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Homogeneous and Heterogeneous Agents in Electronic Auctions

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1. Introduction

When considering the agents mediated electronic marketplace, agents play an active role in both sellers and buyers sides. A seller agent may advertise its products in the market, placing the selling price and looking for the potential buyers in the market. On the other hand, a buyer agent would look for the desired goods or services requested by its user and it has a task to bargain about the price of the products and find the best deal (Dignum, 2001). Besides that, due to the rapid growth of Information Technology and popularities of the Internet, more trading that could be done in bricks and mortar is now available without geographical constraint by using the computer and the Internet. Therefore, sellers are now looking for a larger group of potential buyers while buyers are looking for a better offer of their desired goods in the online marketplace.

1.1 Online auctions

An auction is a bidding mechanism, described by a set of auction rules that specifies how the winner is determined and how much to be paid (Wolfstetter, 1999). By auctioning, sellers find a way to determine the actual values of the items being auctioned especially those items which are hard in valuation process. By auctioning also, items are allocated to the bidders who have the highest valuation. Therefore, auction mechanism is an interesting topic to be studied since it provides an approach to the price formation of the item. Besides, McAfee and McMillan (1987) argued that studying auction is closer to applications than other mathematical economics. The auction theory explains the existence of certain trading institutions and may suggest improvements in these institutions.

In the virtual marketplace which sells a single object, there are basically four types of online auction protocols, namely the ascending-price (English) auction, the descending-price (Dutch) auction, the first-price sealed bid auction and the second-price sealed bid (Vickrey) auction. In the ascending-price (English) auction, sellers start at a low price and the price is successively raised by bidders until the auction end time is reached. The bidder with the highest bid wins the auction and pays based on the bid submitted.

The descending-price (Dutch) auction is the opposite of an English auction. An auctioneer starts announcing an auction with an initial high price. This high price is normally higher than the item's actual price. The initial bid will be lowered progressively until there is an offer from a bidder to claim the item. The winner pays the price offered.

The first-price sealed bid auction and the second-price sealed bid auction are quite similar in terms of the bid submission. Interested bidders submit their bids privately and these bids are concealed until the auction ends. When the auction ends, those concealed bids are disclosed. Bidder with the highest bid will be identified as the winner. However, in the former auction type, the winner pays for the item with his bid, but the second highest bid in the latter type of auction is paid.

Regardless of which auction protocols are used in the online auctions, there are many online auction sites that are available on the Internet. Moreover, as this mechanism is accepted by more people, the number of auctions conducted in this virtual marketplace is increasing drastically. Thus, a bidder would find it very hard to find a suitable auction to participate. This problem leads to a question, is there any alternative method to overcome this dilemma? The answer can be found by using agent technology.

1.2 Agent technology

According to Jennings and Wooldridge (1998), an intelligent agent is a computer entity that is capable of flexible autonomous action in order to meet its design objectives. The term flexible here means that an intelligent agent should be responsive, proactive and social. These intelligent agents should solve their problems encountered in their environment without direct intervention of human or other agents. Furthermore, as intelligent agents, they have their own goals to be achieved (Dignum, 2001). So, when the outside world is changed, they should not simply react to these changes; they should also exhibit opportunistic, goal-directed behaviors and take initiatives where appropriate to achieve their primary objective. On the other hand, they should perceive their environment and respond consistently to changes that occur. This property somehow neutralizes the pro-activeness of agents. It prevents agents from trying to achieve their goals without considering the achievability of the goals. They must also interact with one another (other agents or human) in order to complete their goals and help others with their problems.

To this end, an agent system may seem to be similar to an object-oriented system. For example, an object in the object–oriented system encapsulates some states and has control over these states. These states can only be accessed or modified via the methods provided by the object. So does the agent. But the behaviors of an agent are also encapsulated. For example, if there is an object X that invokes a method m on object Y, then Y has no control over whether m is executed or not. In this sense, Y is not autonomous since it has no control over its own actions. On the other hand, agent has control over its behaviors or actions. The interaction among the agents is more in the request and response manner. An agent may request an action to be done by another agent. But the decision on whether the action is performed lies solely with the recipient agent.

Besides that, intelligent agents in online auctions never overbid. According to Lee and Malmendier (2007), human bidders often overbid their private valuations on items desired. Thus, by using intelligent agents, human bidders can be rest assured that overbidding does not occur to them since agents never bid above the maximum values provided by them.

Due to the agent's properties and capabilities, agent technology is acceptable in electronic commerce, particularly in the online auction. By applying agent technology in online auction, the challenges stated in Section 1.1 may be greatly lightened. However, knowing

which auction to bid is not sufficient to guarantee that the agents can win the auction. It also needs to consider how much should a bidder submit and its efficiency when competing with other human bidders or other bidder agents.

1.3 Bidding issues

When agents are deployed in online auction marketplaces, their owners usually explicitly inform them the maximum price of an item. Nonetheless, winning an auction with a lower bid indicates that the agent not only complete its task of obtaining the item, but also increases the profit or utility of the winner and vice-versa. Hence, many researchers have been studying different bidding strategies in different auction protocols with the hope to maximize the winner's satisfaction. Some of these strategies are reviewed and developed from the perspective of game theory (Yang & Lu, 2007), neuro-fuzzy approach (He *et al.*, 2004, 2006; Lin *et al.*, 2006), grey theory predictive models (Lim *et al.*, 2007; 2008), heuristic models (Anthony & Jennings, 2003; Yuen *et al.*, 2006) or as from bidders' behaviors (Roth & Ockenfels, 2002).

Due to different available bidding strategies and studies on auction environment, more experienced or advanced bidders may obtain useful information to strategize their bidding behaviors in order to increase their winning probabilities. It is even more complicated when agent technology is implemented into this environment. On the one hand, with the help of intelligent agents, bidders can ease their searching and monitoring or even bidding tasks to them and be regularly informed. On the other hand, due to the capability of computational advantages, bidder agents may have more freedom to select and participate in different auctions to purchase their desired goods. In other words, sellers are now facing greater competition from around the world to attract buyers while human bidders are oppressed and have to make decision very carefully to outbid their counterparts.

From another perspective, when homogeneous intelligent agents and heterogeneous intelligent agents are implemented in the marketplace, sellers may react differently due to the market economy and their revenues generated. A seller may assume that as more bidder agents are found in their auctions, this would lower their auction closing prices. It is because agents never overbid and they make wider survey than human bidders before participating in any auctions on the Internet. Nonetheless, as agent technology is becoming a dominant trend in developing online auctions mechanism, it would be interesting to study the reaction of sellers when they are confronted with bidder agents of single type and multiple types.

Hence, this chapter attempts to study the impacts resulted from utilizing intelligent agents in the online auction marketplace. More specifically, the competitions among standard bidders and intelligent agents with various bidding strategies are to be analyzed. Standard bidders are to be categorized into 3 types according to their respective risk attitudes while intelligent agents are to be equipped with a heuristic bidding strategy, the greedy bidding strategy and the sniping strategy. From these competitions, the performance of each type of bidders and agents are to be examined. Furthermore, sellers' reaction on the implementation of bidder agents is briefly examined. A simulated marketplace will be used to conduct these experiments and for further analysis.

The rest of the chapter is arranged as follow: Section 2 discusses the related works on online English auctions, bidding strategies and bidder agents developed by other researchers. In

the next section, the architecture of the simulated marketplace is described. In Section 4, performances of different bidders are analyzed. Lastly, this paper ends with conclusions and suggestions for future works.

2. Literature review

2.1 Online english auctions

In English auction, a price is successively raised through submitting new bids by bidders until there is only one bidder who is willing to buy the item being auctioned (McAfee & McMillan, 1987). In this type of auction, all bids submitted are made known to every participant immediately. Therefore, interested bidders can submit their bids to outbid the current highest bidder. Besides that, before an auction is started, the seller may set a hidden price which indicates the minimum price he is willing to sell the item. This hidden price is commonly known as the seller's reserve price. By implementing this reserve price, the item will only be sold if the closing price of an auction is not less than that. More interestingly, sometimes, the English auction is also known as the second highest price auction since the winner only pays a price that is equivalent to the second highest bidder's valuation.

Many researchers have shown their interests in the field of auction, especially on the English auction protocol since it is the most commonly accepted and widely implemented protocol in selling a single object. Hu and Bolivar (2008) showed their interest in online auctions efficiency, particularly on eBay auctions. They investigated and analyzed multiple online auction properties including consumer surplus and their cross-relationships. In their data analysis, they implemented consumer surplus ratio (CSR) as a measurement to evaluate the winners' profit over the final value. Also, they utilized the concept of median instead of average in this CSR in order to reduce the influence of sparse outliers. By comparing the consumer surplus ratio, they found that the surplus ratio is generally impacted by the nature of the market and the ability to find a replacement. Rareness itself makes the valuation process difficult and thus is leading to high surplus ratios.

Besides that, overbidding is one of the interesting scenarios found in online auctions. Overbidding is a phenomenon in which the winner of an auction finds himself paying too much to purchase the item being auctioned after the auction closes. Lee and Malmendier (2007) studied this phenomenon and found that such overbidding affects both private-value and common-value settings. In the work conducted, they found that even experienced bidders fell into this bidder's curse. At first they may remember the upper limit of the bids. However, this memory fades out as time goes by. Besides that, the cost of switching from auctions to auctions or to fixed price transaction, the structure of outbid messages and the extra winning utility were introduced to explain the bidder's curse. From another perspective, they suggested that sellers may benefit from such scenario in terms of their revenue earned.

David *et al.* (2005) conducted their research in optimal design of English auctions with discrete bid levels. In their research, they aimed to provide the revenue maximizing design for this type of English auction. They identified that there is a case which two or more bidders are found in the same bid level and none of them can further increase the current price to another higher level. Thus, one of them is randomly selected as the current highest bidder and eventually the winner of the auction. Seller's revenue in this case was

underestimated since the second highest bid may not be the second highest bidder's valuation and the outcome may not be efficient as the item is not necessarily purchased by the bidder with the highest valuation. In order to maximize the revenue obtained in this case, they proposed and examined by empirical experiments that as the number of bidders increases, the bid levels become increasingly closer spaced. In their experiments, they also found that the optimal reserve price increases as more bidders participate in the auction.

2.2 Bidder's common behaviors

There are commonly three distinct types of risk behaviors considered, namely risk aversion (RA), risk neutral (RN) and risk seeking (RS). Generally, a RA bidder is willing to compromise his profit to reduce the risk or uncertainty (the loss in an auction). With the same perspective, a RS bidder is willing to take the risk without giving up his profit. Lastly, a bidder is considered as RN if he is not affected by either the risks that come from the uncertainty he faces or the maximized profit (Watson, 2004). Of course, in different situations, the risk considered is varied according to the focus of the study. Also, the degree of risk-aversion or risk seeking are greatly dependent on how much from a bidder's profit he is willing to sacrifice or how risky it is if he loses in an auction respectively. There are many researchers studying the impact contributed by these risks in different auctions such as McAfee and McMillan (1987), Klemperer (1999), Wolfstetter (1999) and Talluri and Ryzin (2004).

On the other hand, Ockenfels and Roth mentioned in their respective papers (Ockenfels & Roth, 2002, 2006; Roth & Ockenfels, 2002) that many bidders (or their agents) tend to submit their bids late (this is also referred to as bid sniping). Hu and Bolivar (2008) also supported this finding by using eBay data collected. According to them, sniping is defined as the process of watching a timed online auction, placing a winning bid at the very last possible moment before an auction is ended. Sniping has an advantage of giving no time to other bidders to respond when they are outbid. Furthermore, they found that by performing sniping strategy, bidding wars are avoided among bidders and thus it will increase the expected bidder profits while decreasing the seller revenues. Therefore, the last-minute bidding is not simply due to naïve time-dependent bidding, but it responds to the strategic structure of the auction format in a predictable way.

As the online auction is widely implemented and practiced in the trading community, there are hundreds of thousands of different auctions running simultaneously. Thus, soon bidders will find that choosing an auction is not an easy task. It is even more troublesome if several desired auctions come from different auction houses. Consequently, searching and monitoring those auctions become time consuming tasks. Fortunately, due to the proliferation of agent technology, these problems may be solved or greatly reduced by implementing this technology into the online auctions.

2.3 Intelligent agents in online english auctions

As mentioned by Dignum (2001), agents will only be used as user representatives if the benefits of using an agent are high and the trust that an agent will realize them is high. Due to the furtherance of the artificial intelligence and computer technology, using such technology in online auctions is at minimal cost.

First of all, Anthony and Jennings (2003) developed a bidding agent equipped with a heuristic bidding strategy for multiple heterogeneous auctions. This bidding strategy consists of four tactics, namely the remaining time tactic, the remaining auctions tactic, the desire for bargain tactic and the desperateness tactic. By combining these tactics and taking into account the priority of these tactics, a suggested bid is generated to its bidder and is to be used in the auction desired.

Besides that, Yuen *et al.* (2006) investigated utility maximizing bidding heuristics for agents that participate in multiple heterogeneous auctions in which auction format and their start and end times might be varied. In their proposed bidding strategy, all four heuristic strategies outperformed the two benchmark strategies (greedy strategy and random strategy) used in their experiment.

In other studies conducted by Lim *et al.* (2007, 2008), they argued that an intelligent agent would greatly help its bidder if the closing price of an auction is predicted successfully. Therefore, they studied several prediction models (ARIMA model, artificial neural network with backpropagation model and the grey theory prediction model) and found out that the grey prediction model successfully forecasted the most accurate data among these three prediction models. Furthermore, the concept of moving data was implemented to increase the accuracy of the predicted price.

He *et al.* (2004, 2006) focused their interest on agent's bidding strategy that is incorporated with neuro-fuzzy techniques, the Earliest Closest First heuristic algorithm. It identifies auctions that are most suited to the bidders' requirements and according to their risk attitudes, bids in some other auctions that have approximately similar expected return, but which close earlier than those in the best return set. The greedy strategy, the fixed auction strategy and the average strategy were used to make comparison with their proposed strategy. From the results obtained, the Earliest Closest First algorithm performed better among these strategies considered.

Park *et al.* (1999) developed an adaptive bidding strategy that would be used by sellers in continuous double auction and it is implemented based on stochastic modeling. They argued that this strategy is capable of taking the dynamics and uncertainties of the auctions into account and therefore agents equipped with this strategy receive higher profit in the auctions participated. However, due to the computational cost and time consumption in this strategy, they further modified the strategy such that an agent equipped with this strategy might decide the time of using it.

Ford *et al.* (2010) concentrated their research on layered bidding strategies for autonomous bidding agents. In their proposed strategies, a complex strategy (top layer) is formed from complex strategies or simple strategies (middle layer); while a simple strategy consists of atomic bidding actions (bottom layer). Users can easily specify a user defined strategy by manipulating the layers. Besides that, they proposed 2 algorithms that would convert those strategies into rule-based bidding strategies which will be executed by the bidding agents and for agents' reasoning purposes.

From the researches and studies discussed and reviewed in this section, it can be seen that studying online auction is not a new topic. By equipping different bidding strategies, computer agents are integrated to make decision in auctions marketplace on their users'

behalf. However, there are still other areas in online auctions where researchers may explore. One of them is the market economy when a market is fully populated by homogeneous agents and heterogeneous agents. Besides that, as the implementation of agent technology becomes more acceptable in the online auction marketplace, sellers' reactions when confronting with them may be an interesting subject to be studied.

3. Simulated online auction marketplace

There are many successful online auction houses that are running on the Internet such as eBay. However, due to different perspectives of houses administrators and researchers, data retrieval from these auction houses is restrictive if not impossible. Furthermore, certain information may not be extracted easily due to the legal responsibilities and sometimes data extraction is subject to disclosure of companies' privacy. Therefore, simulated online auction marketplace becomes an alternative testing platform for researchers to conduct their experiments and retrieve data for further analyses.

In this work, a simulated online auction marketplace is used to simulate a real auction house where multiple English auctions are conducted. Since they may have different start and end times, they are run concurrently in the auction house. Besides that, all auctions in this marketplace are the symmetric independent private values (SIPV) auctions (Matthews, 1995; Wolfstetter, 1999).

In the setting phase, researchers can set a number of auctions to be conducted in this simulation in a range of 1 to 100 inclusive. While the number of auctions is determined by researchers, each auction's start and end times are randomly assigned by the system. By doing so, these simulated concurrent English auctions are similar to the one found in the real online auction houses. Secondly, there are two types of bidders, a group of standard bidders and a group of bidders who use agent technology. Researchers can manually assign the number of standard bidders found in the marketplace in a range of 0 to 3000 inclusive and their risk behaviors. Next, the number of intelligent agents can be assigned in a range of 0 to 3000 inclusive with three different bidding strategies, namely the greedy strategy (Byde, 2002), the sniping strategy (Ockenfels & Roth, 2002, 2006; Roth & Ockenfels, 2002; Hu & Bolivar, 2008) and a heuristic bidding strategy (Anthony & Jennings, 2003). The greedy strategy is selected because of its bidding attribute. Some bidders may use their agents to look for auctions with the lowest current bids. By doing so, they wish to purchase the items with minimal prices. Next, agents that are equipped with the heuristic bidding strategy selected here would represent another group of bidders who are well prepared before participating in any auction. They do not only consider the current bid, but also the number of similar auctions available, the timeline of obtaining the items if won and how desperate they are in procuring the items. Lastly, the sniping strategy is taken into account because it avoids bidding war (Ockenfels & Roth, 2002, 2006; Roth & Ockenfels, 2002). Moreover, another group of bidders who are impatient with longer auction closing time and keen to obtain the items desired without wasting time on surveying other auctions may prefer this strategy.

Next, the system prepares the marketplace by generating auctions, sellers, both standard bidders and intelligent agents according to the predefined settings. Each auction is assigned a reserve price of the item randomly based on a normal distribution. This normal

distribution is generated by providing a mean value and a standard deviation value of the actual closing prices collected from Internet auctions. By doing so, the marketplace simulates the real online auctions pricing scenario. Besides that, the standard bidders and the intelligent agents are assigned their private valuations from the same normal distribution used for the item's reserve price generation. These values are taken as the maximum values that they are willing to pay in obtaining the goods. After that, standard bidders are assigned to different auctions by the system. Whenever it is possible, standard bidders are distributed evenly to all the auctions generated. They are treated as the faithful bidders as they do not move from an auction to another. On the other hand, intelligent agents situate in the marketplace. Every time there is a bidding process conducted, these intelligent agents would find the most promising auction to participate.

Lastly, auctions are started automatically if their start time is reached. Both standard bidders and intelligent agents are free to submit their bids according to their criteria and preferences. In this marketplace, a universal time is used and every time step is discrete and indivisible. In each time step, all auctions are checked if they are active. For each active auction, a standard bidder will be chosen randomly to submit a bid. At the same time, if there is any intelligent agent interested in submitting its bid in the same auction, a competition among the selected standard bidder and the intelligent agent(s) occurs. As a result, a higher bid would outbid lower bids. Besides that, if an auction's end time is reached, the seller would announce the bidder with the highest bid as the winner of that auction if the auctions are closed with trading. Throughout the whole bidding process of different auctions conducted, their bidding histories are recorded for data analyses.

3.1 Participants in the simulated online auction marketplace

In this simulated platform, sellers are the owners of the item to be auctioned and are also the auctioneers who conduct the auctions. They wish to sell their products through English auction protocol. Besides that, there are bidders in these auctions with the aim to obtain the desired goods. They are categorized further into two groups according to the usage of agent technology, the standard bidders and the bidders who utilize intelligent agents.

3.1.1 Standard bidders and bidding behaviors

Standard bidders do not implement any agents to act on their behalf. They would personally join an auction and submit a bid whenever it is possible. Furthermore, these standard bidders can also be categorized as faithful bidders since they will stay in an auction until they win that auction or when their private valuation is exceeded. Moreover, as long as the current bid in an auction is lower than their private valuations, they would submit their bids in the auction. However, bid increments vary depending on the bidders' risk behaviors.

There are 3 types of risk attitudes considered in this simulated marketplace, namely the risk aversion (RA), risk neutral (RN) and risk seeking (RS). In this marketplace, bidders face the risk of not winning an auction at the lowest closing price. By understanding the risk mentioned here, a RA bidder is afraid that he may pay an unnecessary higher price conditional on winning the auction. On the other hand, a RN bidder has no difference between paying more or less conditional on winning an auction. Lastly, a RS bidder is not

afraid of paying an unnecessary higher price conditional on winning an auction. A RA bidder would start bidding at a minimal bid increment (randomly chosen from a range of 1 to 3 inclusive). By doing so, he hopes to submit a bid that is as minimal as possible which in turn would win the auction. However, their bidding strategy changes towards the end of an auction. If they are not the current highest bidder, they would bid more aggressively (randomly chosen from a range of 7 to 9 inclusive) to increase the probability of becoming the current highest bidder and eventually win the auction.

On the other hand, a RS bidder would bid aggressively from the beginning of an auction (drawn randomly from a range of 7 to 9 inclusive). They are less concerned on paying too much as long as he obtains the item desired within his valuation. Moreover, they try to frighten other bidders by bidding aggressively. Nonetheless, as the time goes by, a RS bidder who is not the current highest bidder would try his best to become the leading bidder in the auction. But his private valuation is approaching due to his aggressive bidding from the beginning of an auction. Therefore, by realizing this fact, he changes his bidding strategy from an aggressive act to a more conservative way. He reduces his bid increment choices (in a range of 1 to 3 inclusive) to avoid bidding over his private valuation.

At the same time, a RN bidder starts his bidding with a different strategy. Since he is indifferent with the risk of paying unnecessary higher price with the hope of winning an auction, he would bid constantly in his bid increment. In other words, he would not change his bid increment in his bidding process. His bid increment is almost a constant value from the beginning of an auction until the auction is closed (randomly drawn from a range of 4 to 6 inclusive).

Regardless of the risk attitudes, the bid increments used in this simulated auction house are arbitrary values. They are distributed uniformly and thus have equal chances to be selected. Any other value can be used to simulate their bidding behaviors. Besides that, these scenarios may be further explained by using the von Neumann-Morgenstern utility as explained by Bierman (1998).

When explaining a bidder's strategy with von Neumann-Morgenstern utility, the marginal utility and the motivation of submitting high or low bid are correlated. According to Fig. 1, when a RA bidder submits the first bid, if he wins at this point, he gains the maximum profit as indicated by the end point at the right most. Nevertheless, normally an auction receives more bids from other bidders. Therefore, he would continue to submit more bids until he is the leading bidder in the auction. So, the obtained profit is shifted to the left as more bids are submitted. As the profit decreases from right to left of the graph, the marginal utilities of different bids are compared. As indicated in the figure, the marginal utility from the first bid to second bid submitted is relatively smaller than the marginal utility from the latter bids. This marginal utility becomes larger when more bids are submitted. Therefore, a RA bidder would be motivated to submit a larger bid towards the end of an auction.

Next, when a RN bidder submits his first bid and if he wins, he obtains his maximum profit from the auction as indicated by the end point at the right most of the Fig. 2. However, as more bidders participate in the same auction, he starts to counter bid his competitors by submitting subsequent bids. Hence, the profit gained from winning the auction is shifted to the left of the graph as more bids submitted. Nevertheless, the marginal utilities of his bids are constantly observed. It can be explained as the motivation of submitting subsequent bids

by a RN bidder is always the same. Consequently, a RN bidder would never change his bids either from the beginning of an auction or towards the end of the auction.

Lastly, in Fig. 3, the end point located at the right most of the graph indicates the maximum profit obtained by a RS bidder if he wins an auction with his first bid. Nonetheless, more bids are usually required before winning an auction. Thus, the profit is shifted to the left of the graph. When comparing the marginal utility of each bid submitted, those earlier bids have larger marginal utilities than those bids submitted later. Thus, a RS bidder tends to submit larger bid increments at the beginning of an auction rather than towards the end of the auction.
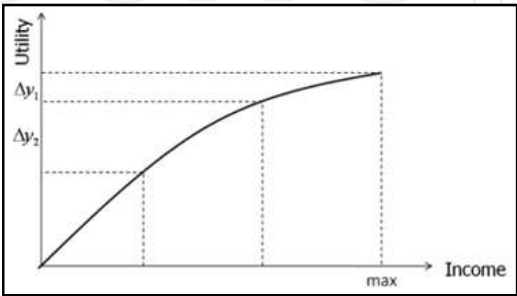

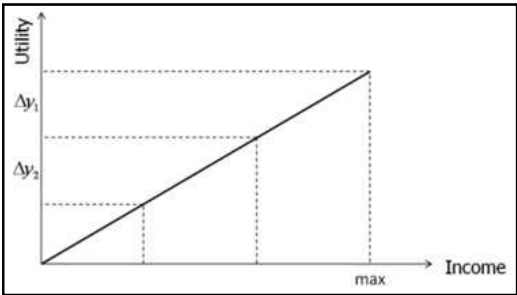Fig. 1. Risk-averse Bidder's von Neumann-Morgenstern Utility.

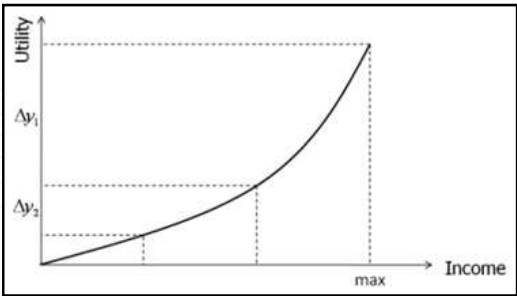Fig. 2. Risk Neutral Bidder's von Neumann-Morgenstern Utility.

Fig. 3. Risk Seeking Bidder's von Neumann-Morgenstern Utility.

3.1.2 Intelligent agents and bidding behaviors

Another type of bidders utilizes intelligent agent technology to represent them in bidding process. Therefore, this type of bidders saves time on searching, monitoring and participating in an auction. These intelligent agents in this simulated marketplace are equipped with different bidding strategies according to the experimental setup. Firstly, by

using greedy strategy, an agent would always look for an auction with the lowest current bid as its target auction. Then it would increase the current bid with an increment from a range of 1 to 10 randomly. These values in the range are just arbitrary values. In the case where multiple auctions are found to have the lowest current price, the first auction found is to be selected as the target auction for an agent (Fig. 4).

---

while ($t < t_{max}$) and (item not obtained = true)

    Build active auctions list

    List all auctions that are active before t_{max}.

    Select target auction as one that has the lowest current bid.

    Calculate the new bid, current bid + randomize bid increment.

    Bid in the target auction with the new bid.

End while

where t is the current universal time across all auctions, t_{max} is the agent's allocated bidding time by when it must obtain the goods or leave the auctions.
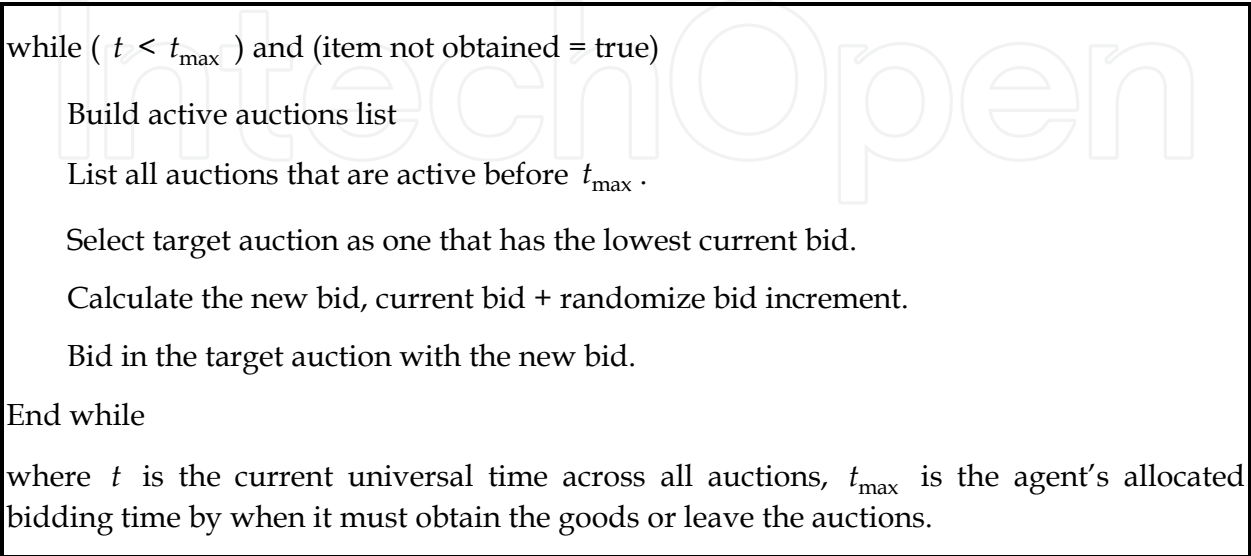

Fig. 4. The Top-level Algorithm for the Greedy Agent.

Secondly, those agents equipped with the sniping strategy would hold their bids until the last time step of an auction with the hope of outbidding others while give them insufficient time to react. Their sniped bids are a sum of the current bid of an auction with an increment from a range of 1 to 10 (Fig. 5). Again, these values are just arbitrary values. Similarly, when there is more than an auction closes on the last possible time step, the first auction found by an agent would be selected as its target auction.

---

while ($t < t_{max}$) *and* (item not obtained = *true*)

    Build active auctions list

    List all auctions that are active before t_{max}.

    Select target auction as one that has t = end time - 1.

    Calculate the new bid, current bid + randomize bid increment.

    Bid in the target auction with the new bid.

End while

where t is the current universal time across all auctions, t_{max} is the agent's allocated bidding time by when it must obtain the goods or leave the auctions.
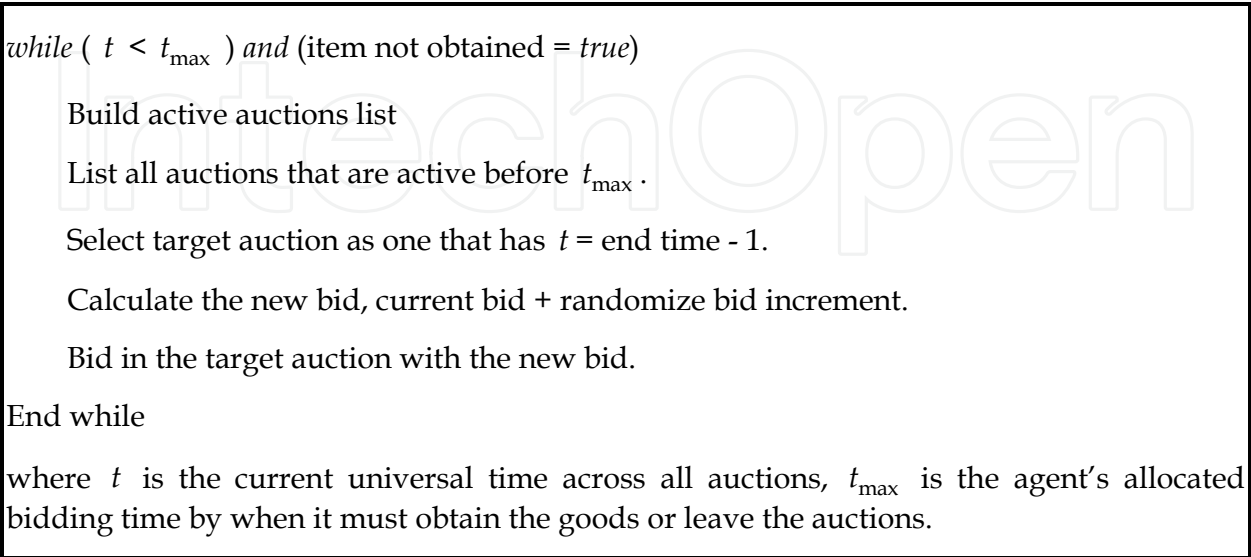

Fig. 5. The Top-level Algorithm for the Sniping Agent.

Lastly, the Heuristic strategy consists of four tactics used in the bidding process, namely the remaining time tactic, the remaining auction tactic, the desire for bargaining and the desperateness of obtaining the item. In the first tactic, as every agent has its own time constraint, this tactic tackles with this limitation. Meanwhile, the second tactic handles the consideration of remaining auctions that are still available before an agent's time is reached. Thirdly, if an agent is willing to bargain the price of an item desired, it would bid minimally to avoid paying a high price to win an auction. Finally, if an agent is desperate in obtaining an item from an auction, it would submit higher bids to increase its probability of winning that auction. After receiving the new suggested bid from the strategy, this new suggested bid is further modified if necessary (Fig. 6).

Next, in order to decide which potential auctions to be participated, these Heuristic agents calculate the expected utility of each auction by using the equations below:

$$\text{expected utility} = P_i(v)U_i(v) \tag{1}$$

and

$$U_i(v) = \frac{pr - v}{pr} \tag{2}$$

where $P_i(v)$ is the probability of winning an auction i at a bid v, $U_i(v)$ is the utility of an auction i at a bid v, pr is the agent's private valuation. After calculating the expected utilities of all auctions available, an auction with the highest expected utility is selected as the most promising auction. The agent would participate in the most promising auction with the bid received from its bidding strategy.

---

while ($t < t_{\max}$) *and* (item not obtained = *true*)

    Build active auctions list

    List all auctions that are active before $t_{\max}$.

    Calculate the new suggested bid using the agent's strategy.

    If the difference(suggested bid, current bid) > a preset threshold,

    new suggested bid = current bid + a portion of difference

    Select potential auctions from active auctions list to bid in.

    Select target auction as one that maximizes agent's expected utility.

    Bid in the target auction with the new suggested bid.

End while

where t is the current universal time across all auctions, $t_{\max}$ is the agent's allocated bidding time by when it must obtain the goods or leave the auctions.

Fig. 6. The Top-level Algorithm for the Heuristic Bidding Agent.

In the next section, different experiments are performed according to the different auction requirements. Under different settings, from auction to a more general view of the marketplace are to be analyzed especially from the economic perspective.

4. Experimental setup and results

In this section, several empirical experiments are designed and conducted. Firstly, heterogeneous standard bidders will compete with homogeneous intelligent agents in an auction market. Secondly, competition occurs among heterogeneous standard bidders and heterogeneous intelligent agents. Thirdly, markets that are populated by homogeneous intelligent agents and heterogeneous intelligent agents are studied and analyzed.

4.1 Methods of measurements

In these empirical experiments conducted, several methods are utilized to evaluate the performance of different bidders and agents. They are the average winner's utility, the average number of winning auctions, the average closing price and the consumer surplus ratio. These methods are measured according to the types of different participants.

4.1.1 Average winner's utility

In every auction traded successfully, winner obtains certain profit from winning the auction. Besides that, since different bidders and agents may have different private valuations generated from the same normal distribution, this profit is evaluated as a ratio with respect to their own private valuations. By doing so, the factor of their different private valuations which would lead to various gains is greatly eliminated. To calculate the average winner's utility, the following mathematical equations are used:

$$U_{ij}(v) = \frac{Pr_i - v_j}{Pr_i} + c \tag{3}$$

and

$$\bar{U}_i(v) = \frac{\sum_{j=1}^{n_i} U_{ij}(v)}{n_i} \tag{4}$$

where $U_{ij}(v)$ is the winner's utility of auction j gained by winners of type i, Pr_i is the private valuation of the winner of type i, v_j is the winning bid of auction j, c is an arbitrary constant set to 0.001, $\bar{U}_i(v)$ is the average winner's utility of type i, n_i is the number of auctions won by winners of type i. In Equation 3, a constant c is used to ensure that in the worst case where a winner pays his maximum valuation to purchase the item being auctioned, he still deserves a small gain compared to those who lose in the same auction.

4.1.2 Average number of winning auctions

In this method, auctions won by different groups of bidders and agents are counted into their respective categories. This method is concerned with the number of winning auctions

in a society of a certain type of winners. To calculate the average number of winning auctions for a given bidder or agent in the marketplace, the following equation is used:

$$\overline{W}_i = \frac{\sum_1^n \text{number of auctions won by winners of type } i}{n} \tag{5}$$

where $\overline{W}_i$ is the average number of auctions won by winners of type i, n is the number of runs conducted in the experiment.

4.1.3 Average closing price

The third measurement is the average closing price. Based on this measurement, the performance of the winners is evaluated in terms of the price paid to purchase the item desired.

$$\bar{C}_i = \frac{\sum_{j=1}^{n_i} C_{ij}}{n_i} \tag{6}$$

where, C_{ij} is the winning bid of auction j submitted by winners of type i, n_i is the number of auctions won by winners of type i.

4.1.4 Average consumer surplus ratio

The consumer surplus ratio (CSR) is introduced by Hu and Bolivar (2008) which considers the number of bids found in an auction and the median number of bids across all the auctions conducted. This ratio is used to show the surplus gained by each winner with respect to his private valuation. Hence, it is similar to the average winner's utility. However, it considers also the number of bids received in each auction and the median number of bids received across all the auctions available. It is assumed that an auction with more bids submitted will most probably ends with higher price compared to auctions with less bids. In this research, intelligent agents are free to select the auction to participate based on their selection model. So, in a market where multiple agents of different types are found, the considerations in this ratio would reduce the extreme bids submitted and the influence of number of bids. This ratio is evaluated as follow:

$$CSR_j = \text{Median }_{\forall j}\left(\frac{\left(V_{H_i} - V_{F_i}\right) \cdot (N_i + N_m)}{V_{F_i} \cdot N_i + V_{H_i} \cdot N_m}\right) \tag{7}$$

and

$$\overline{CSR}_j = \frac{\sum_1^n CSR_j}{n} \tag{8}$$

where j is the type of winners, V_{H_i} is the winner's private valuation in auction i, V_{F_i} is the final winning bid in auction i, N_i is the number of bids of item i, N_m is the median number of bids across all the auctions conducted, $\overline{CSR}_j$ is the average CSR of winners of type j, n is the

number of runs conducted in the experiment. A high value in this CSR would indicate that the winner receives high surplus compared to his own private valuation after minimizing the influences as stated in the considerations.

4.1.5 Average seller's utility

On the other hand, as suggested by Krishna (2002), sellers extract more revenues from auctions with higher number of bidders. In this market, some auctions may receive more bids compared to other auctions. Therefore, by using the ratio instead of the surplus, the factor of having different values of winning bids in different auctions is minimized. The equation is given as below:

$$R_j(v) = \frac{v_j - RP_j}{v_j} \tag{9}$$

and

$$\bar{R}(v) = \frac{\sum_{j=1}^{n} R_j(v)}{n} \tag{10}$$

where $R_j(v)$ is the seller's utility of auction j, v_j is the winning bid of auction j, RP_j is the seller's reserved price of auction j, $\bar{R}(v)$ is the average seller's utility, n is the number of auctions that are closed with winner.

4.2 Normal distribution of data

Before any experiment is conducted, data generated from this marketplace are checked on its consistency and its normality by using statistical software SPSS Statistic. The simulated marketplace is run 10, 30 and 50 times. By doing so, when the market is repeated with a relatively fewer runs, data consistency is checked. With these different numbers of runs, data collected are compared by using ANOVA test to check whether the closing prices are significantly different among these groups. In every run, 30 auctions, 180 standard bidders and 120 intelligent agents are generated by the system. More specifically, within the time t_0 to t_{max}, each auction will start and end according to their randomly assigned time constraints. Meanwhile, participants join different auctions based on their attributes. In this marketplace with the ratio used, standard bidders are distributed evenly across 30 auctions. Counter bidding process happens between standard bidders and intelligent agents until t_{max} is reached, then the market is said to have conducted a complete run.

Before performing the ANOVA test, two assumptions have to be verified, namely the normality of the data distribution and the homogeneity of variances. In the first verification, the hypotheses are given below:

H_0: The population means are equal among the groups of samples.

H_1: The population means are not equal among the groups of samples.

To check the distribution of the data collected, the Kolmogorov-Smirnov statistic with a Lilliefors significance level is used. From the results shown in Fig. 7, the significance levels

of Kolmogorov-Smirnov (Sig.) in different runs are 0.200, 0.200 and 0.199 respectively, which are greater than 0.05. Therefore, null hypothesis is accepted. That is, the normality of data collected (closing prices) is assumed. In other words, data collected from the marketplace can be used to represent the actual scenario found in the real online auction houses since these data collected is distributed normally according to the SPSS analysis.

Next, the second assumption is checked. The Levene's test of homogeneity of variances is used for this purpose. However, from the result shown in Fig. 8, the second assumption cannot be verified ($p < 0.05$). Fortunately, SPSS does provide alternative approaches to verify the homogeneity of variances; they are the Brown-Forsythe and Welch procedures which can still be used to support the ANOVA test. From Fig. 9, the significance levels of Brown-Forsythe and Welch procedures are 0.537 and 0.670 respectively ($p > 0.05$). Hence, the homogeneity of variances is assumed.

Tests of Normality							
		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Number of Runs	Statistic	df	Sig.	Statistic	df	Sig.
Average Closing Price	10	.112	30	.200*	.960	30	.317
	30	.116	30	.200*	.967	30	.452
	50	.131	30	.199	.979	30	.801
*. This is a lower bound of the true significance.							
a. Lilliefors Significance Correction							

Fig. 7. Kolmogorov-Smirnov and Shapiro-Wilk statistic.

By using ANOVA test, a null hypothesis of "there is no significant difference among closing prices across different sets of samples" would be accepted if the significance level (Sig.) is greater than 0.05. From the results shown in Fig. 10, the null hypothesis is accepted since $F(2, 87) = 0.404$, $p = 0.669$ (Sig. value in ANOVA test) which is greater than 0.05. However, due to the violation of Levene's test of homogeneity of variances, therefore, the Brown-Forsythe F-ratio and Welch procedure are reported here. There is no significant difference among these closing prices across different sets of samples, since $F (2, 56.722) = 0.404$, $p > 0.05$ (Brown-Forsythe F-ratio) and $F (2, 53.278) = 0.629$, $p > 0.05$ (Welch procedure). In summary, from analyzing results of this ANOVA test, there is no significant difference found in the closing prices collected from various numbers of runs. Thus, in the following experiments, the simulations are run 10 times for different research purposes.

Test of Homogeneity of Variances			
Average Closing Price			
Levene Statistic	df1	df2	Sig.
12.387	2	87	.000

Fig. 8. Levene's test of homogeneity of variances.

Robust Tests of Equality of Means			
Average Closing Price			
	Statistic[a]	df1	df2	Sig.
Welch	.629	2	53.278	.537
Brown-Forsythe	.404	2	56.722	.670
a. Asymptotically F distributed.			

Fig. 9. Brown-Forsythe and Welch procedures in ANOVA test.

ANOVA					
Average Closing Price					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6.087	2	3.044	.404	.669
Within Groups	655.808	87	7.538		
Total	661.895	89			

Fig. 10. ANOVA test.

4.3 Competition among heterogeneous standard bidders and homogeneous intelligent agents

In this experiment, 3 types of standard bidders are competing with the Heuristic agents simultaneously. Two simulations are conducted in this experiment. The first simulation is conducted to create the competition among standard bidders with assigned risk types and Heuristic agents. In the second simulation, the competition occurs among standard bidders with randomized risk types and Heuristic agents.

4.3.1 Experimental setup

In the first simulation, the numbers of standard bidders according to their different risk types are assigned. However, in the second simulation, the numbers of standard bidders with different risk attitudes are randomized by the system. The total number of buyers in the marketplace is always 300 and the proportion of standard bidders and intelligent agents is maintained in different runs. In a real auction marketplace, intelligent agents may observe their environment and obtain useful information such as the number of bidders. By running these two simulations, the agents' performance is tested when the numbers of standard bidders with different risk behaviors are known or when it is assumed wrongly. More specifically, there are 10 situations in every simulation and each situation is repeated 10 times. Every time a new situation is conducted, 10% of the standard bidders are replaced by the Heuristic agents until the last run, where 90% of the buyers are Heuristic agents. Intelligent agents of type Heuristic are selected to represent the intelligent agents because of their outstanding performance among the three types considered in this work (their performances are analyzed in Section 4.5.2). Nonetheless, there are always 30 auctions and 300 buyers found in the marketplace. Every auction generated has an active period of 100 time steps. Within this period of time, both standard bidders and Heuristic agents are competing to become the leading bidder in an auction.

4.3.2 Experimental results

a. Competition among Heterogeneous Standard Bidders with Assigned Risk Types and Heuristic Agents

In Fig. 11, it is observed that in all the situations where agents are found, their winner's utility is found higher than the other bidders' types. When agents were competing with multiple types of standard bidders in auction marketplace, they outperformed their counterparts by receiving higher intrinsic rewards. Besides that, generally, the rewards received by these Heuristic agents are increasing as more agents are found in the market.

Next, Heuristic agents successfully obtain the goods desired with lower prices compared to other bidders in the same market (Fig. 12). In addition, it is noticeable that the closing prices obtained by all winners' types seem to be converging towards Situation 9. It may be caused by the growing of the agent's population since Heuristic agents are capable on deciding the auction to be participated and the reasonable bids to be submitted. By doing so, they reduce bidding war with other participants but themselves in the market and as a result, the closing price of each auction is approximately distributed in a narrower range.

In Fig. 13, as the number of the standard bidder decreases, their number of winning auctions is also reduced. The two lines plotted in the same figure indicate the sums of auctions won by standard bidders and Heuristic agents. In this case, the number of auctions won by these agents is not as many as achieved by the standard bidders since these agents are equipped with the same strategy and are free to select their most promising auctions within the market, they may concentrate on several auctions while neglecting the less promising auctions. As a consequence, fewer auctions are won by the Heuristic agents.
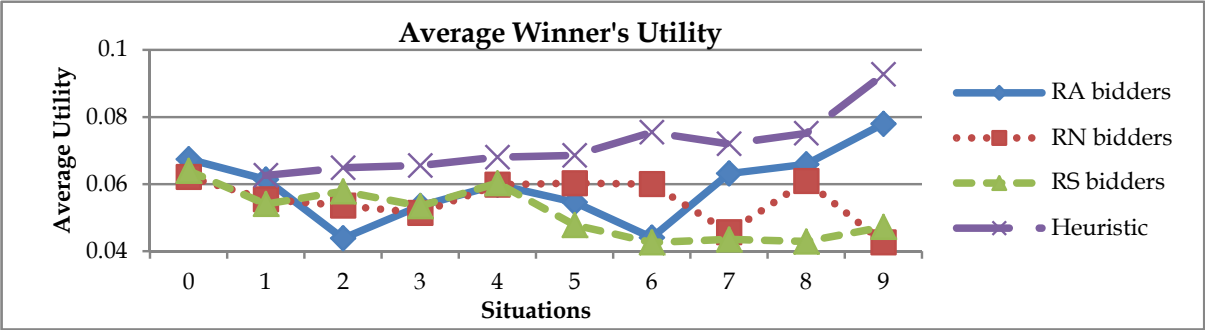
Fig. 11. Average winner's utility according to different winners' types.

Fig. 12. Average closing prices obtained by different winner's types.
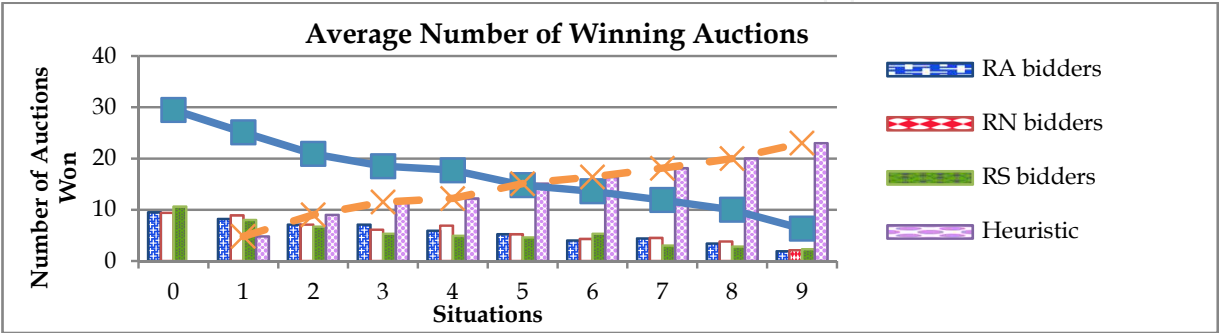
Fig. 13. Number of auctions won by different winner's types.

b. Competition among Heterogeneous Standard Bidders with Randomized Risk Types and Heuristic Agents

In Fig. 14, the winner's utility of the agents is fluctuated across the situations due to the irregularity of the numbers of standard bidders according to their risk behaviors that are found in the marketplace. When these numbers are unknown, Heuristic agents face the difficulty in tuning their bidding strategy appropriately. However, when comparison is made across the situations, the agents still received higher utilities in most of the situations.

Next, Fig. 15 shows the performance of different winners' types in terms of closing price. The most obvious observation is that the Heuristic agents successfully obtained their desired items with the lowest closing prices in all the situations considered. Besides that, the closing prices of all situations seem to be converging towards Situation 9. This is due to the growth of the agent population and thus reduces the bidding war among bidders. Consequently, the differences among closing prices of different winners' types are becoming smaller.

Lastly, as the population of agents is growing, they obtained more auctions compared to their counterparts (in Fig. 16). Nonetheless, the number of this achievement is not as high as the number achieved by those standard bidders. It may be due to the capability of Heuristic agents that are not restricted to any auctions. Therefore, they may select their best auctions to participate. In certain circumstances, some of the auctions are left without much attention from these agents. As a result, the number of winning auctions obtained by Heuristic agents is fewer than the auctions won by standard bidders.
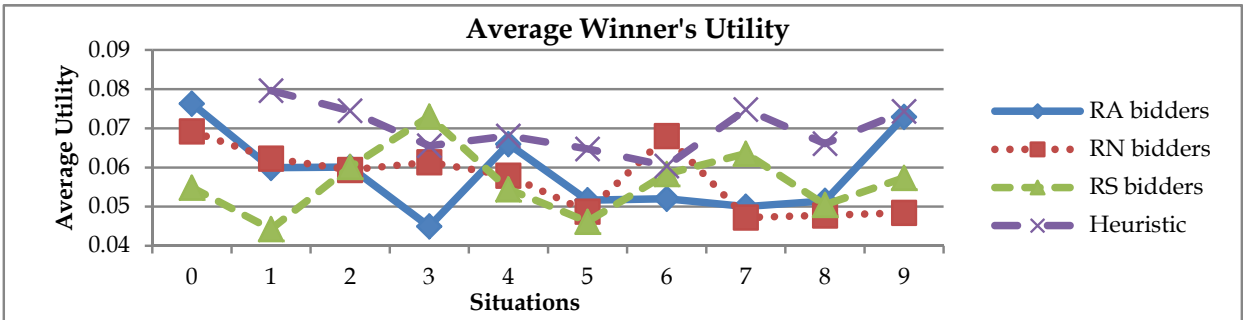

Fig. 14. Average winner's utility according to different winner's types.

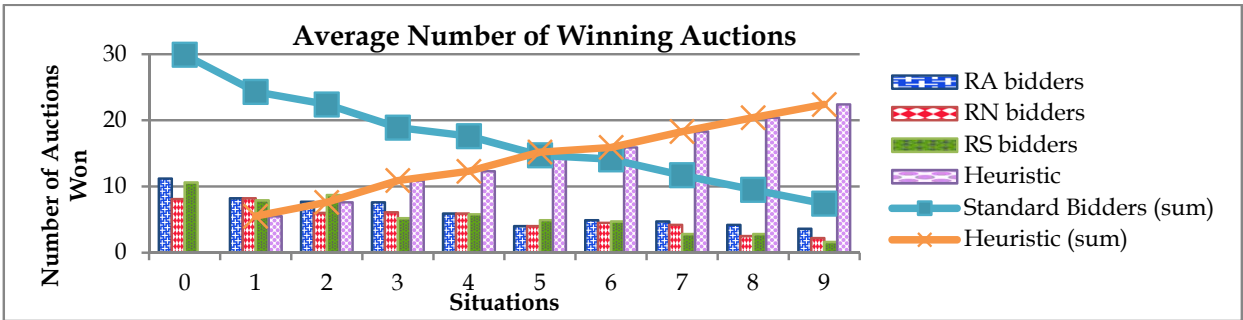Fig. 15. Average closing prices obtained by different winner's types.

Fig. 16. Number of auctions won by different winner's types.

4.3.3 Summary of the experiment

Heuristic agents outperformed their competitors in obtaining goods desired while trying to keep the closing prices cheaper regardless of the correct assumption on the number of standard bidders based on their risk types. Therefore, from the bidders' point of view, it can be concluded that in general, by implementing agent technology, it improves their satisfaction in terms of the intrinsic saving values received and the auction closing prices. On the other hand, sellers' revenues are reduced in this experiment with finite auctions and participants since the auction closing prices are decreasing.

4.4 Competition among heterogeneous standard bidders and heterogeneous intelligent agents

In the next experiment, heterogeneous standard bidders and heterogeneous intelligent agents are generated in the same marketplace. In this experiment, performance of each winner's group is examined. Furthermore, the market economy is also evaluated.

4.4.1 Experimental setup

In this experiment, a simulation that involves both 3 types of standard bidders and 3 types of intelligent agents is considered. Besides the standard bidders and Heuristic agents, the Greedy agents and the Sniping agents are introduced. A Greedy agent is an agent that always participates in an auction with the lowest current bid. A Sniping agent is an agent that always targets on the auction that closes in the next possible moment. In this experiment, the competition occurs not only between standard bidders and intelligent agents, it occurs also within the groups of standard bidders and intelligent agents with different types. Hence, the auctions generated are increased to 90 and the total bidders are set to 900. Besides that, the number of situations used in this experiment is reduced to 4 as shown in Table 1. In this experiment, the focus is shifted from the advantages of using agents to the general market economy. Thus, fewer situations are considered. As multiple intelligent agents and standard bidders are located in a market, it would further simulate the real online auction marketplace where bidders may have different bidding behaviors or implement different bidder agents.

Situation	0	1	2	3
Standard Bidders	900	810	540	270
Intelligent Agents	0	90	360	630

Table 1. Proportion of participants in a marketplace

4.4.2 Experimental results

From Fig. 17, in all the situations analyzed, Greedy and Heuristic agents obtained higher winner's utility compared to other standard bidders. It may be credited to their bidding strategies which would lead them in suitable auctions and suggest an appropriate bid to be submitted. Sniping agents scored the lowest utility in all the situations because of its attitude of always search and snipe in the auctions that would close in the next time step. As a result, they may end up with paying higher prices when obtaining the items.

Next, the average number of winning auctions obtained by different groups of winners is illustrated in Fig. 18. First of all, standard bidders procured fewer items as more agents are located in the market. Besides that, Sniping agents successfully outperformed the other two types of agents in Situation 2 where 40% of the market participants are intelligent agents. It may indicate that sniping strategy is suitable to be used to obtain the items desired when agents' population is relatively smaller. Nonetheless, Heuristic agents performed outstandingly in Situation 3 with 20.6 auctions won on average. In all the situations analyzed, the overall closing numbers are 89.6, 89.4, 89.6 and 89.5 respectively. These numbers may not equal to 90 as some of the auctions are closed without winners (seller's reserve price is not met).

In Fig. 19, as more agents participate in an auction market, the closing price is decreasing. This can be seen from Situation 1 to Situation 3. There is an increase in closing price from Situation 0 to Situation 1. It may be explained as when more bidders' types are found in the market, it affects the competition that occurs within the market. Besides that, when comparison is made among the intelligent agents, it can be seen that Sniping agents pay more in obtaining the items desired. Their winning bids are greatly affected by the winning bids of other standard bidders. They always snipe in auctions at the very last possible moments. Thus, they have to submit higher bids to overbid the current leading bidders and it causes their closing prices to be the highest among the agents community.
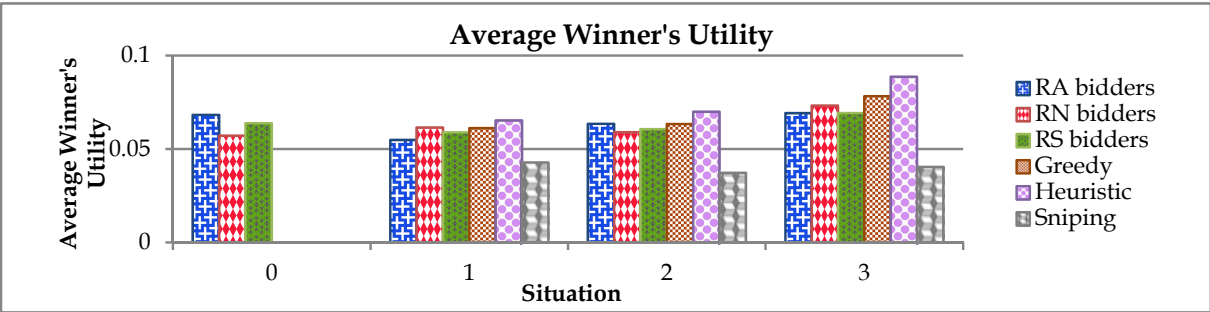

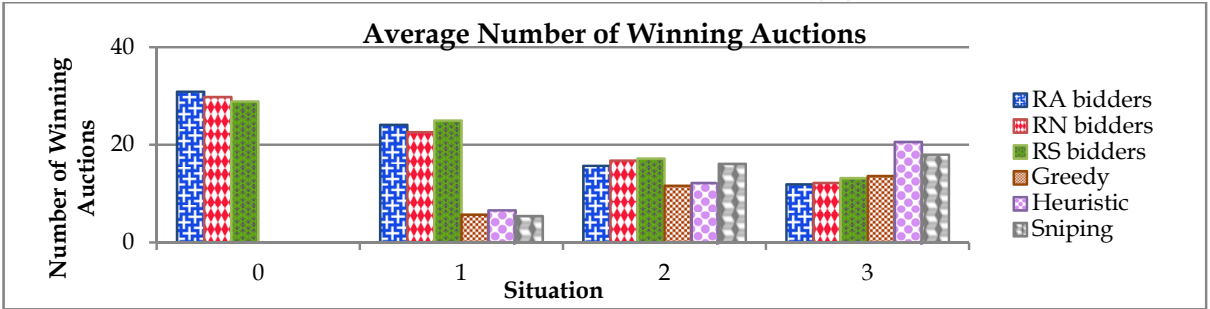Fig. 17. Average winner's utility according to winner's types.

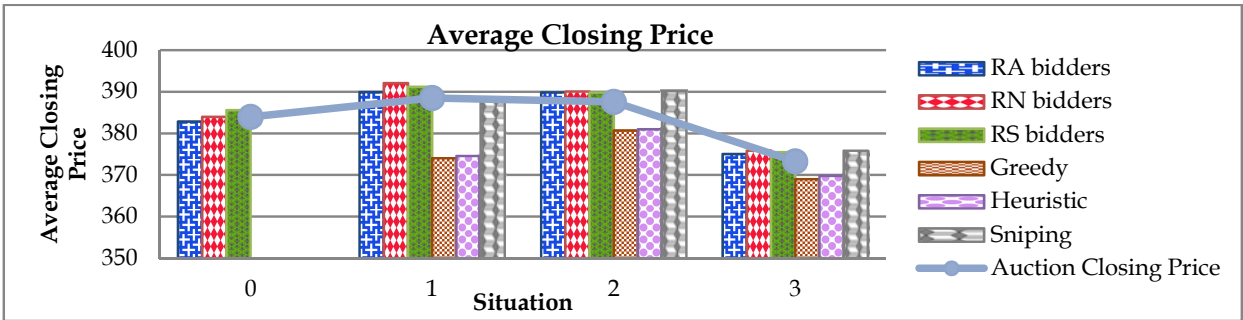Fig. 18. Average number of winning auctions according to winner's types.

Fig. 19. Average closing price according to winner's types.

4.4.3 Summary of the experiment

Generally, in this experiment, the auction closing prices are decreasing as intelligent agents are involved in the market. Moreover, these agents successfully help their bidders to obtain items desired while trying to achieve greater saving. The Sniping agents do not perform well in obtaining desired goods while achieving greater saving as the other 2 types of agents. However, to those bidders who need the item required desperately, the Sniping agents may become one of their options since they would obtain the goods desired within a short period of time and the price paid is always within their private valuations. From the seller's perspective, they may prefer more standard bidders in their auctions than intelligent agents since more standard bidders increase their revenues gained from the auctions.

4.5 Special cases in simulated marketplace

In this experiment, two cases are considered and studied, a market that is fully populated by intelligent agents of single type is simulated and a market that is fully resided by multiple types of intelligent agents is analyzed. In both cases, besides the performances used in the previous experiments, the average CSR, is implemented. Due to the flexibility of agents, there may be an extreme case where several auctions are selected by all the agents while the rest of the auctions are left unattended or receive extremely few bids. Consequently, auctions with fewer bids may most probably close with low prices and vice-versa. Therefore, by using this CSR, it calculates the surplus ratio while minimizing the influence of the bids received by each auction and at the same time, it considers the median number of bids received across all the auctions generated.

4.5.1 Experimental setup

In the first simulation, a marketplace of 90 auctions is generated and the performances of 900 Heuristic agents are evaluated (homogeneous environment). Heuristic agents are selected in this homogeneous environment because of its outstanding performances compared to other types of agents implemented in this work (see Section 4.5.2 for its results). In the real auctioning world, it may be hard to find a market that is only resided by agents of single type. However, if a known strategy can guarantee a win in the auction with profit; eventually everyone will use the same strategy. This will lead to an environment similar to our case. Next, in the second simulation, 900 intelligent agents with various bidding strategies participate in 90 auctions generated (heterogeneous environment). The performances of these intelligent agents are analyzed and lastly a comparison between their performances and the performances of homogeneous agents is conducted.

4.5.2 Experimental results

Table 2 shows the various performances of intelligent agents in homogeneous environment and heterogeneous environment. On average, the homogeneous bidder agents recorded an average winner utility of 0.1318. Meanwhile, in the heterogeneous environment, Heuristic agents, Greedy agents and Sniping agents recorded average winning utilities of 0.1072, 0.0957 and 0.0391 respectively. A higher utility would mean a greater satisfaction for the winners since they receive higher intrinsic saving. The Sniping agents received the lowest utility because they ignored the auctions that are not closing soon but may return to them a better utility if they were winning in these auctions. When comparing the average utilities between Heuristic agents in Environment 1 and Environment 2, they received lower utility in heterogeneous environment as competition arises between groups of various agents.

Next, out of 90 auctions generated, 22.6 and 87.8 auctions on average are closed with winners in Environment 1 and 2 respectively. In Environment 1, since all of these Heuristic agents are equipped with the same strategy and are free to join any auction, they may end up bidding in similar auctions while neglecting the less promising auctions. Conversely, when various types of agents are populated in the market, they may select different auctions to join based on their strategies and thus encourage more successful trades. From Table 2, Heuristic agents obtained 53.56% of the items being auctioned (in Environment 2) in the market. This can be credited to their auction selection strategy and their bidding strategy that considers the available auction information. It is worth noticing that Sniping agents obtained more items than Greedy agents due to their sniping capability of giving insufficient time to their counterparts to react. Besides that, simply looking at the lowest current bid may lead the agents to jump from an auction with higher probability of winning to other more risky auctions.

Performances	Environment 1	Environment 2		
	A Market populated by Homogeneous Agents	A Market populated by Heterogeneous Agents		
	Heuristic	Greedy	Heuristic	Sniping
Average Winner's Utility	0.1318	0.0957	0.1072	0.0391
Average Winning Auction	22.6	16.5	48.2	23.1
Average CSR	0.1315	0.0817	0.1013	0.0110
Average Auction Closing Price	373.1478	344.6544		
Average Seller's Utility	0.3088	0.2497		
Average Median Number of Bids Received in a Completed Auction	26.8	14.7		

Table 2. Performances of Homogeneous and Heterogeneous Agents in a Market of 90 English Auctions Generated.

Furthermore, from Table 2 also, winners of type Heuristic received 0.1315 as their average CSR in homogeneous environment. On the other hand, Greedy agents, Heuristic agents and Sniping agents obtained 0.0817, 0.1013 and 0.0110 respectively as their average CSR in the heterogeneous environment. The Sniping agents received the lowest utility because they ignored the auctions that are not closing soon but may return to them a better utility if they were winning in these auctions. When comparing the average CSR between Heuristic agents

in Environment 1 and 2, they received lower ratio in the latter environment as competition arises among groups of various agents (in Environment 2).

From Table 2 also, on average, each auction that is closed with a winner has a closing price of 373.1478 (in Environment 1) and 344.6544 (in Environment 2). In addition, from the sellers' perspective, they received 0.3088 and 0.2497 as their average utility in Environment 1 and Environment 2 respectively. This utility indicates the gross margin of the sellers. Lastly, on average, there are 26.8 bids (Environment 1) and 14.7 bids (Environment 2) received in every completed auction.

By comparing the results from both experiments, when homogeneous agents are competing with one another in a market, their average auction closing price is higher than the price in a market of heterogeneous agents. Those homogeneous agents with similar bidding strategy would most probably participate in few auctions and leave the rest of the auctions unattended. Therefore, the final closing price increases as the competition among buyers increases. It is supported by the average median number of bids submitted in a completed auction. This finding is also consistent with the suggestion in the work of Krishna (2002).

Even though a market with single type of agents produced a higher returned sellers' margin, in terms of the number of successful auctions, Environment 1 is worse than the Environment 2. Hence, if the average seller's profit is calculated based on the average auction closing price, the average seller's utility and the average number of traded auctions, the former market would generate 2604.1537 compared to the latter market that would produce 7556.0859. Based on the profit calculated, sellers may prefer heterogeneous bidder agents instead of homogeneous bidder agents as their auctions' participants since they bring more profit to sellers.

4.5.3 Summary of the experiment

In summary, in a market that is fully populated by homogeneous bidder agents, even though they obtained the highest average winner's utility and average CSR, they performed badly in terms of the number of winning auctions (25.11%). This finding is similar to the results obtained by Airiau and Sen (2003) and Byde (2002) which stated that multiple strategic buyers with the same strategy performed worse than their performance in situation where other types of bidders are present. Meanwhile, a market fully populated by heterogeneous bidder agents may achieve higher closing rate of 97.56% due to their various bidding strategies that led them to different auctions. Eventually, a healthier competitive environment was created. Moreover, sellers would prefer the participation of heterogeneous agents compared to homogeneous agents since it brings more sales and profit.

5. Conclusion

In this work, 3 distinct groups of standard bidders, namely the risk-averse, risk neutral and risk seeking bidders and 3 types of intelligent agents, namely the Greedy agents, the Heuristic agents and the Sniping agents are introduced to represent the potential buyers in the auctioning world according to their attributes. A market that is occupied by various standard bidders and intelligent agents would represent the real auction market where human bidders of different risk types and bidders who use intelligent agents as their representatives are competing with one another. From the empirical results, intelligent agents are capable in bringing more satisfaction to their owners if the correct agents are selected.

Besides that, markets that are fully dominated by homogeneous intelligent agents and fully dominated by heterogeneous intelligent agents are studied. It was clearly observed from the results obtained that a market that is occupied by intelligent agents of various types would benefit both sellers and buyers if the implementation of agent technology is unavoidable. Even though bidders may receive higher intrinsic saving value in homogeneous scenario, the chances of getting the desired items are greatly reduced. On the other hand, agent technology has been dominating the online auctioning world. Thus, sellers may welcome heterogeneous agents than homogeneous agents since the former encourages more trades than the latter.

There are still many aspects where this work does not cover where further researches can be explored. One of these areas would be the prediction capability. All the intelligent bidding strategies used in this research do not take into account the past historical data of the items being auctioned and therefore are not able to predict the auction closing prices. It would be useful if these intelligent agents are equipped with prediction capability in participating auctions. With the predicted closing price, agents can make better decision based on their private valuation and these predicted prices.

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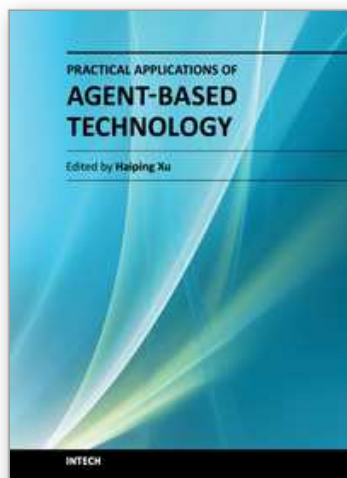
Practical Applications of Agent-Based Technology

Edited by Dr. Haiping Xu

Agent-based technology provides a new computing paradigm, where intelligent agents can be used to perform tasks such as sensing, planning, scheduling, reasoning and decision-making. In an agent-based system, software agents with sufficient intelligence and autonomy can either work independently or coordinately with other agents to accomplish tasks and missions. In this book, we provide up-to-date practical applications of agent-based technology in various fields, such as electronic commerce, grid computing, and adaptive virtual environment. The selected applications are invaluable for researchers and practitioners to understand the practical usage of agent-based technology, and also to apply agent-based technology innovatively in different areas.

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