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Genetic Algorithm based bargaining agent for Implementing Dynamic Pricing on Internet

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Abstract **-This paper proposes a bargaining agent which uses genetic algorithm for implementing dynamic pricing on the internet. Dynamic pricing is about charging different price from different customers. Auction and bargain are two main ways of implementing dynamic pricing on internet. As compared to auction, online bargaining is a "win-win" situation for both the seller and buyer because the mutually agreed deal price is higher than the seller's reserved price but lower than the buyer's reserved price. This problem of online bargaining eventually boils down to an optimization problem where the seller's task is to :- a)offer the best price to buyer so as to reach a deal b) to make maximum profit. The work presented in this paper proposes a simple and elegant way to implement online bargaining using Genetic Algorithm (GA). With an efficient design of fitness function, crossover and mutation operators, this paper shows how online bargaining can be implemented to sell products on the internet.**
Keywords: - dynamic pricing, genetic algorithm, fitness function, online bargaining

1. INTRODUCTION

Dynamic pricing as opposite to fixed pricing allows price to be flexible. The idea of changing prices depending on the situation makes dynamic pricing superior to fixed pricing. There exists many forms of dynamic pricing; however the present work is focused on online bargaining. Neoclassical economics boasts of many bargaining models [7, 8] but the underlying assumptions of all these models render them impractical for real world application. Classical bargaining models assume the availability of complete information about negotiators and unlimited computational resources. However, in real world these assumptions do not apply because bidding strategy of buyer is not known to seller, even the utility value of buyer can not be estimated.

Forms of Dynamic pricing

Some of the worth mentioning forms of dynamic pricing include auctions (there are many variants of auctions like English auction, Dutch auction etc), one-to-one negotiation, exchanges, etc. Today's internet commerce has propelled research on all types of agent- mediated negotiation and many of them can be found successfully working on internet as of now. [5] discusses the state of the art of agent based ecommerce. [9] mentions a fuzzy constraint based model for bilateral negotiation where the agents involved in negotiation aim at maximizing their individual pay off. Fuzzy Constraints are used to express negotiation proposals and to represent trade-offs between the different possible values of negotiation issues.

Auction

Auction is one of the most common methods of dynamic pricing and auctioning websites are in abundance on internet. The best example of auctioning website on internet is www.ebay.com. Ebay does not allow buyers to be automated agents. An ebay seller specifies the minimum price of the product to be sold and buyers interested in that product keep on bidding, the buyer with the highest bid (at the closing time) wins the deal. Kasbah [1] is another example of an intelligent agent developed by researchers at MIT's Media Lab, in which human users delegate the responsibility for buying or selling physical goods to agents that engage in one-to-one negotiations with another agent. [6] talks about designing an intelligent agent using fuzzy techniques for bidding auctions in Trading Agent Competition (TAC). Depending on the prevailing market conditions, proposed agent (called SouthamptonTAC) uses fuzzy reasoning techniques to adapt its bidding strategy to predict closing prices of the auctions. However, despite the popularity of the online auctions that one finds at Amazon, eBay, and hundreds of other sites, bargaining happens to be a better but underdeveloped (on internet) form of dynamic pricing. Auctioning has its own merits and demerits. Auction can be frustrating [3] as a buyer may not tolerate waiting few days for the close of an auction of say a Dell laptop at ebay.com. Another demerit of auction is that buyers have little say in it. The final price is always decided by sellers and on internet; a proxy agent may be involved in raising the product price unnecessarily. All these things make auction one sided game.

Online Bargaining

Bargaining process ends when the buyer and seller agree upon a particular price. It can be different for different customers. Unlike auctioning, bargaining has a say of buyer too. Price bargaining is a process through which a buyer and a seller seek a mutually acceptable price for a product or service. The deal price for the same product or service in different bargaining processes can be different. The agreed upon price is a equilibrium of seller's anticipation and customer's expectation. As seller is also actively involved in determining the price of the product, bargaining is a "win-win" [10] game as compared to auctioning which is one sided. Online bargaining as proposed by [10] is shown in Figure 1.The rest of the paper is organized as follows. Section II discusses related work, section III discusses problem formulation and algorithm design, section IV discusses the result, and section V concludes the paper.

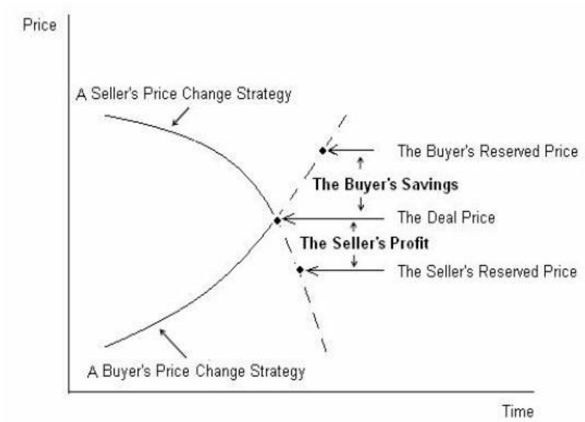

Figure 1. Bargaining Process

II. RELATED WORK

Literature is inundated with various attempts to design intelligent agents on internet to implement agent based auction as well as agent based bargaining. Some of the relevant works related to this paper are discussed in this section. Kasbah [1] as mentioned in section I allows buyers and sellers to design their own agents with a premeditated strategy. The agents do not have any intelligence or machine learning and their behavior is not adaptive. Thus, an agent's strategy is decided by the agent's owner when the agent is created and remains the same through out the bargaining process. The drawback of using the same strategy through out the bargaining process is that agent lacks flexibility and may loose a deal or suffer a loss because of poorly chosen strategy. Lau [4] mentions about designing adaptive negotiation agents using Genetic Algorithm (GA). The negotiation mechanism is based on multi-attribute utility theory (MAUT). Negotiation proceeds in a sequential alternate-offering negotiation protocol in a discrete series of rounds. In each round, each agent puts forward an offer in alternate. An agreement is reached if the offers overlap otherwise the negotiation proceeds to the next round where the agents make a concession. If there is no agreement after the deadline is reached, an agent decides to quit and the negotiation ends with a conflict. Lau's idea of adaptive negotiation agents does not allow human sellers to specify the minimum acceptable price of the product under negotiation. Thus, it is very likely that the human seller may not be happy with the deal made by the software seller agent. One more problem with Lau's adaptive negotiation agent is that the fitness function does not ensure a tit for tat strategy. The fitness function takes only the most recent buyer agent's counter offer as input and then searches for the offer that matches most to this offer and is slightly less than the previous offer made by seller agent. This approach does not ensure a tit for tat strategy. Hence, it is quite possible that even though the buyer agent increases the subsequent bids substantially but the seller agent may decrease the subsequent bids very slowly thereby frustrating the buyer agent and leading to negotiation failure. The work presented in this paper allows the sellers to decide the minimum acceptable price and the fitness function ensures a tit for tat strategy. Hence the seller's subsequent bids will be in proportion to buyer's subsequent bids. This means if a buyer increases his/her subsequent bids considerably, the seller agent will decrease its subsequent bids accordingly.

III. PROBLEM FORMULATION AND ALGORITHM DESIGN

Problem Formulation

Problem Statement: - The task is to design a selling agent which can negotiate with a human buyer on a product. The selling agent has a user specified minimum acceptable price for the product, (the agent can not sell the product below this price). Also, the selling agent has a user specified first asking price for the product (bargain starts at this price).Buyer can accept or reject the price offered by the seller (in this case an automated agent). If the buyer accepts the price, the deal is complete. If the buyer rejects the seller's price, he/she can offer his/her own price. Now it's the seller's turn to accept/reject buyer's price. If the seller accepts the price, the deal is complete. If the seller rejects the price, seller can propose a new price to buyer. This process is repeated limited number of times. If at any moment either buyer or seller accepts the price the deal completes else it fails. The task is to propose subsequent price to the buyer depending on various factors as discussed ahead. This paper assumes that buyer is not an automated agent. In other words, this paper is about agent (seller) to human (buyer) bargaining model.

Assumptions:-

1. Seller (Bargaining Agent) will always be the first to start.
2. Buyer must increase his/her subsequent price. For example, if buyer offers 10USD first time, next time, he/she must offer 11USD or more.
3. Seller's subsequent price may remain same or decrease. For example, if seller offers 10USD first time, next time, it may offer 10USD again or less.

Notations:-

Ω:- Minimum acceptable price for the product
S_0 :- Starting Price to initiate the bargain
S_i :- Price proposed by seller at the i^{th} round of negotiation
B_i :- Price proposed by buyer at the i^{th} round of negotiation
S_d :- Deal price where the buyer and seller mutually agree
n :- Maximum number of allowed negotiations between buyer and seller. The deal must complete or fail within 'n' negotiations.

Constraints:-
1. $\Omega < S_{i+1} \leq S_i$
Since any price proposed by the agent is greater than the minimum acceptable price, this constraint ensures that the deal will always end in a profit otherwise it will fail.

2. If $S_{i+1} \leq B_i$ then $S_d = B_i$
This means that if the price calculated (to be proposed) by the agent is less than or equal to buyer's most recent offer then the agent should accept the deal. This constraint makes sense as there is no point in proposing a price to the buyer which is less than buyer's offer, this will result in a loss.

Algorithm Design

The price proposed by the seller at i^{th} round of negotiation is a function of
$S_i = f(\Omega, B_{i-1}, B_{i-2}, i)$.
Following steps explain how agent determines subsequent prices. A concise block diagram of the whole process is shown in Figure 2.

Step 1. Bargaining Agent will propose S_0 as the starting price to initiate the bargain process. If the buyer accepts this price, deal is complete. If the buyer rejects this price he/she can propose B_0 to the agent. Clearly, B_0 will be lesser than S_0.

Step 2. This step uses the Genetic Algorithm module to compute the new seller price S_1. This step can be further decomposed as:-

2a. Create initial population: - The first step of GA module involves creating feasible initial population. This paper favors decimal encoding rather than the commonly seen binary encoding in GA literature [2]. Let P be one of the candidate solutions in the population then it should satisfy following constraints:-
$B_0 \leq P \leq S_0$ and $\Omega < P$. Hence, the initial population consists of random numbers obeying the above constraint. For i^{th} round of negotiation, it can be generalized as: - $B_i \leq P \leq S_i$ and $\Omega < P$.

2b. Perform Fitness Evaluation: - A well defined fitness function is key to the successful implementation of GA. The objective of seller at any time is to maximize profit and follow a

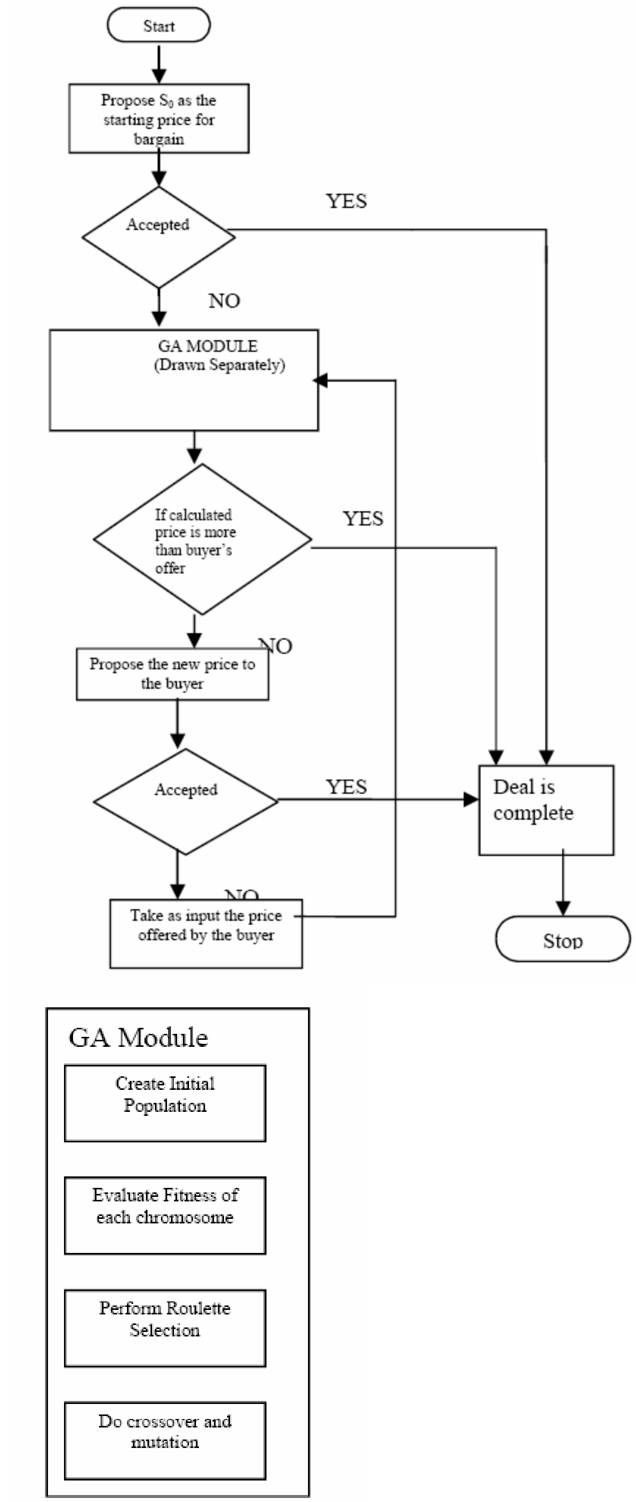

Figure2. Bargaining Process

"tit for tat" strategy. "Tit for tat" strategy will take into account the previous offers made by buyer. Hence the seller's price at any time will also depend on buyer's most recent offer. In sum, this means that a buyer who is risk aversive will not increment his/her offers by big amount and hence the seller will also not reduce the subsequent price considerably. On the other hand, a buyer who increases his/her subsequent offers by large amount will get better offers from the seller. Results in next section describe how the agent will behave towards different buyer's strategy.

Fitness function proposed for i^{th} round of negotiation is given by:-

$F= \alpha (1 - \Omega/P) - (1-\alpha)\Delta$

where

P= One of the candidate solutions in the population pool

Ω= Minimum acceptable price for the product

$\Delta = abs\ [1- abs\ (P-S_{i-1})/abs\ (B_{i-2}- B_{i-1})]$

i= i^{th} round of negotiation

α is a parameter and α Є [0,1].

Design of fitness function can be explained below:-

(1 - Ω/P) ensures that agent makes maximum profit. Since P is always greater than Ω, the ratio, Ω /P will always be less than 1. A higher value of P will result in more profit and hence will be preferred over lower values of P. Δ takes into account the recent offers made by buyer. For i^{th} round of negotiation under consideration, agent will look at B_{i-2} and B_{i-1}offers made by buyer. Agent will try to propose the new price S_i in such a way that $abs\ (S_i- S_{i-1}) \approx abs\ (B_{i-2}- B_{i-1})$ where abs is the absolute value of the difference. In other words, a candidate solution for which Δ is close to 0 will be preferred over another solution for which Δ is 0.6. Since the agent has two objectives, a) make maximum profit b) ensure tit for tat strategy, a parameter α is used to balance these two objectives. For α =1, the agent will work only for profit maximization and for α=0, agent will work only for tit for tat strategy. By hit and trial, α is chosen to be 0.8. This value prefers profit maximization and also ensures tit for tat strategy to a considerable extent.

2c. Roulette Selection: - GA literature [2] consists of hundreds of methods for implementing selection. This paper follows roulette selection, which is one of the most common methods of selection.

2d. Crossover: -One point cross over [2] is implemented with correction mechanism. Correction mechanism makes sure that if the result of crossover on any pair violates the constraints mentioned in Step 2a, then the crossover will be rolled back and some other pair will be chosen for crossover. For example:-Suppose constraint requires that no candidate in the population should be more than 85. Considering following population, result of crossover on first pair will be:-

5 | 9	*Result of crossover*	51
8 | 1	-----------------------	89
60		60
23		23

Since this crossover violates the constraint, it will be rolled back and some other pair will be chosen randomly. Suppose this time, first and third candidate are chosen the final result of crossover will be:-

50
81
69
23

2e. Mutation:-Mutation is also implemented with correction mechanism in a similar way as discussed below. If a particular digit is selected for mutation, then it is simply replaced by any digit randomly chosen from the interval [0,9]. For example:- If '5' is to be mutated in 59, then a random number is chosen in interval [0,9] say 6 and '5' is replaced by 6. So, the end result is 69. Correction mechanism in this case works exactly the same as in crossover. GA module is iterated from steps 2a -2e for a finite number of generations and the best candidate solution (maximum of all having highest fitness) becomes the next price offered by seller, namely S_i.

Step 3. Concession made by the selling agent also takes into account the time factor. The price proposed by selling agent at any point is

$S_i / (1+ 0.001*i)$

Where:-

S_i is the price obtained from GA module

i is the i^{th} round of negotiation

IV. RESULT

Table 1 shows the experimental set up with GA parameters and program input.

TABLE I

GA PARAMETERS AND OTHER PROGRAM INPUTS

Crossover	0.4
Mutation	0.05
Selection	Roulette Wheel
Population pool	100
Generation	50
S_0	50
Ω	20
n	8

Figures 3, 4 show the agent behavior with different buyer's strategy. In figure 3, the deal fails because buyer is highly risk aversive and the price increment is very small. In figure 4. the decrements made by agent are almost in proportion with the increments made by buyer. The deal is made at a point where seller accepts the buyer's price.

Figure 3. Buyer's and Seller's Plot

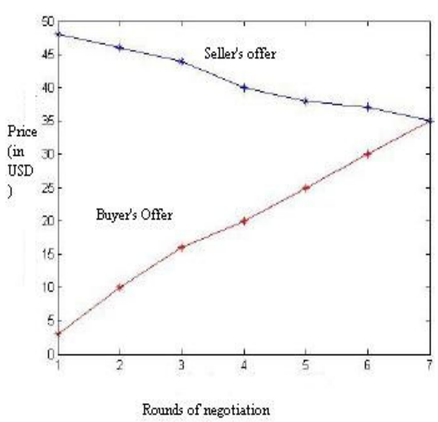

Figure 4. Buyer's and Seller's Plot

V.CONCLUSION

Paper proposes a genetic algorithm based bargaining agent for implementing dynamic pricing on internet. The agent takes into account buyer's most recent offer, minimum acceptable price and the current negotiation as input and proposes new price for the buyer. From the results of the program following can be concluded:-

1. The worst strategy for any buyer would be to increase his/her subsequent offers very slowly (say by unit increment). In this case either deal will never be completed or buyer may have to pay heavy price.
2. If the buyer increases his/her subsequent offers very generously by large amounts he/she may win the deal but may end in paying a more than reasonable price.
3. The best strategy for the buyer will be to start slowly and increase subsequent offers considerably. This way he/she may get a reasonable deal.

In any possible case, the agent will decrement its price in such a way that it would be able to make a profit of at least one unit otherwise deal will not be completed. Hence, the seller will always be in profit.

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