the agents is higher in the SP auction format than FP auction format.

Assesment of the Simulation Results

The results of the experiments indicate that among all of the macro level strategies the highest revenue is generated by the agents who update their bid amounts according to the probability of not winning the auction (MaS-2). When micro level strategies are considered the strategy in which the agent update her bid increment value according to the previous round's bid increments (MiS-5), obtains the highest revenue.

The summary of overall outcomes of the macro level strategies is presented in Table 24.

Table 24 The Overall Outcomes of Strategies in FP Auctions

Bid Ratio Interval		*Total*	*MaS-1*	*MaS-2*	*MaS-3*	*MaS-4*	*MaS-5*
1.00	Number of Agents	675815	24601	0	233835	186610	230769
	Number of Winning Agents	26957	2154	0	11270	2179	11354
	Average Payoff	24.2991	25.7684	0	24.2101	22.5858	24.4374
0.95-0.99	Number of Agents	426232	95915	272187	0	58094	36
	Number of Winning Agents	17615	5795	5137	0	6670	13
	Average Payoff	57.3479	53.3512	84.0627	0	40.2233	68.7254
0.90-0.94	Number of Agents	54974	44511	5919	0	4539	5
	Number of Winning Agents	409	155	69	0	183	2
	Average Payoff	119.250	120.188	120.263	0	118.145	112.67
0.85-0.89	Number of Agents	29804	29748	3	0	53	0
	Number of Winning Agents	1	1	0	0	0	0
	Average Payoff	212.58	212.58	0	0	0	0
0.80-0.84	Number of Agents	21942	21942	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.75-0.79	Number of Agents	16872	16872	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.70-0.74	Number of Agents	13218	13218	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.65-0.69	Number of Agents	9997	9997	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.60-0.64	Number of Agents	7160	7160	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.55-0.59	Number of Agents	5304	5304	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.54-	Number of Agents	8424	8424	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0

In Table 24, the Bid Ratio Interval represents the intervals which are created according to the ratio of bidder's maximum bid amount and her reservation value. To illustrate the interval 0.90-0.95 indicates that the bidder's submitted bid corresponds to a value which is between $0.90 * v_i$ and $0.95 * v_i$. Number of Agents row represents the number of agents whose submitted bid corresponds to the emphasized interval. Number of Winning Agents and Average Payoff rows represent the number of the agents who win the auction and the winners' average payoff from the auction respectively.

The figures in Table 24 indicate that when the participants' maximum bid amounts are getting smaller the number of winning agents decreases, however, the average payoff of the winning agents are increasing. So, it can be said that the probability of winning an auction is decreasing as the agents offer lower maximum bid amounts, on the other hand if they win the auction their payoff will be greater. In this point the decision that an agent has to make is to trade off between winning the item with high probability and low payoff, or winning the item with less probability and high payoff.

Table 25 represents the overall outcomes of the macro level strategies in SP auctions.

Table 25 The Overall Outcomes of Strategies in SP Auctions

Bid Ratio Interval		*Total*	*MaS-1*	*MaS-2*	*MaS-3*	*MaS-4*	*MaS-5*
1.00	Number of Agents	647695	24433	0	230784	176426	216052
	Number of Winning Agents	26952	2308	0	11582	1655	11407
	Average Payoff	37.2025	39.4064	0	36.3308	38.2574	37.4885
0.95-0.99	Number of Agents	436328	94536	266944	0	69352	5496
	Number of Winning Agents	17513	6093	5155	0	6241	24
	Average Payoff	67.8989	65.4802	93.0039	0	49.3654	109.127
0.90-0.94	Number of Agents	66552	45519	6118	0	7959	6956
	Number of Winning Agents	521	195	82	0	244	0
	Average Payoff	135.212	137.675	127.732	0	135.757	0
0.85-0.89	Number of Agents	32968	29843	3	0	225	2897
	Number of Winning Agents	2	0	0	0	2	0
	Average Payoff	220.07	0	0	0	220.07	0
0.80-0.84	Number of Agents	22391	22307	0	0	1	83
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.75-0.79	Number of Agents	16894	16893	0	0	1	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.70-0.74	Number of Agents	12990	12990	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.65-0.69	Number of Agents	9959	9959	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.60-0.64	Number of Agents	7286	7286	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.55-0.59	Number of Agents	5262	5262	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0
0.54-	Number of Agents	8355	8355	0	0	0	0
	Number of Winning Agents	0	0	0	0	0	0
	Average Payoff	0	0	0	0	0	0

The figures in Table 25 indicate the same results as the figures in Table 24. However, the average payoff of the winners are higher in the SP auctions than FP auctions.

As a result of the figures in Tables 24 and 25, it can be said that the likelihood of winning the item is maximum when the agent bids her reservation price as maximum bid amount. However, in that case her average payoff will be minimum.

Another significant result of the experiments is that the SP auctions generate higher payoff than the FP auctions. In the theoretical study of Vickrey (1961), he also attained the same difference between the auction types.

The payoff of the bidders is found to be decreasing when the reservation price differences among bidders reduce. Dinther (2007) also draw attention to the same finding as the heterogeneity of the agents lessen the total payoff generated by the bidders is also decreasing.

The experiment results also indicate that the duration of the auction do not have any significant effect on the outcome of the micro level strategies, however, as stated by Lucking-Reiley et al. (2006), it is found that when the duration of the auction increases, the payoff of the bidders decreases.

CHAPTER 5

CONCLUSION

In this study, an e-auction mechanism is developed for investigating the effects of bidding strategies of the participants to the outcomes of a multi-unit, sequential e-auction. Agent-based modeling and simulation methodology is being used as it is appropriate to model the behavior of boundedly rational, heterogeneous agents in dynamic trading environments.

The model involved agents with independent private values who demand at least a single unit of item from a single seller offering multi-unit items. The items are sold sequentially and only an item could be sold at an auction. Five macro level strategies, in which the agents calculate their maximum bid amount for the item and six micro level strategies, in which the bid increment amounts in an auction is calculated, are assigned to each bidders.

There are twelve simulation experiments conducted in which the distribution of the strategies and/or a parameter of the e-auction mechanism is changed. In order to analyze the significance difference between the profitability of the strategies Kruskal-Wallis test is used. In particular the effects of auction format, the variability of agent's private value and duration of the auction on the profitability of the strategies and the payoff of the winner are investigated.

The results of the experiments indicate that the second price ascending bid auction with continuous bidding format generates higher revenues than the first price ascending bid auction with continuous bidding format.

The agents who update their bid values according to the probability of not winning the auction (MaS-2) generate the highest revenue. Besides, when macro level strategies are distributed evenly, the micro level strategy in which the agent update her bid increment values due to the previous round's bid increments (MiS-5), obtains the maximum revenue.

In addition, it is found that the revenue of the bidders decreases when the variability of the private values of the agents are reduced.

Furthermore, the experiment results show that the outcomes of the micro level strategies are not affected by the duration however the payoff of the bidders decreases as the duration of the auction increases.

This study can be extended in a few directions as a future work. One direction is to use the model to conduct the analysis in a different auction format, such as simultaneous or combinatorial auctions. Another direction is to investigate the effects of the bidders' risk attitudes in the demand satisfaction ratio and the revenue generated in the auctions.

APPENDIX

Contents of the CD

Yildiz_Akkaya_Tez.pdf	A Study on Sequential Internet Auctions Using Agent-Based Modeling Approach
The Code.doc	Source Code of the Sequential e-Auction
ThesisAbstract.pdf	Thesis Abstract
TezOzeti.pdf	Thesis Abstract in Turkish

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