A Heuristic Price Prediction and Bidding Strategy for Internet Auctions

Mohammad Ali Tabarzad [†], *Caro Lucas* [†], *and Poorang Haghjoo* [††]

[†] Center of Excellence: Control and Intelligent Processing, University of Tehran, Tehran, Iran.
[††] PIDEC Company, Eram Blvd, Shiraz, Iran.

Summary
Undoubtedly the most complex part of creating an electronic market is how-to-buy problem. In order to solve how-to-buy problem, first should evaluate presented algorithms using simulated environments which simulates the electronic market and then using obtained results provide procedures for real markets. Not forgetting real markets limitations is a note that should not be ignored in problem solving. In this article some important kind of electronic auctions such as single seller english auction, nth price english auction and continues double auction would be contemplated and a solution would be provided for each. Finally algorithms performance will be tested in simulated environment (TAC).

Key words:
Internet Auctions, Price Prediction, Bidding Strategy, Multi Agent Simulated Markets.

Introduction

Undoubtedly the most complex part of creating an electronic market is how to buy problem. Buy problem solution is purchasing a collection of goods for a special package which these goods are dependant to each other. For example .when the buyer plans to travel, deals with different stores in order to buy airplane ticket, hotel reservation and amusing programs during travel such that buying from one sore is related to another. Not being able to reserve one day hotel during residency, for instance, can completely change decision for purchasing airplane ticket.

Usually there is some kind of secret relationships between real world stores that makes the decision problem much more difficult and secret relationships in purchasing from them is complex and outstretched too.

To solve this problem, in first step some famous kinds of auctions should be selected for deliberation and using simulated environments which simulates these markets, the problem should be solved in smaller and simpler dimensions and then study the problem in general by means of used solutions and completing those solutions.

Having a simulated environment has another benefit and that is in the same circumstances different ways of decision making can be implemented and the output results can be compared. However, testing different ways in certain problem in real world environment is not possible and also test costs in real world environment are much higher than simulated environments.

Nowadays, the best simulation environment available for electronic markets is TAC environment. Many researchers have tested their suggested algorithms in this environment and a competition is held each year for challenging offered strategies by different teams. Reference [1] checks available trade offs in this environment. Performed tasks are summarized in two categories in this field. Statistical methods and using mass data for setting offered formula parameters is the first category. For example in [2] which is published by the year 2005 championship reviews presented strategies in this competition. In this agent a creative method for estimating auction price and defining proper buying time is offered. A problem here is that 50 thousand games have been played for algorithm training step and defining parameter. The other article category has used machine learning methods. Reference [3] is one of these which estimates market price using simple learning treatment methods. Like previous one, this category of algorithms needs much more time to convergence too. It should always be considered that offered algorithms finally should be usable in a real market and these amounts of buying in a real market for setting algorithm parameter is impossible. From now these auctions and tested strategies for each will evaluated. Also in test results section, suggested methods for each auction will be compared. Generally three steps should be considered in studying each auction. First step is ability of properly estimating goods' final prices in store. In next step decision should be made whether the price is in proper range for buying or not, using performed estimation for final price which should be simply possible and also considering current price. In third and last step prices should be offered in proper auctions considering the relevancy of auction and related auctions influences on each other. In continue important auctions implemented in TAC[1] environment and their used strategies contributor agent in 2006 matches will be discussed.

[1] http://www.sics.se/tac/

Manuscript received September 5, 2006.
Manuscript revised September 20, 2006.

2. Single Seller English Auction

In this kind of auction, desired goods are sold be a specific seller. Goods price are mostly related to production circumstances, goods production procedure and environmental conditions, but instant goods price has nothing to do with number of instant customers.

Actually in this kind of auction goods are adequately available and proffer is proper to buyers' demands and so there is no competition between buyers in purchasing goods.

The first problem appears in this kind of auction is calculation of goods general price that can be estimated by checking auction treatment in long period of auction's life or maximum and minimum of acceptable good price can be defined by a specialist and can by fixed by buyers' maximum and minimum acceptable price finally. Fig. 1 shows eight instances of price treatment in simulated auction of this kind in TAC environment.

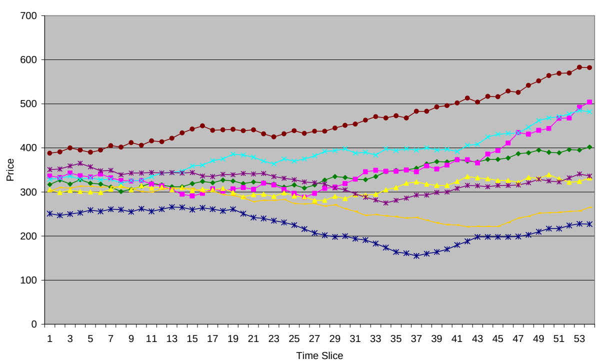


Fig. 1 Flight ticket fluctuation / Time in TAC environment

As affective factors on this kind of auction have generally long term affects and prices don't change suddenly, this auction price can be estimated in short ranges using following method:

Suppose when current time is t_n its price is p_n, also price announcing period is constant. If these announcing periods are not constant in order to solve the problem, periods can be divided by largest common denominator of periods using suggested method.

In first step end of fluctuation procedure declivity k in auction should be calculated. Eq. 1 can be used for this which α for i from one to k is equivalent to last to k^{th} price fluctuation declivity before that in auction.

$$\alpha_i = \frac{p_{n-i+1} - p_{n-i}}{t_{n-i+1} - t_{n-i}} \qquad (1)$$

Now declivity difference of previous parts from estimation part should be calculated by eq. 2 in which i shows the i^{th} and $(i+1)^{th}$ declivity difference.

$$\delta_i = \alpha_i - \alpha_{i+1}, i = 1..k-1 \qquad (2)$$

After defining δ_i s, it's turn of calculation estimation difference between next part of diagram with current declivity which this estimation is shown as $\bar{\delta}$. For calculating this value a weight average as eq. 3 is used which declivity differences closer to estimation value will have more effect than older declivity differences.

$$\bar{\delta} = \frac{\sum_{i=1}^{k-1} \delta_i \times i}{\sum_{i=1}^{k-1} i} \qquad (3)$$

Next, estimated price value can be obtained using $\bar{\delta}$. This value $\bar{p}$ is calculated by eq. 4.

$$\bar{p} = p_n + (t_{n+1} - t_n) \times (\alpha_1 + \bar{\delta}) \qquad (4)$$

Results for price prediction in one flight price example will be seen in Fig. 2.

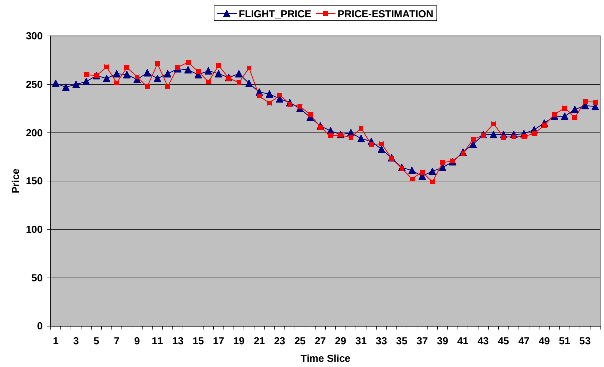


Fig. 2 Price prediction for a sample flight price

Now if estimated price was less than current price, good purchase should be postponed. Also if obtained estimation was in acceptable range and a little higher than current price this good purchase can be supersetured considering buying or not decision of this good can be changed by related auctions' circumstances modification or estimated price is a local minimum and store's price is going to decline in future. If price starts going up rapidly or prices get much higher value than maximum available and if current decision is to buy from this auction, this decision should be made as soon as possible.

3. Nth Price English Auction

In these kinds of auctions offers and requests are not necessarily proportional because amount of offered goods are constant and equal to n. So sometimes requests for buying goods are higher than amount of limited offers and in this case offered prices raises higher and higher and this auction has a high risk about adapted final price. In this case prices are raised rapidly by buyers considering high demands and absurd prices are created in these kinds of auctions due to high demands. Fig. 3 shows eight price increase procedure diagrams in this 16th Price English Auction ($n = 16$) in TAC environment.

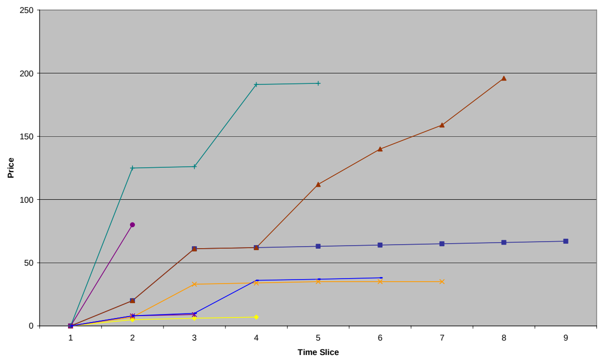


Fig. 3 Hotel reservation price fluctuation by time in TAC environment

Another note is that in these auctions that n similar goods are presented, all are sold by the price of n^{th} proper suggestion not by price of each of the suggestions. This subject that high suggestions can be made in order to buy goods which are not necessarily sold by that price to demandant unless n^{th} suggestion is proper price, can be one of raising reasons in this category of stores by itself.

Anybody may offer their highest desired price at first to the store hoping to buy the good with a lower price that have been offered by another client. In these stores first should estimate general approximate good's price. Previous buy and sell history of this good and its final price can be used averagely for current price primary estimation and primary decision. Then suggested price increase procedure should be traced continuously.

Next price estimation can be made by help of a simple linear regression using last three price values. Fig. 4 demonstrates estimation for two samples of hotel reservation in TAC.

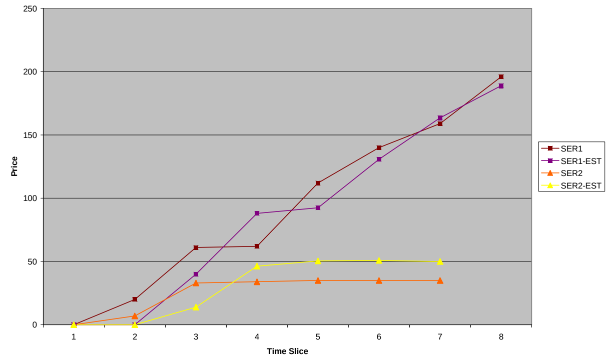


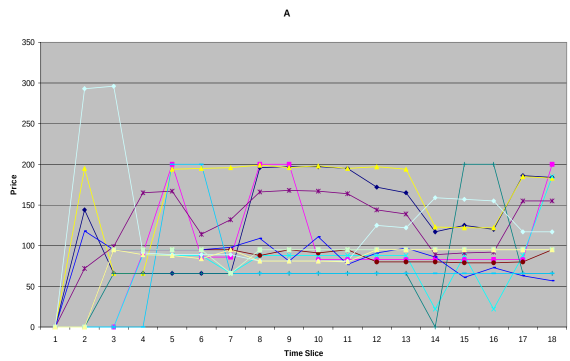
Fig. 4 Nth English Auction price estimation in TAC

Now if the price growth rate be higher that an acceptable value, considering that this store has a high risk in final price estimation, buying from other alternative proper markets with lower price or less growth rate should be tried.

If possible using similar auctions that can offer another appropriate package for purchasing which their risk of increasing price rate is less than current package, should be considered in decision making. For example in hotel reservation problem in TAC match, hotels with similar conditions ad probably different qualities but acceptable by client can be reserved.

4. Continuous Double Auctions

In these auctions any one can sell their goods in any desired price so there is no special law for increasing or decreasing price, also these auctions price treatment is too complex and un-modelable actually because there are different and arbitrary factors on this treatment. Fig. 5 shows twelve sample of price of these auctions fluctuation rate in TAC environment. Upper and lower appropriate sell and buy price limits can be specified.



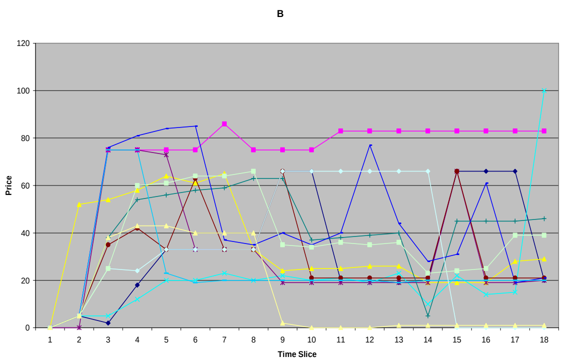


Fig. 5 – Junket ticket price fluctuation / time diagram A:
Goods demand price fluctuation in auctions B:
Goods offering price fluctuation in auctions

Because in these auctions raising or declining price treatments usually have a special procedure, and prices fluctuates continuously, client's desired price and auction closing remaining time has a principal role in decision making. Usually when auction closing time is nearer probability of successful dealing is less and expected benefit decreases inevitably. Main method is that for example about selling a good an equation like eq. 5 is considered for appropriate price estimation

$$p_{t_{current}} = p_{\min} + \frac{t_{close} - t_{current}}{t_{close} - t_{start}} \times p_{profit} \qquad (5)$$

In eq. 5 $p_{\min}$ is the least good's price, t_{close} auction closing time, t_{start} auction start time and $t_{current}$ is current time. Also p_{profit} is the maximum selling benefit for seller that should be selected how that availability of buyer is probable.

Result of this equation is $p_{t_{current}}$ that estimates proper price for current time. Of course more complex prices can be used for specifying proper price, but this function acts appropriately for proper price prediction in these auctions. After specifying appropriate price, if a request for buying be in price rage of $\lfloor p_{t_{current}} - \delta, \infty)$ (δ is a small value for covering prices very near to $p_{t_{current}}$), the good would be sold in proper price. Also in case of not having an appropriate offer, an offer with this price can be added to the auction for selling that of course new specified price which is obtained from eq. 5 is announced to auction in specific periods. It is the same in case of buying a good too, with the difference that the maximum good's proper price will be replaced by equation's constant value, and estimated price is always less than acceptable maximum price, At the end of auction estimated price would be very near to acceptable price. Eq. 6 can be used for estimating proper buying price.

$$p_{t_{current}} = p_{\max} - \frac{t_{close} - t_{current}}{t_{close} - t_{start}} \times p_{profit} \qquad (6)$$

That $p_{\max}$ is maximum acceptable price. In this part more complex functions by time can also be used for specifying price. Actually in these categories of markets we should consider that as the market does not have a specific price treatment, the deal should be started whenever any appropriate buying or selling price were available in the market.
Using these relations new parameters can be added to related auctions' estimated price so price un normal growth in these auctions which are caused by events in other related auctions, would be considered in price estimation functions.
For example price growth coefficient of an auction related to another closed auction can be multiplied by a constant value that represents price higher risk in this auction.
Full extraction of these relations and setting available parameter in this problem can lead to future researches.

5. Experiment results

Suggested methods for price estimation and pricing strategies in separate stores is not perusable considering hidden relationships available among decision makings in stores. So all strategies were tested and studied in one agent who played the buyer group role in TAC environment together. This environment is the most important and the best electronic shopping simulation environment since year 2000 till now in scientific associations and has always been considered by researches in field of electronic market.
Of course there were problems such as short time between research starts and implementation in TAC environment and year 2006 matches (that approximately longed 4 months and was less than most of teams which usually several years passed from their research starts and implementations.) and internet network problem (that connection between match server in Switzerland and participant agent disconnected continuously because of internet disconnection s.). There were no correct result till nearly end of the matches but in last final round 54 matches considerable results were obtained regarding to unavailability of technical problems, which Tehran University's agent gained a higher score than last round winner of year 2006 agent. Scores obtained diagram is shown in Fig. 6. Our agent (UTTA06) obtained the average score of 3879 and 2005 winner team's this year agent (MerTACor) average score was 3844.

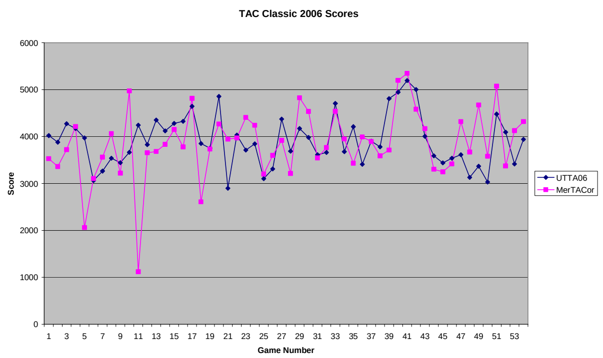


Fig. 6 Obtained scores by Tehran University (UTTA06) agent and last year matches championship of year 2006 (MerTACor) at the end of final matches

In continue, for observing impression of price estimation and price offering strategy algorithms in store, each of strategies were omitted from main agent and finally considering three different available auctions, three new agents competed main agent in 60 matches which their results are as follow.

Fig. 7 demonstrates impression of Tehran University omission in airplane ticket auctions. This category of auctions is very similar to single seller English auctions and is designed for simulation of these kinds of markets. In this match main agent average score was 3964 and agent's score without suggested strategy in airplane ticket was 3389.

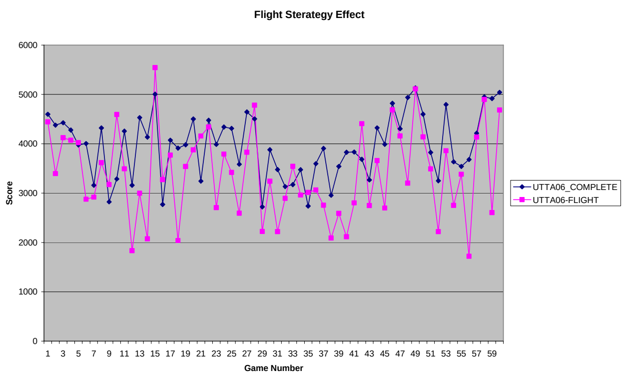


Fig. 7 Impression of agent strategy omission in airplane ticket auctions

Result of Tehran University's strategy omission in hotel reservation auctions in match environment is demonstrated by Fig. 8 Hotel reservation auctions are from n^{th} price English auctions category which goods are sold by n^{th} appropriate proposal. In this environment $n = 16$ which causes auctions to be converted to sixteenth price English auction. In this comparison main agent's average score was 3964 and agent's score without suggested strategy in hotel reservation was 3372.

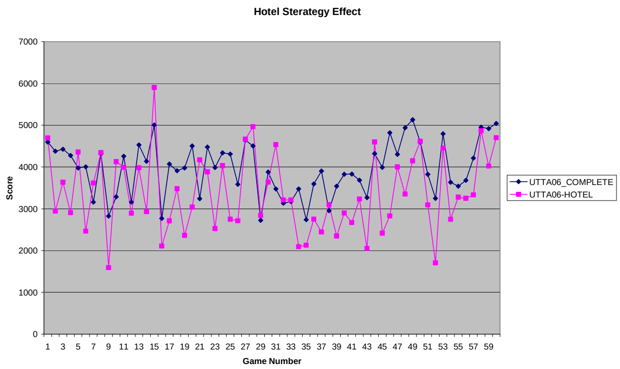


Fig. 8 Impression of agent's strategy omission in hotel reservation auctions

Finally impression of University's agent's strategy omission in tourism ticket auctions can be observed in Fig. 9 this group of auctions simulates continuous double auctions which each agent can buy or sell their goods with their desired prices. In this comparison main agent's average score was 3964 and agent's score without suggested strategy in tourism ticket was 3819.

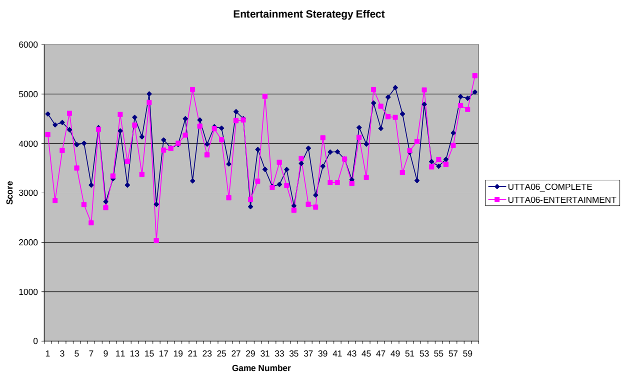


Fig. 9 Impression of agent's strategy omission in tourism ticket auctions

6. Conclusion

In this article some usual auctions and pricing estimation in them were discussed. Then impression rate of proposed algorithms for each part were indagated using experiments in an appropriate environment. Although these algorithms were simple, they didn't need much time in order to obtain proper estimation in market and this could be found from primary steps score differences comparison with last year championship. Although in continue, year 2005 championship's treatment was better step by step, but should consider that a user won't keep on buying from an auction and a specific good continuously, and so algorithms which need much time for learning the auction's treatment is not useable in few clients markets. In future other appropriate algorithms can be offered which will be useable in very short time and so can be used in real world markets for these kinds of stores or price growth procedures can be estimated using statistical methods in these kinds of stores. Actually the important point in these algorithms is that there is not so much learning time in stores and any learning or statistical method which needs much information for appropriate action is not useable for these environments.

Acknowledgement

This work is supported in part by grants from TAKFA (National Information and Communication Technology Agenda, High Council of Informatics, Iran).

References

[1] I. A. Vetsikas and B. Selman, Autonomous Trading Agent Design in the Presence of Tradeoffs, Seventh International Conference on Electronic Commerce, Xian, China, 2005.

[2] P. Toulis, D. Kehagias, and P. Mitkas, Mertacor: A Successful Autonomous Trading Agent, Fifth International Joint Conference on Autonomous Agents and Multi Agent Systems, pages 1191-1198, Hakodate, Japan, 2006.

[3] P. Stone, R. E. Schapire, J. A. Csirik, M. L. Littman, and D. McAllester, ATTac-2001: A learning autonomous bidding agent, In Agent Mediated Electronic Commerce IV, LNCS vol. 2531, Springer Verlag.