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Studying Retailer Strategies through an Integrated E-Business Model: a Multi-Agent Approach

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ABSTRACT

Agent technology has been widely applied in today's electronic business, such as mobile agents, multi-agent information systems, etc. In particular, multi-agent systems have been applied as powerful simulation tools to study complex business networks composed of various self-interested trading firms and/or human beings. In this paper, we build an integrated model that consists of a multi-agent B2C market model and a B2B trade network model, and incorporate more reality than much of prior work. Then with this model, we carry out experimental studies on two different strategies that are common in electronic business – "loyal" strategy (retailers try to build stable cooperation with suppliers to ensure material supply) and "cost-saving" strategy (retailers try to reduce cost by choosing suppliers with lower wholesale price).

Keywords: Agent-based Simulation, Trade Network, Integrated E-Business Model

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1. INTRODUCTION

Agent technology has been widely applied in today's electronic business. The concept of agent has been applied in various new business applications, such as mobile agents, multi-agent information systems, etc. It is becoming increasingly evident that in the future the Internet will host large numbers of software agents that aid or even act on behalf of companies/consumers to make decisions and carry out transactions. These agents act as decision makers and play important roles in various activities of electronic commerce, such as negotiations, sales and purchase.

However, making decisions under complex e-business environments is generally a difficult task: agents do not have complete information about the market and other agents; they only have limited intelligence and rationality; the effectiveness and efficiency of a single agent's strategy is generally dependent on the business environment and the competitor's strategies. Related work has shown that some strategies that perform well in single-agent cases may have disadvantages when competing with other strategies. For example, Greenwald and Kephart [1] show that the derivative follower strategy performs better than other strategies when the agents all adopt this strategy; however, this strategy shows apparent disadvantages when competing with other strategies such as MY and NR. Therefore, it is important to understand and anticipate the performance of strategies through agent-based business models before they are employed into the real world.

Till now, there is a rich literature that discusses strategies through agent-based electronic business models. In the field of computer science, some work has been carried out on designing algorithms for the agents to make price decisions on B-C electronic markets. Greenwald and Kephart [1] discuss different pricing strategies for the retailers who compete to sell a single indivisible commodity to a large number of buyers, and compare the performance of these strategies through simulation. Dasgupta and Das [2], Kutschinski, etc. [3] extend Greenwald and Kephart's work by designing some more elaborate and refined algorithms.

There are also researches on strategies of B-B partners in electronic markets by constructing multi-agent models. For example, Oprea [4] presents an adaptive negotiation model that uses a feed-forward artificial neural network as a learning capability to model other agents' negotiation strategy; Faratin [5] presents a negotiation mechanism for a real world problem of task distribution among a set of autonomous computational agents within a business process. Besides, there are also studies on trade networks. McFadzean and Testfatsion [6] construct an economic world where there are heterogeneous endogenously interacting traders with internalized data and models of behavior, through which the formation and evolution of trade networks can be studied.

However, although there are many researches that study strategies through multi-agent models, almost all of them focus either on B-C market [1, 2, 3] or on B-B trade [4, 5, 6], none has studied an integrated case that contains both B-B and B-C trade processes. Such an integrated model is complicated that agents' strategies involved in these two processes are interdependent, and the performance of a strategy is even harder to anticipate. Thus, some strategies that perform well in simpler cases may even not work in this case. Such integrated models are valuable for us to study strategies in more realistic and complex cases and get deeper understandings to design new strategies or to refine current strategies.

In this paper, we first build an integrated model that contains both B-B and B-C trade processes. Then based on this model, we study two types of retailer strategies – "loyal" and "cost-saving". Retailers adopting "loyal" strategy try to build stable cooperation with one or several suppliers to get better service, higher supply priority or other benefits. This strategy is quite common in real world. For example, the electrolytic aluminum manufacturers in China often try to become long term partners of Aluminum Corporation Of China Limited which monopolizes the production of alumina in China, in order to lower the risk of price inflation of alumina. Under electronic business environments, prices may change more quickly, and the "loyal" strategy may be more beneficial. Retailers adopting "cost-saving" strategy try to reduce cost by seeking suppliers with lower wholesale prices. For example, Wal-Mart always tries hard to find suppliers with lowest wholesale prices around the world, by which it can charge rather low product prices and keep competitive advantage. In electronic business environments, retailers can easily get more information of suppliers, thus the cost of search for low-price suppliers is much lower, and the "cost-saving" strategy is more effective.

Traditionally, we always discuss these two strategies separately and know that they both have advantages. However, what if retailers adopting these two strategies compete with each other? Which strategy is better under complex business environment? With the integrated model we have built in this paper, we can try to answer these questions through experiments.

2. THE INTEGRATED MODEL

The basic structure of the model is shown in Figure 1.

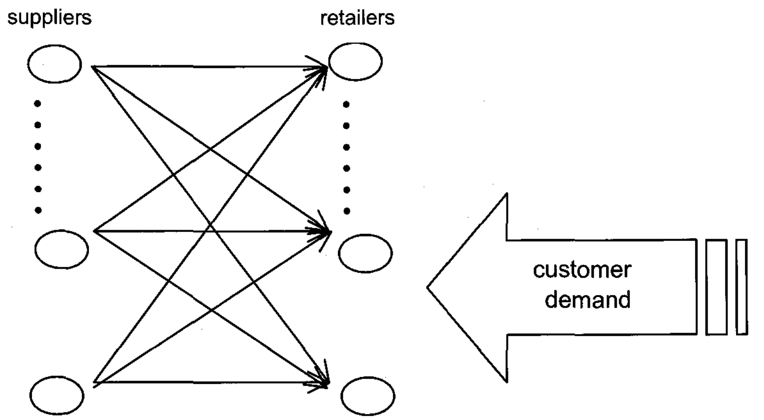

Figure 1. Model Structure

The chronology of this model is composed of a sequence of periods. During each period, the following sequence of events takes place:

(1) At the beginning of the period, each supplier chooses his wholesale price. All the suppliers produce a single product. Different supplier's wholesale price may be different, yet is equal for all the retailers.
(2) Then each retailer determines how many units of the product to order for this period.
(3) Retailers then place orders to their most preferred suppliers; and suppliers accept or reject retailer orders according to their capacity limitations and their preferences to these retailers; then the rejected retailers place orders again. After several rounds, no excess supplier capacity or retailer demand remains. We call this process the "matching process", and describe it in detail in section 2.2.
(4) Each supplier produces product units and satisfies retailer orders she has accepted.
(5) After received ordered product units, retailers determine their retail prices.
(6) Customers arrive. Each customer chooses a retailer and buys one unit of the product. All unsatisfied customer demands are lost. Retailers' unsold product is carried over into the next period without any loss in value.
(7) At the end of the period all suppliers and retailers calculate their revenues and costs, and update their current states.

The above basic settings sketch the model roughly. Following we will turn to the model details.

2.1 Customer's behavior

We adopt the discrete choice model [7] to represent customers' arrival and retailer-selecting behavior. This model is based on random utility maximization, which is well-established in the economic literature [8].

With this model, we assume that in each period, there is a population of customers, whose number is a Poisson random variable. The arrival of the customers is a Poisson process. When a customer arrives, he chooses a retailer from the set of retailers $N = \{1,2,\cdots,n\}$ to purchase one product unit. He associates a utility U_j with each retailer $j \in N$, which indicates his preference to this retailer. In addition, there is a no-selection option, denoted $j = 0$, with associated utility U_0, which means the preference of not purchase at all. He chooses the retailer with the highest utility and buys the product if possible. For example, if $Max\ U_j = U_2$, he chooses the second retailer. But if $Max\ U_j = U_0$, he returns home without buying anything. If he chooses a retailer which is out of stock, he makes a choice again.

The utility U_j consists of two parts: one part, denoted u_j, represents the nominal (expected) utility; the other part, denoted ξ_j, is a zero-mean random variable representing the difference between U_j and u_j. Thus $U_j = u_j + \xi_j$. Nominal utility u_j is determined by some identified factors that a customer cares when selecting retailers. In this paper, we define $u_j = \beta a_j - \gamma p_j$, $u_0 = \beta a_0$, where a_j is a quality index (such as service quality) and P_j is the retail price of retailer *j*. We assume the quality indexes (a_j) are equal for all $j(j \neq 0)$. a_0 denotes the quality index of no selection, which represents customers' unwillingness to buy. Generally, we assume that a customer prefers buying to not buying, i.e., $a_j > a_0$. β and γ represent the sensitivities of a customer to quality index and retail price respectively.

The noise part ξ_j represents the effect of those unidentified factors, such as retailer's location and customer loyalty. $\xi_j (j \in N \cup 0)$ for all the customers are independent identical (iid) random variables. We assume each ξ_j follows Gumbel distribution:

$$P(\xi_j \leq x) = \exp(-\exp(-(x/\mu) - \tau))$$

with mean zero and variance $\mu^2\pi^2/6$, τ is Euler's constant.

With the definition of utility U_j, we can see that retailers compete with each other in their prices. Retailers with lower prices will be more attract for the customers.

2.2 Matching Process

In each period, after suppliers have determined wholesale prices and retailers have determined order quantities, they will select partners to carry out transactions, i.e., retailers will choose suppliers from whom they will buy the product, and suppliers will choose retailers to whom they will sell product. We assume each retailer associates a preference with each supplier and chooses suppliers according to this preference; and the suppliers choose retailers in the same way.

The matching process is carried out in following steps:

(1) Each retailer submits a purchase order with the quantity he wants to buy to his most preferred supplier. When the supplier receives the order, she accept it temporarily and put it into a temporary order list.
(2) Each supplier handles her order list. If the total order quantity of all the orders in the list exceeds her capacity, she will begin to refuse or cut the quantity (e.g., cut the quantity 50 of an order to 20) of the most un-preferred orders until the total order quantity in the list equals her capacity.
(3) Those retailers who have unsatisfied quantities place orders to their most preferred suppliers who have not refused or cut the quantity of their orders during previous steps.
(4) The suppliers add the new orders in their lists and then handle lists that contain both new orders and orders they have temporarily accepted in former steps (thus some formerly accepted orders may be refused or cut quantity in this step). If there are still retailer orders being refused or being cut quantity, then go to step 3).
(5) When there are no retailer orders being refused or being cut quantity, all the orders in suppliers' lists are confirmed, and the matching process terminates.

The above matching process is based on Tesfatsion's deferred choice and refusal (DCR) algorithm [6], which extends Gale and Shapley's deferred acceptance algorithm [9]. It can be proved that the matching process will terminate in finite time, and the matching result of this process is stable (the definition of the matching result's stability can be found in [9]).

This matching process well represents the bi-directional selecting process between suppliers and retailers, especially in the e-business environment where the information of each supplier/retailer can more easily be obtained.

2.3 Supplier's and Retailer's Preferences

As we have mentioned in section 2.2, suppliers and retailers maintain preferences for each other and based on these preferences carry out the matching process. Suppliers' and retailers' preferences are determined by a few key factors that they care about.

For the suppliers, we assume they only care about retailers' loyalty. Here, we refer the work of Kirman and Vriend [10] and represent the loyalty with the degree of familiarity of the "face" of a retailer to a supplier. The more familiar a supplier with a retailer, the higher loyalty the supplier considers this retailer. The degree of familiarity of the "face" of a retailer is modeled by a weighted average of the number of past transactions of this retailer with this supplier, which is calculated as follows:

$$c_i^j(k) = c_i^j(k-1) + \gamma \cdot (\delta_i^j(k) - c_i^j(k-1))$$

$c_i^j(k)$ represents the familiarity of to retailer j to supplier i in period k. $\delta_i^j(k)$ is a 0-1 variable, equals 1 if supplier i and retailer j carry out transactions in period k, and equals 0 if they do not. If δ_i^j equals 0 in recent periods, c_i^j will decrease, which means supplier i gradually "forgets" retailer j. Parameter γ is the "learning factor" in reinforcement learning [11]. Greater γ means the supplier forgets the history more quickly, and cares more about recent transaction records.

For the retailers, they care not only a supplier's familiarity, but also the supplier's wholesale price. The degree of familiarity of a supplier to a retailer is calculated in the same way as the above. Each retailer also maintains a "sensitivity to price" parameter. When a retailer compares two suppliers, if the gap between their wholesale prices is less than the "sensitivity to price" parameter, he will neglect these two suppliers' price difference and only compares their familiarities; otherwise he will only choose the supplier with lower wholesale price.

2.4 Supplier's Price Decision

Suppliers should decide their wholesale prices at the beginning of each period. It is clear that neither wholesale price is too high nor too low is good. If it is too low, the suppliers will get little marginal profit; if it is too high, retailers will turn to other suppliers. Then what price should each supplier take to maximize her revenue in each period?

Generally, suppliers cannot use a formal optimization model to determine an optimal wholesale price with the lack of enough information. The quantity that a supplier can sell is the result of the complicated matching process among all the suppliers and retailers. It is of great difficulty to approximate how many units a supplier can sell with the absent of the information on the retailers' preferences, other suppliers' preferences, retailers' order quantities, etc. Here we assume the suppliers adopt an adaptive algorithm to adjust their wholesale prices in each period. Suppose a supplier's wholesale price in period t is $w(t)$, and it is updated in the following dynamics:

$$w(t+1) = w(t) + \delta_w \cdot sign(\pi(t) - \pi(t-1)) \cdot sign(w(t) - w(t-1))$$

where

$$\begin{array}{lll} sign(M) & = 1 & \text{if } M > 0 \\ sign(M) & = 0 & \text{if } M = 0 \\ sign(M) & = -1 & \text{if } M < 0 \end{array}$$

$\pi(t)$ is this supplier's revenue in period t. δ_w is the step-size of wholesale price, which is constant through time. This equation means that if revenue in this period is more than that in the previous period, then the price-change direction of the previous period is effective, and this period the supplier will still follow this direction; otherwise the direction should be reversed.

This dynamics is called "derivative follower strategy" by Greenwald and Kephart [2], and is widely adopted as an important strategy in e-business markets.

2.5 Retailer's Order Quantity Decision

Similar with the suppliers, retailers cannot use a formal optimization model to determine an optimal order quantity for each period. We assume the retailers adopt the same adaptive algorithm with the suppliers to adjust their order quantities. Suppose a retailer's order quantity in period t is q_t, and it is updated in the following dynamics:

$$q(t+1) = q(t) + \delta_q \cdot sign(\pi(t) - \pi(t-1)) \cdot sign(q(t) - q(t-1))$$

$\pi(t)$ is this retailer's profit in period t. δ_q is the step-size of order quantity, which is constant through time. The meaning of this equation is similar with that of the suppliers.

2.6 Retailer's Price Decision

After the retailers received product units, they determine their retail prices to maximize total profits for this period.

We assume the retailers believe the relationship between their customer demand d and their price p follows this equation:

$$d_i = a_i + b_i p_i$$

d_i is the customer demand that retailer i will face when his retail price is set to p_i. Coefficients a_i and b_i are constants. Based on the historical data of customer demand and retail price, retailer i can use linear regression to calculate $\hat{a}_i(t)$ and $\hat{b}_i(t)$, which are the approximations of a_i and b_i at period t, i.e., the relationship between $\hat{d}_i(t)$ (the expected customer demand of retailer i at time t) and $p_i(t)$ (the retail price of retailer i at time t) follows:

$$\hat{d}_i(t) = \hat{a}_i(t) + \hat{b}_i(t) p_i(t)$$

Then retailer i calculates the optimal retail price $p_i^*(t)$ through the following optimization model:

$$\max \pi_i(t) = \min\{\hat{d}_i(t), I_i(t)\} \cdot p_i(t) - C_i(t) - \max\{0, I_i(t) - \hat{d}_i(t)\} \cdot h$$
$$\text{s.t. } \hat{d}_i(t) = \hat{a}_i(t) + \hat{b}_i(t) p_i(t)$$

$\pi_i(t)$ represents the profit of retailer i in period t. The first part of this formula is retailer i's revenue when his retail price is set to $p_i(t)$. $I_i(t)$ is this retailer i's current inventory. $C_i(t)$ is retailer i's purchasing cost, which has already occurred. The third part is retailer i's inventory holding cost, and h is the inventory holding cost for each product unit.

Then retailer i adopts price $p_i^*(t)$ as his retail price at period t.

2.7 Retailer's Account

We assume each retailer keeps an account that records his total asset throughout the simulation. In each period, retailer's profit will be placed on this account. Retailer's profit equals the revenue minus the operation cost. Retailer's revenue is his sales income. Retailer's operation cost is composed of two parts – purchasing cost and inventory holding cost. Inventory holding cost occurs at the end of each period, and is caused by those unsold product units. For the suppliers, we assume they only care about revenue and do not consider costs.

In addition, each retailer is also charged with a fixed cost and a variable cost that is not considered in the calculation of profit. The fixed cost represents the costs that are constant through time such as depreciation cost, overhead cost; the variable cost is a fraction of the total asset, which represents the cost for managing the total asset.

If the account ever is depleted, the retailer is financially ruined and forced to leave the simulation.

3. LOYAL VS. COST-SAVING, AN EXPERIMENTAL STUDY

Based on this integrated model, we can study the two different types of strategies that are quite common for the retailers in electronic markets – "loyal" strategy and "cost-saving" strategy. These two strategies both sound reasonable – when suppliers fall short of production capacity, they will satisfy their "loyal" retailers with higher priority, thus the "loyal" strategy will benefit; when suppliers raise wholesale prices, those "loyal" retailers cannot switch to other low-price suppliers in time, thus the "cost-saving" retailers will benefit. However, it is hard to say which strategy is better then retailers adopting these two strategies compete with each other under complex business environments.

To study this question, we first discriminate two types of retailers – the "loyal" ones and the "cost-saving" ones, they both care about wholesale price and suppliers' familiarities, yet the "cost-saving" retailers put more emphasis on the former, and the "loyal" retailers put more emphasis on the latter. We assume the "sensitivity to price" parameter of "loyal" retailers is larger than that of the "cost-saving" retailers (which means that the "cost-saving" retailers are more sensitive to suppliers' wholesale prices). Then we let these two types of retailers compete with each other and watch what would happen.

3.1 Experimental Setup

We construct 6 supplier agents and 6 retailer agents in this model. In each period, the total customer number is a Poisson random variable with mean 1000. The parameters in the customer choice model are: $\beta = \gamma = 1$, $a_j = 7.06$, $a_0 = 4$, the variance of ξ_j is 1.18 (these values resemble those used by Xie and Chen [12], which well reflect the uncertainty when the customers are choosing retailers: the customers do appreciate retailers with lower prices, but the retailer with lowest price will not attract all the customers). The production capacity of each supplier is 80, and is constant through time. Each retailer's inventory holding cost per unit unsold is 0.2.

The initial 60 periods are "trial-play time", during which all the suppliers and the retailers do not count costs and revenue: only the retailers try different prices to become familiar with the market, and get initial approximations of the relationship between retail price and customer demand. During these periods, each supplier's wholesale price is set to 3.0, each retailer's order quantity is set to 80, and each retailer's retail price is set to $2 + \alpha \cdot 4$, where $\alpha \sim U[0,1)$.

At the end of the "trial-play time", all suppliers' and retailers' states are set to their initial values, except the retailers' approximations of the relationship between retail price and customer demand. Each retailer's initial on-hand inventory is set to 0; initial order quantity is set to 80; initial total asset is set to 150. Each supplier's initial wholesale price is set to 3.0. The step size of suppliers' price decision and retailers' order quantity decision are set to 0.1 and 5 respectively. The initial value of supplier's and retailer's familiarity is set to 0, and the learning factor is set to 0.2. The fixed cost of each retailer is set to 30, and the variable cost is 1% of the total asset.

The "sensitivity to price" parameter of the "loyal" retailers is set to 0.5, and that of the "cost-saving" retailers is set to 0.

Some experiments with a range of other parameter values do not lead to significantly different results from those described above. These values ensure that the retailers have a sufficient starting credit to reach more profitable prices unless in very competitive environments. The fixed cost, variable cost and marginal inventory holding cost give the retailers pressure to obtain more profits, but the pressure will not be too heavy to make the retailers bankrupt early on. And the model shows the same behavior as when examined with slightly changes on the other parameters.

3.2 Simulation Results

Under the above settings, we run the model 700 periods (the "trial-play time" is not counted) for several times with different random seeds, and concentrate on one single, randomly selected run of the model. All the runs of the model show that the main properties reported here are representative.

The time series of each retailer's total asset is presented in Figure 2. For presentational reasons, each observation in this figure and following figures is the average of 20 periods.

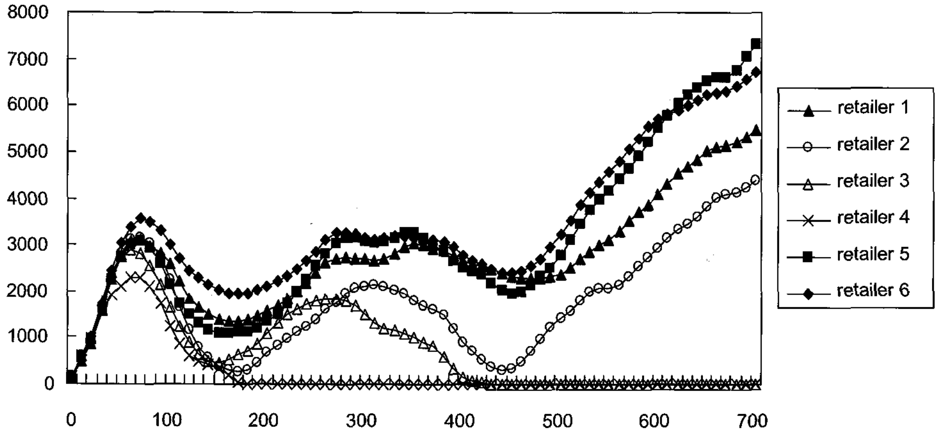

Figure 2. Retailers' total assets

It can be seen from Figure 2 that each retailer's total asset changes over time, and retailer 4 and retailer 3 bankrupts and leave the simulation successively. Note that in this simulation run, retailer 2, 3, 4 are "loyal" retailers, and retailer 1, 5, 6 are "cost-saving" retailers. Thus the "cost-saving" retailers perform better than the "loyal" ones: first, the bankrupted retailers are all "loyal" ones; second, in most time the "cost-saving" retailers' total assets are higher than the "loyal" retailers.

The performance of total assets is the cumulative result of the performance of profit in each period. From Figure 3 we can also see clearly that in most time the "loyal" retailers' profits are lower than the "cost-saving" retailers.

When designing the simulation, we have thought that both "loyal" and "cost-saving" strategies have their merits, but why the latter one actually performs better? To answer this question, we have to take a closer look at the decisions and states of the suppliers and retailers during the simulation.

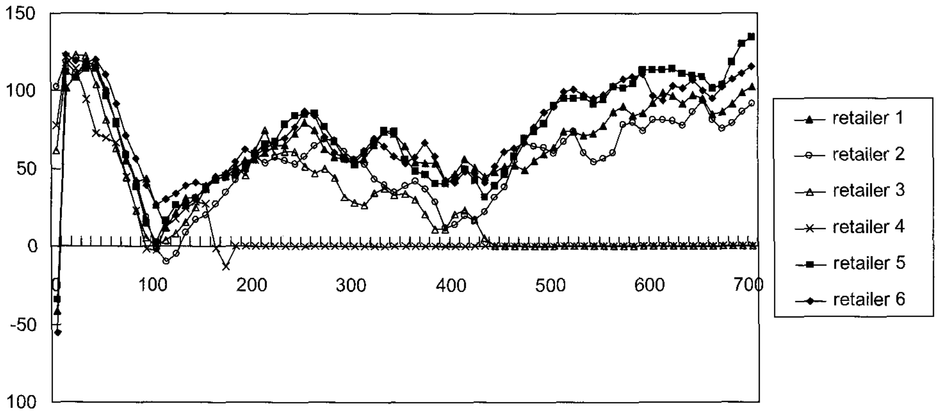

Figure 3. Retailers' profits

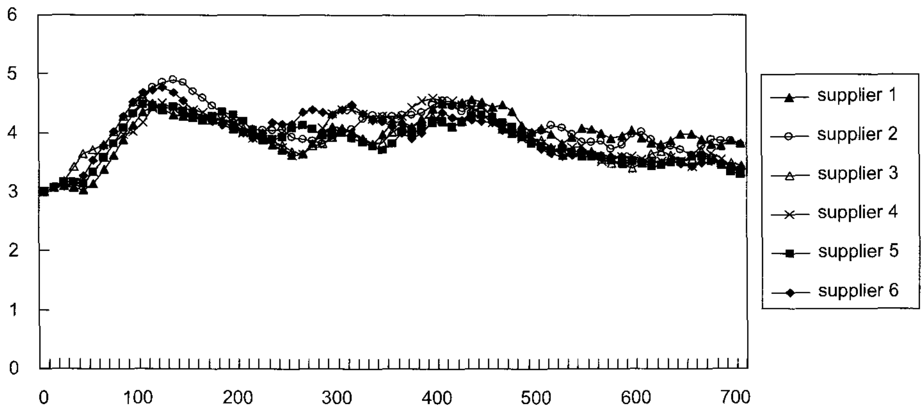

Figure 4. Suppliers' wholesale prices

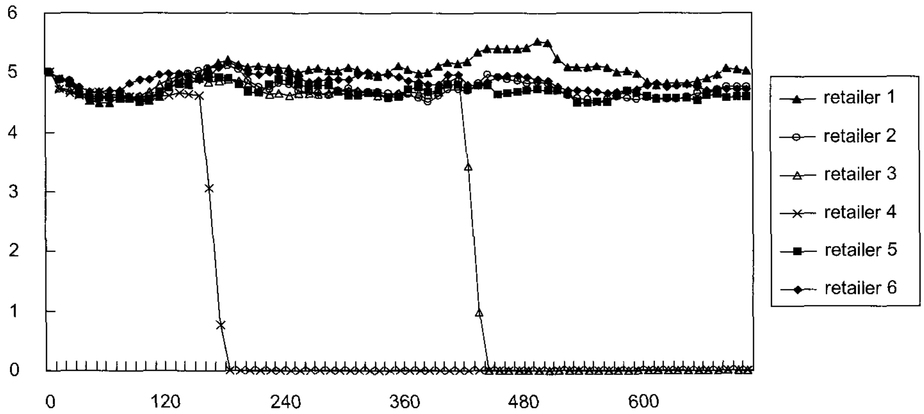

Figure 5. Retailers' retail prices

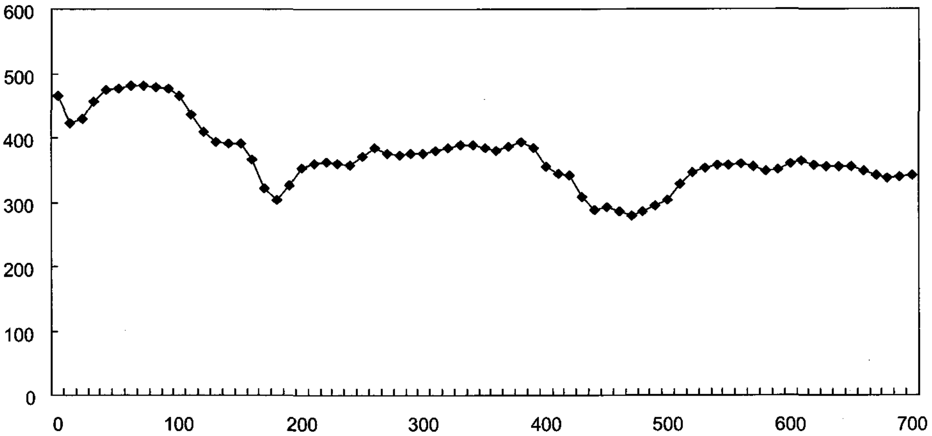

Figure 6. Total quantity of suppliers' sold units

Figure 4 presents time series of each supplier's wholesale prices throughout the experiment. From this figure we can see that suppliers' wholesale prices are rather high in most time, the highest approaches 5, and the lowest is over 3.3 (except the initial several periods). Such high wholesale prices caused even higher retail prices, which are presented in Figure 5.

From the results of our previous work [12] we can see that these retail prices are fairly high, and a great number of customer demands will be lost. This can be confirmed from Figure 6.

Figure 6 presents the total quantity of suppliers' sold units, which is approximately equals the total quantity of the units that retailers sell to the customers. We can see that in most time the total sold quantity is below 400, whereas the total number of customers in the market is about 1000. Therefore, there are quite a lot of customers that do not buy anything in each period. Furthermore, from Figure 6 we can also see that after period 120, the total quantity of suppliers' sold units is below 400, which is less than the suppliers' total production capacity (recall that in the experimental setup, we set each supplier's production capacity to be 80, thus the total production capacity is 480). This answers why the "cost-saving" retailers outperform the "loyal" ones – the suppliers always charge high wholesale prices, thus in most time they have excess production capacities, which leads to the advantage of "loyal" retailers does not exist – they cannot benefit from the higher priority of getting products from the suppliers. On the contrary, when their preferred suppliers raise wholesale prices, they cannot switch to other suppliers in time, and thus suffer higher costs. The disadvantage of the "loyal" retailers can be observed clearly from period 200-400 in Figure 3.

Why the suppliers charge such high wholesale prices? In section 2.4, we assume each supplier only adapts her wholesale price in order to get more revenue. This is a simplest and least computationally intensive dynamic pricing strategy, which do not base on any information that pertains by other agents in the system. According to Greenwald and Kephart [1], although without any communications, the agents that adopt such a strategy tend towards what is in effect a collusive state, in which all these agents charge the monopolistic price (this is called "tacit collusion"). Although the scenario that the suppliers face in this model is different with that the retailers face in Greenwald and Kephart's model, the suppliers still tend to the "tacit collusion" state, and all charge high wholesale prices.

The "loyal" strategy and "cost-saving" strategy are very common and both can be successful in real world business. However, when we put them together and compare them with simulation, the "cost-saving" strategy outperforms the "loyal" strategy. In this models, we attempt to set a scenario with shortage of production capacity (the total number of customers is about 1000, whereas the total production capacity is set to 480). whereas, because of the adaptive behaviors of the suppliers and retailers, total production capacity eventually becomes excess, and leads to the inferior of "loyal" strategy. These results can hardly be anticipated before simulation. From this we can see that testing and comparing different strategies through simulation before they are employed into practice are of great value under electronic business environments.

4. CONCLUSIONS

In this paper, we build an integrated model that consists of the trading process among suppliers and retailers and the marketing process that retailers sell product units to customers. This model is an integration of existing multi-agent B-C market models and B-B trade network models. Based on this model, we study two retailer strategies – "loyal" strategy and "cost-saving" strategy by letting them compete with each other. The result illustrates that it is quite important to understand and anticipate a strategy's performance in an integrated and more realistic model before it is employed into real business environments, and agent-based simulation is a powerful tool to carry out this work.

The result also shows that although "loyal" strategy and "cost-saving" strategy both can be successful in real world business, yet when they compete with each other, the "loyal" strategy will be inferior under the cases in which supplier's wholesale price and retailer's order quantity are adapted following the "derivative follower" dynamics. This dynamics is widely studied and applied in agent-mediated electronic business. It is possible that the "loyal" strategy may be superior when suppliers and retailers adopt other adapting dynamics. This will be investigated in our future work.

There are also other valuable extensions. In this paper, the only advantage of "loyal" retailers is their priority to get product from suppliers. We know that in real world suppliers usually offer more benefits to the loyal retailers, such as price discount and better services. Based on the integrated model of this paper, we can easily go further to study those more complex cases.

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