SELLER AGENT FOR ONLINE AUCTIONS

P. Anthony
School of Engineering and Information Technology, Universiti Malaysia Sabah
Locked Bag 2073,88999 Kota Kinabalu Sabah, Malaysia
J. A. Dargham
School of Engineering and Information Technology, Universiti Malaysia Sabah
Locked Bag 2073,88999 Kota Kinabalu Sabah, Malaysia
Correspondence Email: {panthony, jamalad@ums.edu.my}

ABSTRACT

Online auctions are becoming extremely popular because of the convenience that it offers to the consumers. Much work has been done of designing bidding strategy that can be utilized by bidders who want to participate in online auctions. However, very little work has been done on the seller's strategy for online auctions. In online auctions, the reservation price of an item set by the seller determines whether the item can be sold or not. Unfortunately, deciding on the reservation price of an item to be auctioned off is not a straightforward decision. This paper reports on a design of a seller agent that recommends a reservation price of a given item to be auctioned off by the seller. The seller agent will endeavor to suggest a reservation price that guarantees the sale of the item within a given period (as required by the seller) with a profit.

Keywords: online auctions, agent, seller's strategy.

1. INTRODUCTION

Online auctions are becoming extremely popular because of the convenience that it offers to the consumers. Thousands of items are sold at online auctions everyday that ranges from books, toys, computer, antiques and even services. The practice of auctioning goods has been popular throughout the years because auctions are an extremely effective way of allocating resources to the individuals who value them most highly [1]. Many of the geographical and temporal limitations of the traditional auctions are removed [2]. Specifically, the consumers can be sitting in the comfort of their home while participating in an online auction that may be located many thousands of miles away. Moreover, online auctions generally last for days and weeks giving the bidders more flexibility about when to submit bids. Online auctions also allow sellers to sell their goods efficiently and with little action or effort required. Apart from that, sellers have fewer problems of getting a large group of bidders together in a short notice because of the availability of large number of online bidders distributed across the globe. This creates a larger market for the goods on sale. In summary, online auctions provide a selection of goods that Internet communities can buy or sell, allowing consumers a greater chance of getting their goods and the sellers a greater chance of selling their goods.

Online auction is a method that is based upon competition, in which a buyer wants to pay as little as necessary and a seller wants to obtain as much money as possible. To date, much work has been done on designing bidding strategy that can be utilized by bidders who want to participate in online auctions with the goal of obtaining the item within a certain time period and at the lowest price possible. However, very little work has been done in designing a seller strategy for online auctions.

There are several issues that need to be considered by the sellers before they sell their item in online auctions. One major issue is the pricing. Pricing an item to be sold in an auction can be tricky since items that are sold in online auctions can be categorized into three types namely new, used and reconditioned. A new item will definitely be more expensive than a used item or a reconditioned item. The price of the used item is dependent upon condition of the item. Apart from that, the pricing of an item is affected by the desperateness of the seller. If the seller's intention is to get rid of the item, a lower pricing strategy may be acceptable, but if the seller's intention is to obtain a profit, then a higher pricing strategy is inevitable. The number of competitors is another determinant to the pricing mechanism for the sellers. The price would be higher if there are a few identical items being auctioned. However, if there are a lot of identical items on sale, the seller may be forced to sell the item at a lower price. As mentioned earlier, the main thing for the seller is to gain as much profit as possible. In auction, this can be translated to deciding the best price for the item. This best price will be the reservation price for the item before it is auctioned off. The reservation price for the item is defined as the minimum price that the seller is willing to sell the item. At the end of the auction, a seller can refuse to sell the item if the highest bid is less than the item's reservation price.

In this scenario, the main problem is to determine what value of reservation price the seller should impose on the item to ensure that the item is sold at a given time with the possibility of earning a profit. This decision is not a straightforward one because the auction environment is very complex, dynamic and unpredictable making it very difficult to come up with a single optimal value for the seller [3]. To address this shortcoming, we believe that it is necessary to develop an autonomous agent that is capable of making its own decision based on the available information. In more detail, the agent should monitor and collect information from the ongoing and completed auctions, makes decision of the pricing on behalf of the customer and endeavors to guarantee that the item will be sold at the stipulated time with the best price.

To this end, this paper reports on our work in developing a seller agent that makes pricing decision on behalf of the seller. The seller agent's decision takes into account several constraints such as the given time in which the item should be sold, the competitors' information, and whether the seller is looking for a profit. The suggested reservation price is computed by combining these three constraints. Each constraint will suggest a price in isolation and these prices are then given a weighted combination according to their importance as requested by the seller.

The paper advances the state of the art in the following way. First, we develop a high level decision making framework for an agent to determine the item's reservation price based on the user preferences. Secondly, the pricing strategy that we are proposing takes into account the dynamic nature of online auctions by updating the auctions information and makes future prediction for the ongoing auctions. This information is used in the decision making model of the seller agent.

The remainder of the paper is structured in the following manner: In the next section, we describe our electronic marketplace scenario in which our algorithms are evaluated. Section 3 describes the fundamentals of the bidding algorithm and our initial evaluation of the various constraints that will be used to determine the reservation price. Section 4 describes and demonstrates a working example of the strategy. Section 5 discusses related work and finally, section 6 presents our conclusions and further work.

2. THE ELECTRONIC MARKETPLACE (RoboSAR)

The simulated electronic marketplace consists of a number of English auctions that run concurrently. These English auctions have a finite start time and duration generated randomly from a uniform probability distribution. The start and end times vary from one auction to another. There are several agents running in the marketplace, each performing very specific tasks. The Generator Agent generates auctions, bidders and the item properties (such as reservation price, description of the item, duration of the auction). The Scheduler Agent prepares a calendar to be used in the auctioning process detailing when a particular auction is to be launched. There is also the Timer Agent that starts the internal clock from the beginning of a particular auction until its completion. Finally, the Selection Agent determines the current status of a given auction and selects bidder from the pool of bidders to bid in a given auction. The architecture of the electronic marketplace is shown in Figure 1.

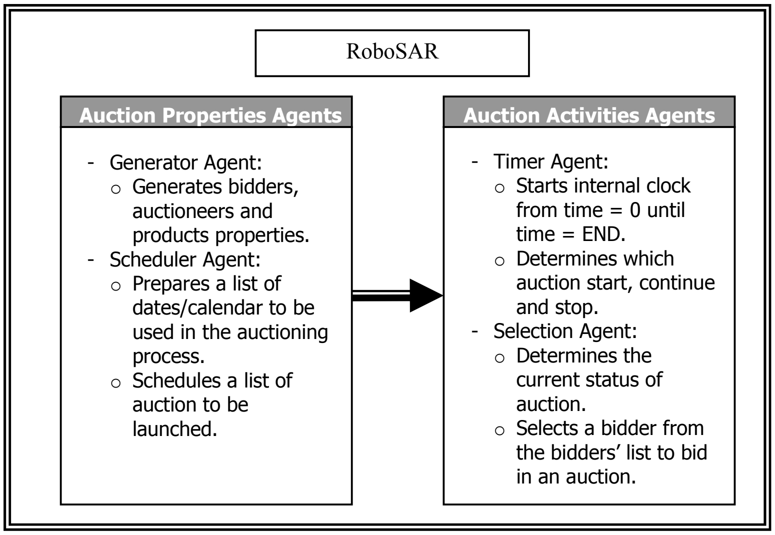

Figure 1: Structure of RoboSAR

Based on a given parameter, the Sheduler Agent generates a global time (auction calendar year) for a given period. A list of bidders, auctioneers and product profiles will be generated randomly. As an example, in one run 1000 bidders, 100 sellers and 20 items are generated randomly. The sellers of the 20 products are allocated randomly among the 100 sellers. Each item is assigned a random reservation price based on a uniform probability distribution. The Scheduler Agent takes the generated global time and assign dates on which auctions will be started. Based on the activity list, the Timer Agent will then start any auction that are due to start and checks any that are due to stop. While the auction is ongoing the Selection Agent select bidder randomly to bid in the auction and update the bid history. When a given auction concludes, a winner is declared as the one with the highest bid value that exceeds the reservation price for the item being auctioned. The algorithm for the RoboSAR simulation is shown in Figure 2.

```
Prepare Global Time
Prepare bidders, auctioneers and products profiles
Randomly assign products to auctioneers and bidders
Based on products profile randomly generate private valuation for
bidders and seller.
While (global_time)
Begin
    If (global_time=auction_start)
        Start auction
        Randomly select bidder to bid
    Else if(global_time>auction_start AND global_time<auction_end)
        Continue auction
        Randomly select bidder to bid
        Update 'bid_holder'
    Else if
        End auction
        If (current_price>reservation_price)
            Declare winner
        Else
            Mark as unsuccessful auction
        End if
    End if
End
```

Figure 2: RoboSAR's Algorithm

The marketplace is flexible and can be configured to run any number of auctions and operate for any length of discrete time. We assume that any bidder can submit their bids for any of the item being auctioned and that the sellers may sell more than one non-identical items. Each auction can be configured to last for a maximum of one month. However, the duration of each auction can also be configured to last longer than a month. The bidding history for each auctions (past auctions and ongoing) are also captured and this information is made available at all time.

3. DESIGNING THE SELLER'S STRATEGY

To ensure that the seller is able to sell the item at a given time and at a profit, it needs to possess a strategy that takes into account several constraints. These constraints (referred to as the selling constraints) are the determinants to the recommended reservation price for a given item to be sold by the seller. The constraints being considered here are the sell period (a time frame in which the seller wishes to dispose the item), the number of competitors and the desire for a profit. The seller is required to state his preferences by indicating the date by which he must sell the item as well as the amount of profit that he wishes to obtain (in percentage) and whether competitors need to be considered. Here, we assume that the items being sold are used or reconditioned. We do not consider new items since the prices of new items can be easily obtained from fixed shopping outlets. The seller agent considers these constraints and combined it with the analysis of the available information obtained from the electronic marketplace to generate the recommended reservation price based on the preferences indicated by the seller.

In the marketplace, we categorize the online auctions into three groups, namely the successful auctions (completed auctions that succeed in disposing the item being sold), the failed auctions (completed auctions but unable to sell the item) and the ongoing auctions (auctions that have started but are not completed yet). The relationship among these 3 criteria is shown in Figure 3. Analysis of the available information can be conducted at any point in time and takes into account the three groups of auctions. First, we will present our notation.

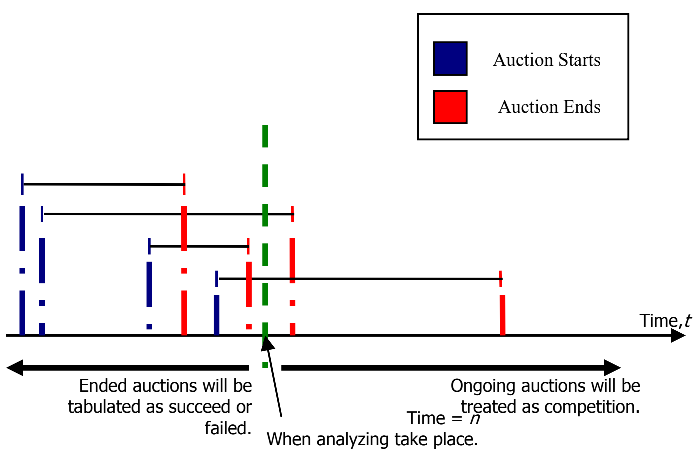

Figure 3: Successful, Failed and Ongoing Auctions

3.1 Successful Auctions

Let α be the number of auctions that have completed successful and let β be the closing price for the each of the auctions that has completed successfully. Let ASP_v be the average price for the successful auctions, and is defined as the division of the summation of the ending prices by the number of successful auctions in the marketplace.

$$ASP_v = \frac{\sum \beta_i}{\alpha} \quad \text{(Equation 1)}$$

Let ϕ_i be the duration for each of the auctions that has completed successfully. Let ASD_v be the average number of days for successful auctions. This is calculated by summing up the durations of all the successful auctions and dividing it by the number of successful auctions.

$$ASD_v = \frac{\sum \phi_i}{\alpha} \quad \text{(Equation 2)}$$

3.2 Failed Auctions

Let σ be the number of failed auctions and let δ_i be the highest bid value for the individual auctions that did not complete successfully. Let AFP_v be the average price for the failed auctions. It is defined as the summation of all the maximum price for the failed auctions divided by the total number of failed auctions.

$$AFP_v = \frac{\sum \delta_i}{\sigma} \quad \text{(Equation 3)}$$

Let χ_i be the duration for the individual failed auction. Let AFD_v be the average number of days for failed auctions. This is defined as the summation of the duration of all the failed auctions divided by the total number of failed auctions.

$$AFD_v = \frac{\sum \chi_i}{\sigma} \quad \text{(Equation 4)}$$

3.3 Ongoing Auctions

Ongoing auctions cannot be excluded from the analysis, hence to compensate for the this, we calculate the estimated price for the successful auctions and the estimated price for the failed auctions. Let ESP_v be the estimated price for the auction that is expected to complete successfully. This is defined as:

$$ESP_v = \lambda_i + \left(\frac{\eta_i}{ASD_V} \times ASP_v\right) \quad \text{(Equation 5)}$$

where λ_i is the current bid value of a particular auction and η_i is the number of days left for that particular auction to complete.

Let κ be the number of ongoing auctions. The ESP_v is calculated for every individual ongoing auction, therefore the $AESP_v$ is defined as the summation of the estimated prices for all the auctions that are expected to complete successfully.

$$AESP_v = \frac{\sum ESP_v}{\kappa} \quad \text{(Equation 6)}$$

Similarly the EFP_v is defined as the estimated price for a particular auction that is expected to fail.

$$EFP_v = \lambda_i + \left(\frac{\eta_i}{AFD_V} \times AFP_v\right) \quad \text{(Equation 7)}$$

And finally, the average estimated failed price for all the auctions that are unsuccessful is defined as:

$$AEFP_v = \frac{\sum EFP_v}{\kappa} \quad \text{(Equation 8)}$$

3.4 The Sell Period Function

The sell period function generates a single price that is based on the sell period requested by the seller. This price can be easily generated by looking at the past transaction history as well as the ongoing auction. Let f_{sp} be the function that will suggest the price based on the sell period and is defined as:

$$f_{sp} = \frac{ASP_v * duration\_required}{ASD_v} \qquad \text{(Equation 9)}$$

3.5 The Competitors Function

The number of competitors that are selling the same item in the same marketplace needs to be considered as well as this directly affects the pricing of the items. A small number of competitors will suggest a higher pricing and more competitors implies a lower price. Assume that n is the number of competitors in a given auction. Let f_{co} be the function to determine a single price based on the competitors information. f_{co} is then calculated as:

$$f_{co}(n) = p(n) \qquad \text{(Equation 10)}$$

where p is the average price for a given number of competitors. This average price is calculated by taking the average of all the prices for the same number of competitors in all the auctions including the ongoing auctions.

3.6 The Profit Function

The profit function f_{pr} generates a single price based on how much profit is required by the seller. Computing the price for this function is done in two stages. Firstly, the actual recommended price, p_{in} is computed, then this price is inflated according to the percentage of profit that the seller wishes to obtain. p_{in} is computed in the following manner:

$$p_{in} = \frac{\sum \beta_i + \sum ESP_v}{\alpha + \kappa} \qquad \text{(Equation 11)}$$

f_{pr} is then computed as follows:

$$f_{pr} = (1.00 + PP) * p_{in} \qquad \text{(Equation 12)}$$

3.7 Generating the Final Reservation Price

At any given time, the agent may consider any of the selling constraints individually or it may combine them depending on the seller's preferences. In this work, if the agent combines multiple selling constraints, it allocates a weight to denote their relative importance. Thus, let ω_j be the weight on constraint j where $\forall j \in Selling\_Constraint$, $0 \le w_j \le 1$, and $\sum w_j = 1$. The final reservation price is then calculated as:

$$p_v = \sum w_j f_j \qquad \text{(Equation 13)}$$

4. A WORKING EXAMPLE

At the point of writing, no experimental evaluation has been conducted but this selling strategy can be demonstrated using a worked example. The purpose of this example is to show that a realistic reservation price can be computed using our selling strategy. Assume that an item A is auctioned off and the data is shown in Table 1, 2 and 3.

Table 1: Failed Auctions for Item A

No.	Duration	Start Price	Highest Bid
1	3	25	26
2	6	18	20

3	7	20	22
4	2	30	30

Table 2: Successful Auctions for Item A

No.	Duration	Start Price	End Price
1	3	10.5	15
2	6	15	17
3	7	8.5	19
4	2	20	23
5	4	13	18
6	5	10	17
7	7	15	25
8	8	13	16
9	9	12	15

Table 1: Ongoing Auctions for Item A

No.	Days Left	Highest Bid
1	2	10.5
2	4	15
3	5	8
4	6	9

The calculations of ASP_v, ASD_v, AFP_v, AFD_v, ESP_v, $AESP_v$, EFP_v, $AEFP_v$ are shown below.

$$ASP_v = \frac{165}{9} = 18.3$$

$$ASD_v = \frac{51}{9} = 5.67$$

$$ASF_v = \frac{98}{4} = 24.5$$

$$AFD_v = \frac{18}{4} = 4.5$$

Table 2: Calculated ESP_v for each ongoing auction

No.	Days Left	Highest Bid	ESP_v
1	2	10.5	16.97
2	4	15	27.94
3	5	8	24.18
4	6	9	28.41

$$AESP_v = \frac{97.5}{4} = 24.38$$

Table 3: Calculated EFP_v for each ongoing auction

No.	Days Left	Highest Bid	ESP_v
1	2	10.5	21.38
2	4	15	36.77
3	5	8	35.22
4	6	9	41.66

$$AEFP_v = \frac{153}{4} = 33.77$$

It can be observed from the result obtained that the estimated failed price ($AEFP_v$) is a lot higher than the estimated success price ($AESP_v$). Thus seller should try to select a reservation price between 16.97 to 28.41 as Item A's reservation price.

To compute the actual reservation price that will be recommended by the seller agent, we consider the three selling constraints. Here we assume that the seller wants to sell Item A within 7 days, and that he is interested in a 10% profit and that information about competitors is very important to him. The seller also values the profit more than the competitors or the selling period. The calculation is as follow:

$$f_{sp} = \frac{18.3 * 7}{5.67} = 22.60$$

$$f_{co}(4) = 21.50$$

Assume here, that there is a table that will generate the average value for prices that are dependent on the total number of competitors.

$$p_{in} = \frac{165 + 97.5}{9 + 4} = 20.19$$

$$f_{pr} = (1.00 + 0.10) * 20.19$$

And finally, the recommended reservation price for Item A is:

$$p_v = 0.25(22.60) + 0.25(21.50) + 0.50(22.21)$$

$$p_v = 22.13$$

The recommended reservation price obtained falls in the range of the estimated selling price in which if the auction complete successfully, the seller will obtain a 9% profit which is very close to the seller's preferences. If the seller chose to ignore the sell period and the competitor constraints, then a 10% profit can be obtained.

5. RELATED WORK

There have been several attempts to design sophisticated and efficient bidding strategies for agents participating in online auctions. However, very little work is ongoing for seller's strategy. The work on developing seller agent was drawn from previous work conducted by other researchers in the development of bidder agents. Anthony and Jennings [4] developed a heuristic decision-making framework that an autonomous agent can exploit to tackle the problem of bidding across multiple auctions with varying protocols. In this particular environment, three auctions protocols are considered: English, Dutch and Vickrey. All auctions have a known start time and English and Vickrey auctions have a known end time. The bidding agent is given a deadline by when it must obtain the desired item, it is told the consumer's private valuation and it must not buy more than one instance of the desired item.

Dumas et al. addresses the issue of developing autonomous agents capable of participating on behalf of the user in several potentially simultaneous auctions, with the goal of achieving the best price for a single item [5][6]. The agents participate in several auction houses that run first-price sealed bids, Vickrey and English auctions. Each auction is assumed to be for a single unit of item and has a fixed deadline. It is also assumed that the outcomes of the auctions are available immediately after their deadlines. The proposed architecture is a multiagent system in which a manager agent cooperates with several expert agents. The manager agent has information about the user's constraints and preferences and it cooperates with multiple expert agents. Each expert agent specializes in a specific kind of auction for a type of item within a given auction house. Based on the feedback of the expert agents combined with a probability function, the manager agent will generate a bidding plan and this plan may be revised from time to time depending on the current situations at hand.

The Decision Procedures for Multiple Auctions is a decision theoretic framework that an autonomous agent can use to bid effectively across multiple simultaneous auctions [3]. This decision-theoretic framework combines probability theory with utility theory to give a general theory that can distinguish good actions from bad ones [7]. It is assumed that the users are interested in purchasing multiple items and have private valuations for each item. The auctions have varying start time and end times and they embody different protocols. The auctions considered are English, Dutch, first-price sealed bid and Vickrey. The main concern here is that a rational agent should choose to bid in a given auction if the expected return from the future is greater than the expected return from the future if the agent does not bid.

6. CONCLUSION AND FUTURE WORK

This paper presented a selling strategy that can be used by a seller agent to recommend the reservation price for a given item with the objective of disposing the item at a given period of time as well as obtaining a profit from the sale of the item. Although, no experimental evaluation has been conducted the working example provided in Section 4 showed that the proposed selling strategy can guarantee that the item is auctioned off with a profit. This framework is flexible enough to allow any additional constraints to be added to the existing ones. To prove this theory, experimental evaluation will be conducted in the simulated marketplace to analyze the efficiency of our selling strategy. The strategy will be refined further to improve the performance the of the seller agent. Some of the techniques that will be explored include genetic algorithm, fuzzy logic and machine learning. This will enable the seller agent to be more adaptive and receptive to the existing environment and to address the complexity and dynamic of the online auction environments. The marketplace will be improved further by including other auction protocols (such as Dutch and sealed bid auctions) apart from English auctions.

REFERENCES

[1] Reynolds, K, "Auctions Going, Going, Gone! A Survey of Auction Types", http://www.agorics.com/Library/auctions.html.

[2] Lucking-Reiley, D, "Auctions on the Internet: What's Being Auctioned, and How?", *Journal of Industrial Economics*, 48(3), 227-252 (2000).

[3] Byde, A., C. Preist, and N. R. Jennings, "Decsion Procedures for Multiple Auctions", In Proceedings of *The First International Joint Conference on Autonomous Agents and MultiAgent Systems, Part II*, 613-620 (2002).

[4] Anthony, P. and Jennings, N. R. "Developing a Bidding Agent for Multiple Heterogeneous Auctions", *ACM Transactions on Internet Technology*, 3(3) (2003).

[5] Dumas, M., G. Governatori, A. T, Hofstede, and N. Russell. "An Architecture for Assembling Agents that Participate in Alternative Heterogeneous Auctions", In Proceedings of the *Workdhop on Research Issues in Data Engineering*, 75-83 (2000).

[6] Dumas, M., L. Aldred, G. Governatori, A. T. Hofstede, and N. Russell. "A Probabilistic Approach to Automated Bidding in Alternative Auctions". In Proceedings of *The Eleventh International Conference on the World Wide Web*, 99-108 (2000).

[7] Russell, S. and P. Norvig (1995). Artificial Intelligence A Modern Approach. New Jersey, USA: Prentice Hall International Editions.