A DYNAMIC AND ADAPTIVE BARGAINING ALGORITHM FOR INTELLIGENT SELLING AGENTS IN ELECTRONIC COMMERCE

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ABSTRACT
Prior research has found that customers prefer retailing websites that offer online bargaining service. Online bargaining indeed is an attractive field in today's e-commerce. However, as compared to online auction, it has been much underdeveloped. A few online bargaining systems have been proposed but their bargaining strategies do not react to the change of market situation. In a typical bargaining process, there is an information asymmetry between the seller side and the buyer side, which could benefit the seller side if the seller side adopted a dynamic price change strategy during a bargaining process. This paper investigates the market behavior and the benefits to the sellers under a dynamic price change strategy based on the real-time market bargaining information.

Keywords: Information Asymmetry, Online Bargaining, Intelligent Agent, Bargaining Strategy

1. INTRODUCTION

Prior research has found that consumers prefer online retailing websites that offer bargaining opportunities even though they may not end up getting the lowest price (Liang and Doong, 2000). This indicates that companies having online retailing web store will be better off if they could offer online bargaining services through their website. But hiring a large number of sales staff to bargain with customers online could be very costly for companies. Intelligent software agents can be good substitutes for online human sales bargainers in such circumstances.

As compared to online auction, online bargaining has been a much under-researched topic in the dynamic pricing field. There only have been a very few research papers proposing methods and algorithms for using intelligent agent (IA) technology to offer online Business-to-Consumer bargaining service (e.g., Lin and Chang, 2001). Furthermore, these models were based on fixed bargaining strategies, i.e. once a selling IA adopts a bargaining strategy at the beginning of a bargaining process, it holds on that strategy until the bargaining process ends. This type of strategy does not take the dynamics of the market into account, which is rather inappropriate. In today's global online marketplace, the market condition changes instantly. A good bargaining strategy a moment ago might not be good for now. An online selling IA engaging in a bargaining process should be able to adapt to the instant market changes as swiftly as possible to reap higher revenue and profit.

In fact, the seller side, i.e. the selling IAs of the company, does have greater advantages over the buyer side, i.e. the customers side, during online bargaining processes because of the existence of the information asymmetry between two bargaining parties. For example, only the seller side knows how many buyers are currently bargaining with the company on a particular product at a given time; the buyer side has no way of knowing it. And, only the seller side knows what are the past and current bidding/deal prices from the other customers on a particular product;

the buyer side is not aware of this either. Information asymmetry like this gives the seller side greater power over the buyer side during an online bargaining process and the seller side certainly could and should capitalize on it to maximize its profit gain. This paper develops a dynamic adaptive online bargaining algorithm for the seller-side IAs to utilize this type of information asymmetry during online bargaining processes to help the seller side obtain higher revenue and profit.

2. RELATED RESEARCH

2.1 Online Hunting for Low Price

Consumers have been familiar with the fixed pricing in the traditional commerce market. Companies usually sell their merchandises to customers at a fixed "menu" price. Customers could either take it or leave it. Fixed pricing has been prevalent in western world since the industrial revolution, the mass production and widespread delivery of good made price negotiation impractical (Wurman, 2001). The cost of changing price at a high frequency could be too high in the traditional brick-and-mortar business environment. However, the use of the Internet in commerce can certainly make the pricing strategy much more flexible and dynamic. The Internet has provided infrastructural basis for implementing dynamic pricing in the e-marketplace, thus dynamic pricing strategies have been increasingly seeing in many e-commerce websites. For example, buy.com continuously searches its competitors' website for low price and then sets its price even lower (Smith, Bailey and Brynjolfsson, 2000). Amazon.com tried to offer different prices to different customers (Baker, Line, Marn and Zawada, 2001).

Dynamic pricing is defined as the flexible pricing strategy that could change the price of a product at any time (Kephart, Hanson and Greenwald, 2000). Under dynamic pricing strategy, the price of a product can be changed from customer to customer, from transaction to transaction or even within a transaction (Kannan and Kopalle, 2001). Dynamic pricing is not a new invention of today's information age. It has been in the business world for many years. Auction is certainly one of the historic dynamic pricing strategies and has many variations. In English auction, the price of a product being auctioned keeps being bid up until no one submits a new bid. ebay.com is an online version of the English auction. In Dutch auction, price keeps automatically dropping from the high until a bidder stops it; whoever stops the price drop will get the deal at that price. In reversed auction, there is one buyer but multiple sellers; the buyer has only one chance to name his or her price. Once the price is named, sellers will decide to either take it or leave it; the seller who accepts the buyer's offer first gets the deal. Priceline.com is an online version of reverse auction. In an auctioning process, there are usually multiple buyers or multiple sellers participating in price negotiation. When the number of the buyers and the number of sellers in price exchange is reduced to one, it becomes a bargaining process (Guttman and Maes, 1998). A bargaining process ends when both parties agree on a price or either of them quits. There have been quite a few successful online auction websites on the Internet, such as ebay.com, amazon.com's auction site, etc., but online bargaining websites are still very much underdeveloped. Surprisingly, retailing websites with online bargaining service have been found to be more attractive to customers than the ones without (Liang and Chang, 2000).

Although the Internet has been known as an excellent channel for price hunting and there are indeed many consumers using the Internet to search for the lowest price of the merchandises of their interest, price negotiation between the seller side and the buyer side is still a very important way of conducting sales business. On the one side, the Internet does carry a huge amount of information; on the other side, it has its own limitation too.

First of all, the searching costs for finding a real lowest price of a particular merchandise is not trivial. Commonly, consumers either use search engines like google.com to conduct an exhaustive price search by themselves or rely on information provided by price aggregators like pricescan.com or mysimon.com to find the lowest price. However, the amount of time and effort involved in using search engines to find prices makes the lowest price hunting practically much less feasible. Search engines usually return too much information; sorting the price information out from the overwhelmingly large amount of information returned by search engines could be a nightmare. Price aggregators like pricescan.com and mysimon.com could greatly reduce the effort of price searching, but the search task consequently become search for the lowest price among price aggregators, not the lowest price on the Internet. Price aggregators usually sign agreement with a list of vendors to obtain price information from them, rather than search price information from the Internet. Because vendors usually do not frankly publish their lowest price to the public to avoid potential price “war”, and many vendors also do not want to compete on price only, the lowest price displayed on the price aggregators’ websites might not be the real lowest price possible.

Second, obtaining the lowest price information of a merchandise is one thing, to actually get the merchandise on that price is another. For example, pricescan.com often returns the price from stores which do not have online retail websites and many of these stores are not nationally well known. It is unlikely that a customer in Chicago would travel to New York city to buy a Sony 36” WEGA Color TV set for a saving of $100, because the extra travel expenses involved exceed the saving on the TV set. It is also unlikely that the customer would order it through mail or telephone from these stores because of the potential risk of being ripped off, providing that store has mail order service. Another often-seen phenomenon is that some retailers publish a very low price on a product. When a customer wants to order the product, the customer will be told that the product has been sold out and then will be introduced to a different model or a similar product that often has a higher price or higher profit for the retailer. This type of misleading activities substantially increases buyer’s online search costs and potential risk of the transaction, and eventually makes the ultimate price saving almost worthless to the buyer.

Third, from the product variety perspective, products whose price is widely compared on the Internet are usually commodity-type merchandises, such as books, music CDs, movies, and consumer electronic products, etc. Each of these commodities usually has similar features across different brands and its price is usually the most important factor toward a customer’s purchase decision (Gurley, 2001; Kaphart *et al*., 2000). Merchandises like furniture are much more difficult to compare because factors like style, color, material, combinations and configurations are important to consider too (Kaphart *et al*., 2000). In these kinds of situations, bargaining is usually the best way for customers to get a low-price deal.

Overall, the online search costs and potential risks could hinder buyers to acquire merchandise through searching for vendors offering lowest price on the Internet. Furthermore often times, buyers need consider multiple factors when acquiring merchandise, such as product configurations, vendor reputation and delivery speed, etc. Due to these factors, price bargaining appears to be the best method for buyers to get what they want at the price they can accept. After all, business is all about offering the right product to the right customer at a right price. The price should be right to the seller as well as to the buyer, not necessarily to be the highest or lowest.

2.2 Online Price Bargaining

Bargaining can be viewed as a process by which bargaining parties jointly search for a mutually acceptable solution in a multidimensional space, such as price, quality, quantity, etc. (Oliver, 1996). Price usually is not the only driven motivation (Kahneman and Tversky, 1979, 1984); the dimensions could be price, different product features, delivery time, etc. Price bargaining could benefit both involved parties in many ways through exchange of information. For example, sellers could know more about buyers’ desires toward product features and pricing; buyers could have a better understanding toward a product’s current features. This could reduce the chance that a buyer acquires something which turns out to be not what he or she wants, therefore customer satisfaction could be improved. Actually, the bargaining process itself could improve shoppers’ satisfaction even when the amount saved was insignificant or did not directly benefit them (Darke, Freedman and Chaiken, 1995). Furthermore, although the Internet reduces buyer’s search costs for price comparison as compared to the search conducted offline, and thus buyers could be well aware of different prices offered in different online stores, buyers’ price sensitivity, i.e. the degree of influence of the price toward a customer’s purchase decision, does not increase accordingly (Clay, Krishnan and Wolff, 2000). Also, as buyers have more information about a product, they become less price sensitive (Carmon and Ariely, 2000), which justifies why buyers do not always stick with the lowest-price strategy. It also leaves much room for online bargaining providers to reap higher profit by focusing on (unique) product attributes other than price during bargaining processes.

Although selling through bargaining is beneficial to both sellers and buyers as discussed above, it is not realistic for companies in the traditional commerce practice to offer bargaining services to their customers because of the high cost involved, such as the cost of hiring sales bargainers, office space to conduct bargaining, time cost involved in bargaining processes, etc. But in the e-commerce practice, the costs associated with making frequent price change are greatly diminished (Smith *et al*., 2000); the price change is as easy as changing a number in the database (Kannan and Kopalle, 2001). The application of IAs in today's e-commerce reduces the cost even further. IAs have been widely used in comparing price such as BargainFinder, selling and buying merchandises on behalf of the owner of the agent, representing the owner to participate online auction on ebay.com or amazon.com, etc. (Maes, Guttman and Moukas 1999; Kaphart *et al*., 2000). The majority of the current applications of IA so far have aimed to serve the buyer side in the electronic marketplace, a few IA-based online bargaining systems serving the seller side just started to emerge. For example, Lin and Chang (2001) developed a multiagent online bargaining system for sellers to offer automated bargaining service to buyers. Their system first generates a large number of bargaining patterns using the past bargaining data. During an online bargaining process between a selling IA and a customer, the IA make offers and counteroffers based on a matched pattern, found in the pattern database, similar to the current bargaining development. Sardine is a simulation system investigating the outcome of different dynamic pricing strategies for sellers in the airline industry. It is not a bargaining system but a system to let airlines set airfare dynamically according to the ticket sales in past days (Morris, Ree and Maes, 2000).

2.3 Dynamic Pricing Strategies

Even in the traditional brick-and-mortar business environment, dynamic pricing has been widely used for items such as oil, securities, and airline tickets. The prices of these items are set according to the dynamic change of the supply and demand of these items.

A simple dynamic pricing strategy can be illustrated by the model used at buy.com and books.com. Buy.com uses IAs to scan its competitors' website and then sets its price lower than its competitors' prices (Smith *et al*., 2000); whenever its competitors make a move on the price, buy.com countermoves accordingly. Books.com uses the same kind of agents to check the price of a given book on its competitors' websites, e.g. amazon.com and border.com, and then lowers the lowest price from its competitors further about 1% (Greedwald, Kephart and Tesauro, 1999). This simplistic dynamic pricing strategy obviously helps increase the revenue at buy.com and book.com, but the over-simple strategy might hurt their profit because the strategy solely competes on the merchandises' price regardless of their costs, such as the acquiring cost of the merchandises (DiMicco, Maes and Greenwald, 2003).

A more complicated dynamic pricing model is the revenue management model widely used in the airline industry (Bitran and Caldentey 2003; Boyd and Bilegan, 2003). Airlines use sophisticated software to forecast future, monitor ticket sales activities, etc., they then adjust the number of seats assigned to different class categories (coach, business class and first class) and their prices (Boyd, 1998; Boyd and Bilegan, 2003). The success of airlines' revenue management is largely based on two conditions: its straightforward customer segmentation and its sophisticated assumptions and predictions about the behavior of the marketplace. Also, the prices in each fare class are fixed, which means that the customers in the same class pay the same price for a ticket.

While under a fully dynamic pricing model, customer demand is the dominant factor and price can be changed from customer to customer regardless of the segmentation, provided that there are customer segmentations for the product being sold (DiMicco *et al*., 2003). The prediction based on historic data could be useful in the macro sense, but the tactics used to set price in real time, i.e. the micro structure of the dynamic pricing, needs to be emphasized too. Like the stock market, the fundamental analysis is necessary in order to find the real value of a particular stock, but the technical analysis on the trading of the stock is equally important for reaping higher return through proper timing. In addition, prediction based on historic data has its risk of being wrong because history does not promise to repeat itself. So, the dynamic price change strategy used in real-time bargaining is an important contributor to the ultimate profit. In the MIT Media Lab's Kasbah marketplace (Chavez and Maes, 1996), sellers' agents and buyers' agents actively search and bargain with each other to strive for the best deal for both parties. The agents' price change strategy, as shown in the Figure 1, is selected by the agents' owner when the agents are created and is strictly followed during the whole bargaining process. The drawback of using the same price change strategy for the whole bargaining process is that the agent is not able to react to the real time information, such as the popularity of the product measured by, say, the number of the buyers who are currently bargaining for it or the number of deals made on the product in the near past.

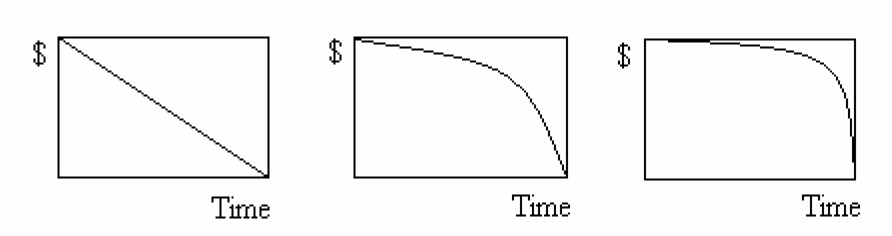

Figure 1 Three Pricing Change Strategies used by the Agents in the Kasbah Marketplace

The automated multiagent bargaining system developed by Lin and Chang (2001) uses dynamic pricing change scheme, but it relies on pattern matching. Before the seller agent makes an offer or counteroffer, it attempts to find an exact pattern matching to the current bargaining history and then follow that pattern to make the next offer. The pattern to be followed could be changed at any step, depending on the counteroffers from the buyer. Although the price change strategy varies during the bargaining process, it is solely based on historic price data and does not respond to the other changes of market conditions, such as a product's popularity, in real time.

In a real business bargaining situation, participants take multiple factors into account and make offer or counteroffer accordingly. When building IA-based automated bargaining system, the seller side agents should utilize the real-time bargaining information and the information asymmetry, i.e. the fact that some information is only known by one of the two bargaining parties, as much as possible to maximize the overall profit. For example, only the selling side knows 1) how many buyers are currently bargaining for a particular product, and 2) how many deals have been made in the near past, buyers do not have this type of information. Online selling agents can certainly use the recent bargaining information in the market to select initial price change strategy for upcoming bargaining tasks, and dynamically changes the pricing strategy afterwards according to the real-time bargaining situation in the market. For example, when a selling agent finds that there are many buyers currently bargaining for the same product, it could switch to a more conservative pricing strategy to slow down the price dropping speed for the purpose of selling products to high-price paying buyers and avoiding low-price paying buyers. On the contrary, if the selling agent finds that not many buyers are bargaining for a particular product, it might move to a more aggressive price dropping strategy to attempt to sell a large quantity of the products to low-price paying buyers. A real-time dynamic pricing strategy like this could improve sellers' profit based on this type of asymmetric information. I propose our method to utilize the information asymmetry in the next section.

3. OUR APPROACH

Price bargaining is a process in which both a seller and a buyer change (either increase or decrease) the price of a merchandise to reach a consensus. Generally, sellers gradually decrease their price and buyers gradually increase their price by following their own rules until they reach a consensus, as illustrated in Figure 2. However this by no means is the only case in price bargaining. For example, a seller might increase, instead of drop, its offer price during the bargaining if the seller perceives that the merchandise is under huge demand. Any premium above the seller's reserved price, i.e. the seller's minimum acceptable price, is regarded as the profit gain for the seller, and any price room below the buyer's reserved price, i.e. the buyer's maximum acceptable price, is regarded as the saving for the buyer. If the final deal price is higher than the seller's reserved price and is lower than the buyer's reserved price, it is a win-win situation for both parties.

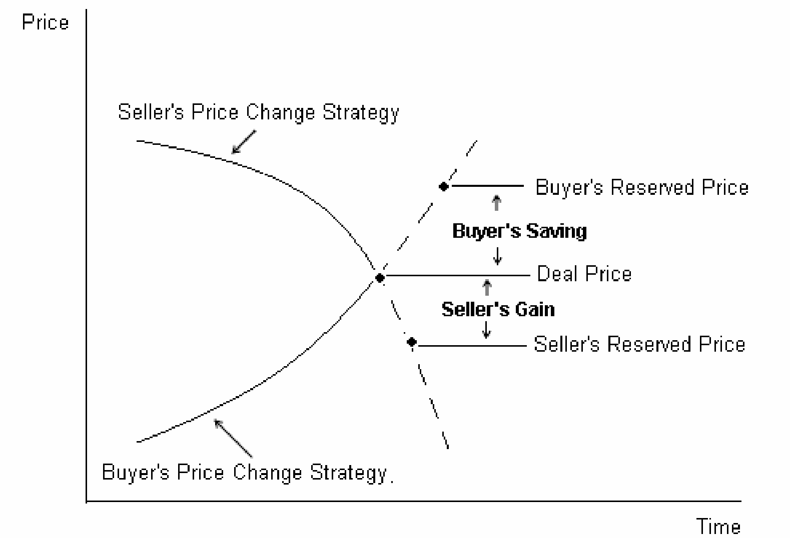

Figure 2 Bargaining Process

3.1 Sellers' Dynamic Price Change Strategies

Figure 3 illustrates two clusters of price change strategies with varying speed. Strategy cluster A (A_1, A_2, …, A_n) drops price very fast in the beginning of a bargaining process and then slows down toward the end of the bargaining. Strategy cluster B (B_1, B_2, …, B_n) drops price slowly in the beginning of a bargaining process and then the price change accelerates toward the end of the bargaining. Each strategy cluster can be described by a polynomial function ($y = ax^n$) with necessary rotations and shifts; different values for the parameters a and n of the function determine the shape of the curve. Chavez and Maes (1996) used similar price decay functions on the buying and selling agents in the Kasbah system.

The mathematical notations of these strategies are as follows:

$$price_s = \begin{cases} scale_p \times [1-(\frac{i}{scale_o})^{\frac{1}{n}}],\ n \geq 1, 0 \leq \frac{i}{scale_o} \leq 1,\ for\ Strategy cluster A \\ scale_p \times [1-(\frac{i}{scale_o})^{n}],\ n \geq 1, 0 \leq \frac{i}{scale_o} \leq 1,\ for\ Strategy cluster B \end{cases}$$

$price_s$ is the seller's offer price on the i^{th} offer. n determines the shape of the curves (e.g. A_1, A_2, …, A_n). $scale_p$ and $scale_o$ change the scale of the *price* axis and the *offer* axis; and they varies from product to product and company to company and can be determined through experiments.

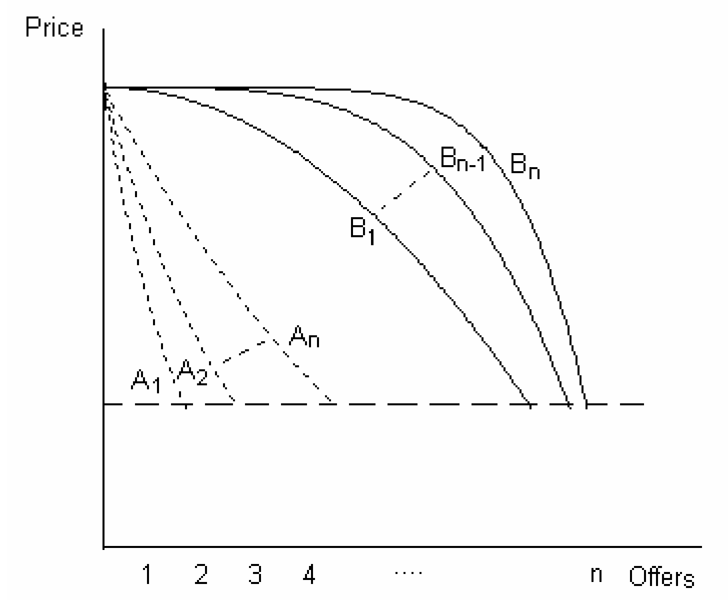

Figure 3 Price Chang Strategies

Under the strategy described by the above mathematical formula, the *n* determines the shape of the curve, i.e. the changing speed of the price curve. During a bargaining process, the changing speed of the price curve on a particular product is determined by the aggressiveness of the price change strategy adopted by a sales IA selling that product at a given time. And the aggressiveness of the price change strategy is determined by a *popularity index* of the product currently under bargaining at the time when the seller IA makes an offer.

The *popularity index* is measured by the number of customers currently in the bargaining process (*numBargainers*) for the product, the number of deals of that product made in the near past (*numRecentDeals*) and the recent deals' prices (*RecentDealPrice*), as illustrated below. The *numBargainers, numRecentDeals* and *RecentDealPrice* change all the time during an online bargaining process as activities occur in the market, so does the *popularity index.*

$$popularity\ index = \frac{numBargainers}{scale_{nb}} + \frac{numRecentDeals}{scale_{nd}} + \frac{RecentDealPrice}{scale_{np}}$$

scale$_{nb}$, *scale*$_{nd}$ and *scale*$_{np}$ are the scaling factors for *numBargainers*, *numRecentDeals* and *RecentDealPrice* respectively. The values of these scaling factors vary from product to product and company to company; they can be decided through experiments.

When a selling agent is ready to make an offer to the potential buyer, it calculates the *popularity index* to determine which price dropping strategy to use. There are two types of strategy clusters in Figure 3, Cluster *A* and Cluster *B*. Strategies in Cluster *A* drop price very quickly so they should be used only when the selling agents are really desperate, i.e. the *popularity index* is really low. A *threshold* value can be set to indicate when a strategy in Cluster *A* should be chosen. For example, if *popularity index* varies from 0 to 7 and *threshold* is set to 2, this means that the selling agent should use strategies in Cluster *A* when *popularity index* is between 0 and 2, and use strategies in Cluster B when *popularity index* is from 2 to 7. The algorithm for choosing strategy cluster and determining *n* is illustrated as follows:

$$\begin{cases} strategy\_cluster = A \text{ and } n = threshold - popularity + 1, & \text{if } popularity \leq threshold \\ strategy\_cluster = B \text{ and } n = popularity - threshold + 1, & \text{if } popularity > threshold \end{cases}$$

threshold varies from product to product and company to company; it can be set to be any value from 0 to the maximum value of the *popularity index*.

During the whole bargaining process, the selling IA continuously monitors and updates the *popularity index* in real time. The *popularity index* changes dynamically and determines the price change curve used to make next offer, thus the selling IA moves among the price change curves along with the change of the *popularity index* in real time during the whole bargaining process. When *popularity* grows, the seller changes the strategy to a shallower curve; when *popularity* decreases, the seller moves to a steeper curve.

4. A FRAMEWORK DESIGN

An online agent-based bargaining system supporting dynamic price change strategy can be modeled after an agent-based decision support system (DSS). According to Hess, Rees and Rakes (2000), an autonomous software agent is "a software implementation of a task in a specified domain on behalf or in lieu of an individual or other agent" (p.6). The advent of autonomous software agents, which are goal-oriented, persistent and reactive, leads the DSS to its second generation (Hess *et al*., 2000). One of the main benefits of using agent-based system, as compared to nonagent-based implementation, is to reduce human interaction (Bradshaw, 1997; Maes, 1994). An autonomous software agent empowered with intelligence allows it to fulfill its task in a more efficient and effective way with less assistance from the user. In this case, intelligent selling agents are the substitutes of human online sales bargainers. Once an intelligent selling agent is created or activated, it immediately engages in a bargaining process with an online potential buyer with the goal of selling the merchandise to the potential buyer at a price as high as possible. The reactivity of the intelligent selling agents is manifested through their reactions to the popularity change of the merchandise under bargaining. When a selling agent perceives the change of the popularity of the merchandise under bargaining in the market, it shifts its price changing strategy accordingly. The agent's shifts among different price change strategies are autonomous and no human interaction is needed. The algorithm for dynamic price strategy change provides intelligence to the agent so that it can more efficiently and effectively reach its goal, i.e. selling the merchandise at a price as high as possible.

A framework for an online bargaining system supporting dynamic price change strategy is shown in Figure 4. It is modeled after Hess *et al*.'s agent-enhanced general DSS framework which consists of three systems: the Dialog Generation Management System (DGMS), the Model Based Management Systems (MBMS), and the Database Management System (DBMS) (Hess *et al*., 2000). The DGMS is responsible for managing the dialogs, i.e. the interactions, with the DSS users; the MBMS is to manage the different modeling tools and packages for DSS; and the DBMS manages the data involved in DSS.

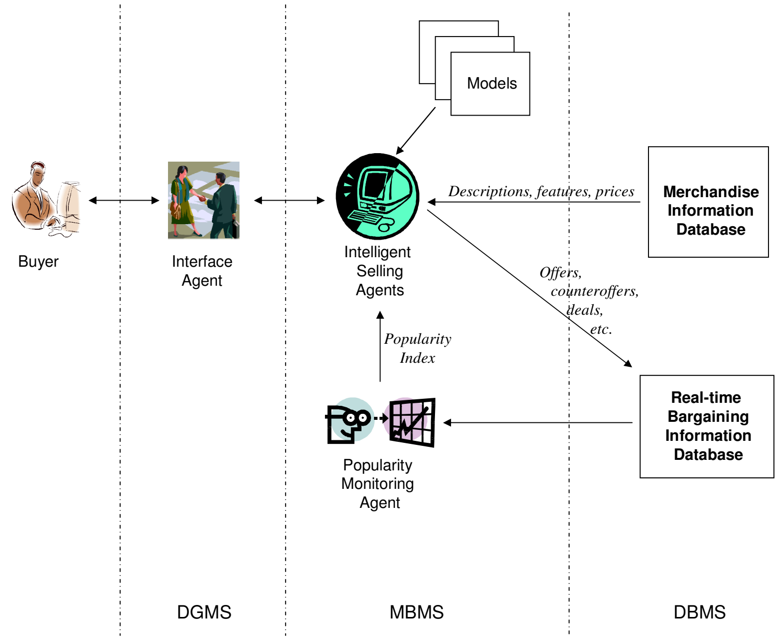

Figure 4 A Framework of an Online Bargaining System Supporting Dynamic Price Change Strategy

In our system, the Interface Agents make up the DGMS. These Interface Agents take care of the interactions with potential online buyers, such as presenting merchandise information in HTML format, taking offers from buyers, displaying counteroffers from the intelligent selling agents, etc. Interface Agents have been widely used in many agent-based systems involving human contact (e.g. Ba, Kalakota and Whinston, 1997; Hess *et al*., 2000). An intelligent Interface Agent with learning ability can organize the human-computer interface fitting to the individual buyers' personal preferences to give the buyers a personal touch.

The Intelligent Selling Agents in the MBMS get inputs, i.e. the *popularity index*, from the Popularity Monitoring Agents and choose an appropriate price change strategy/model from the Model database to make offers and counteroffers. Model Database stores all the price change models represented by various polynomial functions ($y=ax^n$). Meanwhile, Intelligent Selling Agents also update the Real-time Bargaining Information Database to record all the bargaining activities, such as offer prices, counteroffer prices, duration of a bargaining process, deal prices, unsuccessful bargains, etc. The Popularity Monitoring Agents query the Real-time Bargaining Information Database to supply the popularity information of certain merchandise to the Intelligent Selling Agents upon request.

The DBMS has two databases: the Merchandise Information Database and the Real-time Bargaining Information Database. The Merchandise Information Database stores the information about merchandises to be sold, such as merchandise descriptions, features, specifications, starting bargaining price, reserved price, etc. The Real-time Bargaining Information Database records all the bargaining activities of all the Intelligent Selling Agents as discussed above. Popularity Monitoring Agents analyze this database to determine the popularity of a particular merchandise, such as the number of online bargaining buyers of certain merchandise, the number of deals made on certain merchandise in the near past, etc.

4.1 Workflow with an Illustrative Example

The workflow of an intelligent selling agent is depicted in Figure 5. Every time when making a new offer, the selling agent gets the latest *popularity index* of the merchandise under bargaining and pick a price change curve based on that *popularity index*.

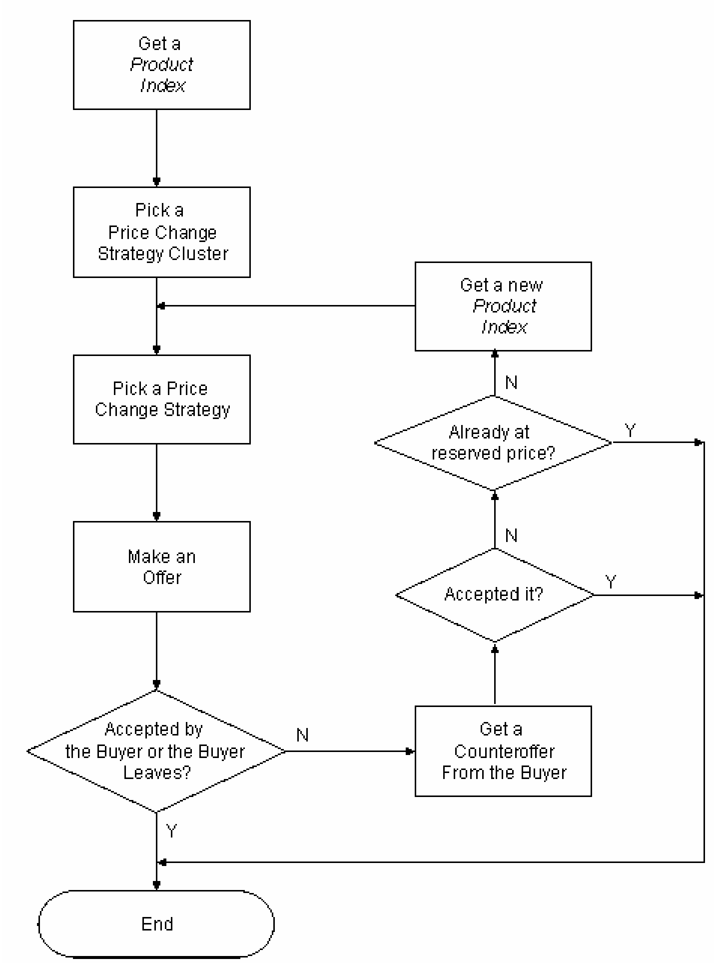

Figure 5 Workflow of the Intelligent Selling Agents

Figure 6 provides an example of how a selling agent dynamically shifts among price change strategies. At the beginning of a bargaining process, let's assume that the selling IA calculated the *popularity index* of the merchandise under bargaining and decided to choose a price change strategy in Cluster *B*. The chosen price change curve was denoted by the polynomial function of $y = x^a$ (here a = *popularity*). The agent's first price offer was P_1 based on the selected curve. When it was the time for the selling IA to make the second offer, the selling IA re-calculated the *popularity index* of the merchandise under bargaining, and found the *popularity* was changed from a to b due to increased popularity of that merchandise measured by the number of buyers currently bargaining for it and the number of deals made on this merchandise in the near past. The selling IA then changed to a more conservative price change strategy by switching to the price curve $y = x^b$ (here b = *popularity* and $b > a$). In the current example as illustrated in Figure 6, the price calculated on the new price change curve was actually higher than the first price offer P_1, which was not abnormal according to the favorable demand change, or popularity change, of that merchandise. If the selling IA did not make the second offer based on the dynamic price change algorithm, it would stick with price change curve $y = x^a$ and offer P_2' as the second offer, which was apparently not a wise choice.

Before the selling IA made the third offer, the *popularity index* had been re-calculated again and had not changed, so the selling agent used the same price change strategy to make the third offer at P_3. When the time came to submit the fourth offer, the recalculation of the *popularity index* showed another favorable popularity change from b to c, the selling IA then used the new price change curve as denoted by the function, $y = x^c$ (here c = *popularity* and $c > b$), to make the fourth offer at P_4. Again, if the selling IA did not use the dynamic price change strategy, it would make the fourth offer at P_4', which was not appropriate according to the favorable popularity change of the merchandise at that time. The thick (red) line in the Figure 6 shows the real price change trajectory based on the dynamic adaptive price change algorithm.

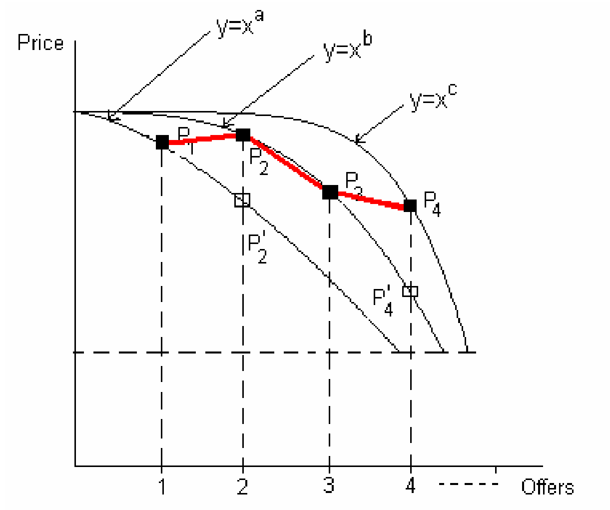

Figure 6 An Illustrative Example of the Dynamic and Adaptive Bargaining Algorithm for Sellers

5. DISCUSSIONS AND IMPLICATIONS

Dynamic pricing was common in industries like airlines, hotels and electric utilities even before the era of e-commerce. The goods in these industries, i.e. airline seats, hotel rooms and electricity, all have three major characteristics: perishable, fixed capacity and segmented (Jayaraman and Baker, 2003). These mean that 1) the goods have to be sold before a preset date; 2) the capacity of the goods cannot be easily increased or reduced in a short period of time without incurring high cost; 3) the quality or service level of the goods can be segmented to meet different customer needs; examples include business-class seats vs. economy-class seats. Dynamic pricing methods were used to arrange the sales of these goods to maximize the yield or revenue. Another important feature of these goods is that the sales information of these goods during the sales can be collected and sent to a central location for analysis and prediction in a fairly timely manner through the use of information technology.

However, using dynamic pricing strategy to sell non-perishable goods is relatively new. The territory expansion of the application of the dynamic pricing method did not happen until the commercialization of the Internet. According to Elmaghraby and Keskinocak (2003), the expansion of the practice of dynamic pricing strategy into other industries is largely due to three factors: "1) increased availability of demand data, 2) the ease of changing prices due to the new technologies, and 3) the availability of decision support tools for analyzing demand data and for dynamic pricing" (p.1287). The online bargaining system and the bargaining algorithm proposed in this paper obviously match their opinions. The online bargaining system monitors the market conditions, mainly the demand change, in real time. The demand data of the merchandise under bargaining is captured through the number of current bargainers, the number of deals made recently, and their prices. This real-time demand data was almost impossible to obtain in real time in the traditional brick-and-mortar business environment. In the e-commerce environment, the sale of merchandise is on the Internet, which implies that changing the price of merchandise is as easy as changing a number in a computer. The framework of the online bargaining system proposed in this paper includes a decision support sub-system that converts the captured market demand data to the data determining bargaining strategies for the selling agents. When a selling agent is about to make a counteroffer, the decision of which particular price changing curve to choose is made in real time by this sub-system. The dynamics of dynamic pricing is fulfilled here.

Dynamic pricing has different forms. The implementation of revenue management in industries like airlines is certainly the most popular one. Online auction is another well-known one. Online bargaining should be a major one as well to complement the prior two forms of dynamic pricing. Fixed menu pricing assumes that all the customers are the same, i.e. every customer has the same utility function towards a particular merchandise. This is certainly not true in the real world. A fan of Britney Spears is probably willing to pay more for a ticket to Spears' concert than a non-Spears fan for the same ticket, because the fan usually gains more pleasure from attending the concert than the non-fan. A computer programmer might be willing to pay more for a notebook computer, which would server as the tool for him to do his job to generate his income, than a user who would use the same notebook computer just to check emails from friends. These two examples explain that different consumers have different utility functions towards the same merchandise. A buyer's utility function towards a particular merchandise is an important determinant of the price a buyer is willing to pay. If buyers' utility functions is different, the price the buyers are willing to pay will certainly be different as well. Using dynamic pricing to manage revenue does not address the issue of buyers' different utility functions towards the same merchandise; it only focuses on how to optimally segment merchandise, such as how many airline tickets should be allocated to Y, M, B, and Q class respectively with Y-class tickets carrying no purchase or return restrictions and a high price, and M, B, Q-class tickets carrying various degrees of restrictions (Boyd and Bilegan, 2003). The allocation of tickets to different classes is dynamic based on the historic or current sales data. However, the buyers of the same class tickets pay the same price.

Using online auction to implement dynamic pricing method addresses the issue of different buyers' different utility functions towards the same merchandise. The buyers who value the merchandise high are willing to pay more for the same merchandise. The high price paying buyers will outbid the low pricing paying buyers. The drawback of online auction is that it is the bidding buyers who determine the final deal price; the seller side has little to do with it. After the auction process starts, the seller side becomes a passive participant in the process; the final deal price is largely determined by the market demand only and the seller has no control over it.

Online bargaining goes further in using dynamic pricing methods to address the issue of different buyers having different utility functions towards the same merchandise. In online bargaining, not only is the market demand fully reflected through the changing price in each offer and counteroffer, but also has the seller side the equal role in deciding the price movement. In online bargaining processes, the seller side is an active, rather than passive, participant in the whole sales process and is able to control the price whenever necessary.

Furthermore, during a bargaining process, price is not the only thing that can be bargained. The negotiation nature of online bargaining allows two parties engaged in a bargaining process to discuss multiple dimensions of a deal in great detail, such as warranty, configuration, price, delivery methods, etc. This is what revenue management or online auction cannot easily fulfill. When demand data becomes richer and more available and when the seller side knows more about the buyers, mass personalization, as compared to mass production, will be a dominant business model in the marketplace. Online bargaining or negotiation will prevail in the future in implementing dynamic pricing because personalization implemented through bargaining can be quite attractive to both product/service providers and consumers. Neither revenue management nor online auction can reach a deal in such detail.

6. LIMITATION AND FUTURE WORK

In order to examine the real performance of this dynamic and adaptive algorithm, a computer simulation needed to be conducted to study the effects of this algorithm. Simulation is the preferred method in the cases where mathematical reasoning and modeling are very complicated or even impossible. A bargaining process is indeed fairly complicated because it involves many factors, such as the buyers' reservation price distribution, the distribution of the buyers' arrival at the market, the buyers' negotiation patience and aggressiveness, etc. Computer simulation would be a very good method to study behaviors of the bargaining market and its outcome. DiMicco *et al*. (2003) used computer simulation to study their dynamic pricing strategies under different models. The Information Economies group at IBM Research also used simulation to investigate the potential impact of widespread use of shopbots on prices (see Kephart *et al.*, 2000).

This paper only deals with price bargaining which is only one of the dimensions in the bargaining space (Kahneman and Tversky, 1979, 1984). More dimensions such as product features, warranty, delivery time, etc. could be included too. A bargaining process is also a process to let buyers know the product better. A multimedia bargaining support system that shows product features and compares features with the competing products could be very helpful in educating potential buyers. The benefit gain for both buyers and sellers under this type of support system can be studied, and the results can be useful to guide the development of more complete and complex bargaining systems.

Buyers' behaviors were not considered in this paper. Future work could consider dividing buyers into multiple groups, such as a price-oriented group and a product-oriented group. Buyers in the price-oriented group value getting the product at a low price more important than merely getting the product. They usually do not increase their price aggressively in any circumstance despite the risk of getting no deal. Price is the most important dimension for them when bargaining. Buyers in the product-oriented group present opposite behaviors. Acquiring the product is their first priority, but they still want to save as much as possible through engaging in a bargaining process. These two groups of customers react to a seller's offers differently. The outcome of our dynamic bargaining strategy on these two groups and a mix of these two groups are certainly worthwhile to investigate.

7. CONCLUSIONS

Online customers prefer e-commerce websites that provide online bargaining service. Hiring human sales staff to offer bargaining services to online customers could be very expensive for companies, but intelligent software agents equipped with proper bargaining algorithms are good substitutes.

Moreover, the information asymmetry between the seller side and the buyer side during bargaining processes gives companies another reason to offer online bargaining service through their websites because the information asymmetry could be a source of higher profit for the seller side. At least, the information exclusively available to the seller side could enable the seller to price the merchandise based on much more accurate and timely market demand data.

In the agent-based online bargaining processes, it is usually a difficult task for agents to pick a price change strategy because there is usually not much of guidance to refer to when selecting a strategy. However, which one to pick directly determines the outcome of a bargaining process. This paper developed a dynamic and adaptive algorithm that captures the market dynamics and uses it to select corresponding price change strategy. The algorithm is dynamic in the sense that an agent does not stick to any price change strategy, but moves among different strategies all the time based on the current market dynamics. The algorithm is adaptive in the sense that the change of strategy is the result of adapting to the real-time changing popularity of the merchandise under bargaining. The strategy an agent adopts at a given time is fully determined by that merchandise's popularity at that time. The merchandise's popularity in the market changes at a real-time manner, and so does a selling agent's price change strategy. By following this strategy, agents are able to price the merchandise high when the product popularity is high and price it low when the popularity is low. This could enable the seller to pursue higher profit when demand is high and high sales volume when demand is low.

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