Proceedings of the 2003 Winter Simulation Conference
S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, eds.

AGENT-BASED MODELING AND SIMULATION OF STORE PERFORMANCE FOR PERSONALIZED PRICING

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ABSTRACT

In this paper, a simulation-based approach of optimizing a grocery store's performance is discussed. Currently, most of the grocery stores provide special discounts to their customers under different loyalty card programs. We believe that a more determined approach such as personalized pricing could enable retailers to optimize their store performance. The objective of this paper is to determine the feasibility of personalized pricing to optimize store performance and compare it with the traditional product-centered approach. Each customer is modeled as an agent and his/her shopping behavior is obtained from transaction data using factors such as customer's product consumption rate, brand loyalty and price sensitivity. Then, the overall shopping behavior is simulated and the store performance is optimized. The results showed that personalized pricing outperforms the traditional product-centered approach significantly. It is expected that successful implementation of this work will impact grocery retail significantly by increasing the customer satisfaction and profits.

1 INTRODUCTION

As the competition in retail industry increases, retailers are becoming much more obligated to optimize their store performance. For sectors that have tighter profit margins and where customer loyalty is highly dependent on the prices offered, it becomes crucial to understand the customer behavior. Grocery retail is one of these sectors. Currently 70% of all U.S households participate in some type of loyalty card program for grocery shopping (AC Nielsen, 2001). However, these loyalty programs apply *blanket couponing* technique by giving same coupons to their subscribers. This means that the information about each individual's shopping behavior is underutilized by aggregating and averaging the data and assuming that most people have similar product and price preferences. However, consumers are different in nature and each individual has his/her own preference of products and price levels. Therefore modeling each customer separately and providing him/her individual coupons could improve the store performance. This type of offering is also known as *one-to-one marketing* in the literature (Peppers and Rogers, 1997).

In order to realize the feasibility of individual pricing concept, let us assume that it is possible to record the shopping behavior of each customer of a grocery store - how often they come into the store, what they buy and how often, for which products they are especially price sensitive. This information can be utilized by building a predictive model for each individual. Although this type of information is currently being collected at the checkout by grocery stores, it is not being utilized.

Our proposed approach assumes that using sufficiently rich transaction data, it is possible to capture each regular customer's shopping behavior. Then, individual models (agents) can be generated using this behavioral information to simulate the overall shopping behavior. The inputs for this agent-based simulation system can be provided by a store manager based on a strategy defined by the relative importance of three factors: *profits*, *sales volume* and *customer loyalty*. Finally, the system can use agent-based simulations to identify the set of discounts for each customer. Figure 1 shows the overall approach.

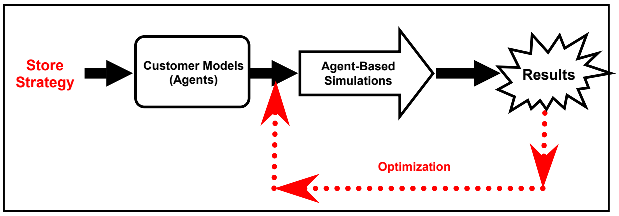

Figure 1: Outline of the Proposed Approach

In our early work (Baydar, 2001a), we have discussed a conceptual framework for personalized pricing and suggested that using agent-based simulations would be useful to analyze and optimize grocery store performance. Furthermore, we have discussed the preliminary results of an optimization algorithm which can be used for personalized pricing (Baydar, 2001b). In this paper, we will describe our implemented work and its results in detail. Our results showed that one-to-one marketing outperforms the traditional blanket couponing approach significantly. We expect most grocery stores will start targeted couponing in the near future. This approach will even be more important if, in the future, the use of hand-held devices equipped with Bluetooth or other wireless connections will become widespread. Shoppers will use them to get personalized information about the products they see and even to purchase them. In this context, dynamic individual promotion of products will become a competitive necessity.

2 PROPOSED APPROACH

Our approach uses *agent-based* (Ferber, 1999) modeling and simulation which is different from the more focused store optimization research found in the literature. In agent-based computational modeling, only equations governing the micro social structure are included (i.e., shopping behavior of each individual). Then, the overall macroscopic structure of the system grows from the bottom-up. Typically for grocery store optimization, revenues, costs and sales volume are taken into account as complex mathematical equations. However in agent-based approach, these values are determined by summing up each customer's shopping activity such as his/her shopping frequency and spending. The implementation steps of our approach are as follows:

- Model each customer's shopping behavior from transaction data.
- Create agents using these models.
- Perform agent-based simulations and optimize the store performance for a given store strategy.

2.1 Problem Statement and Formulation

A grocery store manager has to decide on the store strategy based on the *relative* importance of three goals: *profits*, *sales volume* and *customer satisfaction*. These goals are contradictory (i.e., a store manager could maximize customer satisfaction by reducing all prices to zero). Therefore, what determines the overall store performance is the difference between each objective.

One way to solve this multi-objective optimization problem is using a weighted sum approach and turning it into a single objective optimization problem. Now the objective is:

$$\text{Maximize } f(x, y, z) = \mathrm{w}_1 * x + \mathrm{w}_2 * y + \mathrm{w}_3 * z \qquad (1)$$

where:

x = profits
y = sales volume
z = customer satisfaction

and w_1, w_2 and w_3 are the appropriate weights determined by the store manager.

Since we are using agent-based models, there is no way of exploring x, y and z dimensions directly. Therefore, they are not the decision variables. The decision variables of this problem are the set of discounted products and discount values for these products. Both of these variables are different for each customer since we are giving individual discounts. Therefore if we have n customers, this assumption enables us to write the objective function for each customer as:

$$\text{Maximize } f_i(x, y, z) = w_1 * x_i + w_2 * y_i + w_3 * z_i \qquad (2)$$

Subject to:

$P_i = \{\mathrm{P}_1, \mathrm{P}_2, \ldots \mathrm{P}_r\}$
$D_i = \{\mathrm{D}_1, \mathrm{D}_2, \ldots, \mathrm{D}_r\}$

where:

i = Customer ID
n = Total number of customers
r = Size of the product and discount sets (i.e., number of coupons)
P = Set of products containing product ID's.
D = Set of discounts containing the coupon face values

For a typical grocery store, there are about 1000 customers and 50000 products at SKU level. Our previous analysis showed that (Petrushin, 2000) a typical customer buys nearly 300 different products a year. Even with this reduction, the size of our search space still stays large enough to find optimal discount values for each customer.

2.2 Problem Modeling

There are two types of models that we consider for this problem: *store model* and *customer model*.

2.2.1 Store Model

The store model consists of several parameters such as:

- The number of products.
- Quantity stored from each product.
- Sales price of each product.
- Product replenishment rate.
- Replenishment threshold.
- Replenishment size.
- Daily stock keeping cost of each product.

The parameters about replenishment determine the supply rate of a product (i.e., truck arrival rate). Assume that the rate is 4 days, the threshold is 200 items and the size is 300 items. Then the stock is checked once in every 4 days and if the amount in the stock is less then 200 items, another 300 items are added. In addition to measure inventory costs, a daily stock keeping cost for each product is used.

2.2.2 Customer Model

Each customer is modeled with several shopping properties such as:

- Shopping frequency.
- Price sensitivity for each product.
- Buying probability for each product.
- Quantity purchased from each product.

Shopping frequency is modeled with parameters of first day of shopping (phase), frequency of shopping and probability of arrival at the expected day. For example a customer may prefer shopping once a week on Saturdays with 90 % probability. During the simulations, a uniform probability distribution function is used to sample the parameter of probability of arrival.

Price sensitivity is defined for each product since a customer may have different shopping behavior towards each product. For example a person may prefer buying milk all the time regardless of its price but on the other hand he/she may be very price sensitive about beef.

A person's buying probability can be modified by giving a discount. This change is formulated as:

$$\Delta BP = (1 + \Omega(k * d)) , \quad (3)$$

where:

ΔBP is the change in buying probability,

d is the discount rate,

k is the price sensitivity and

Ω is a normal distribution function with mean and standard values as *k*d* and *1/3*(k*d)* respectively.

In addition to these properties, there are two behavioral rules:

- As customers buy a product continuously, they start building loyalty towards that product (i.e., buying probability increases).
- If customers find the prices high or can not find a product from their list, they get frustrated and their probability of arrival decreases.

2.2.3 Developed System

The developed simulation environment is used for evaluating and optimizing store performance by simulating "what-if" scenarios for different pricing strategies. Fig.2 shows the architecture of the system. Inputs and outputs are shown in circles, while system components are shown in squares.

2.2.3.1 System Inputs

The system has three types of inputs. These are product price variables, customer models and user inputs for simulation.

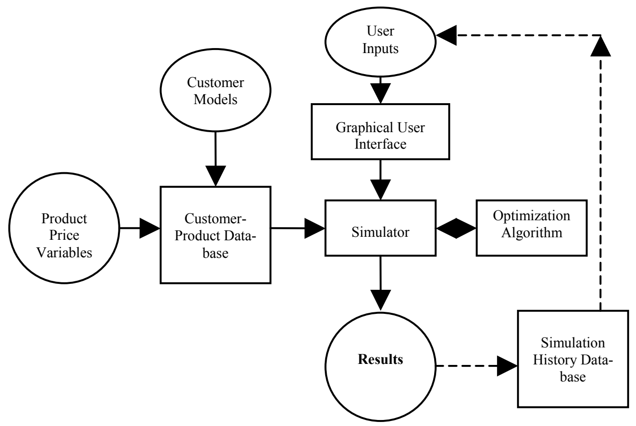

Figure 2: Architecture of the System

2.2.3.1.1 Product Price Variables

A product has three price variables. These are the *purchasing cost* and the *stock keeping cost* (inventory cost) and the *sales price*.

2.2.3.1.2 Customer Models

Customer models are the mathematical representations of shopping behavior for each customer as discussed in the problem modeling section.

2.2.3.1.3 User Inputs for Simulation

The user inputs for the simulation are:

- Store strategy.
- Number of days to simulate.
- Replenishment cycle of the products.
- Replenishment threshold of the products.
- Replenishment size of the products.
- Number of times to simulate one shopping day (Monte-Carlo simulation size).

The parameters about replenishment determine the supply rate of a product and discussed in the store modeling section. Since shopping behavior is probabilistic, we have to simulate the shopping process several times to obtain average output values. The user can enter this value (the number of times to simulate) as an input. The simulator uses Monte-Carlo simulation to calculate the outputs. Fig.3 shows the inputs screen.

Apart from these inputs, the user can supply either

- a store strategy to be optimized (in terms of *profits*, *sales volume* and *customer satisfaction*) or,
- individual discounts determined by the user to simulate and compare with the store performance before discounts.

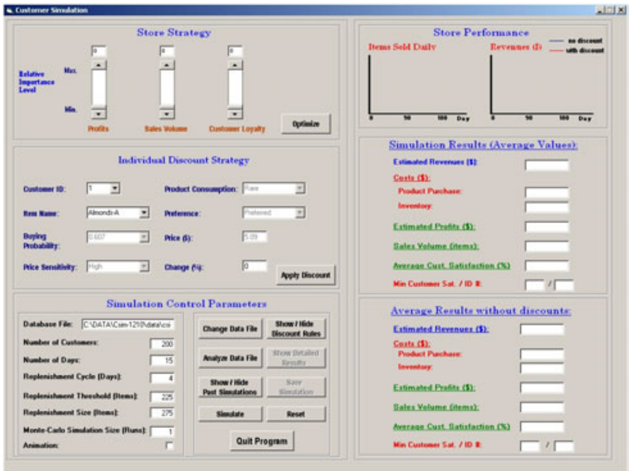

Figure 3: Inputs Screen

2.2.3.2 System Components

The system has four components. These are:

- Customer-Product Database.
- Simulator.
- Optimization Algorithm.
- Simulation History Database.

2.2.3.2.1 Customer-Product Database

Customer-Product Database holds the customer models and product price variables explained in the previous section.

2.2.3.2.2 Simulator

The simulator takes input parameters for the simulation and simulates the shopping behavior for a specified period of time. A typical simulation of a shopping day is as follows:

1. Customer comes to the store.
2. Customer looks at the prices of the items in the store.
3. Customer buys products based on their buying probability, which is influenced by discounts.
4. If the item which customer is looking for is out of stock, he/she gets frustrated and the satisfaction level drops. This also affects his/her next time arrival to the store.
5. Customer leaves the store.

This procedure is applied for all customers who come to the store on the same day. In simulation, the process parameters are each customer's shopping behavior, which consists of their price sensitivities, buying probabilities, likelihood of arrival to the store, etc.

2.2.3.2.3 Optimization Algorithm

As discussed in our previous work (Baydar, 2001b), a hybrid optimization algorithm, which uses parallel simulated annealing and evolutionary computation is used for the store performance optimization. If the user defines an overall strategy (i.e., maximizing profits and customer loyalty), then the algorithm starts searching the best discount set for each customer to maximize the objective function.

2.2.3.2.4 Simulation History Database

It is used for storing the outputs of previous simulations.

2.2.3.3 System Outputs (Results)

The following outputs are obtained from the system as also shown in Fig.4:

- Average and standard deviation values for estimated revenues, costs (both inventory and product purchase), sales volume, customer satisfaction.
- Sales and profits performance compared to the performance without discounts.
- Inventory change of each product over time.
- Inventory cost of each product.

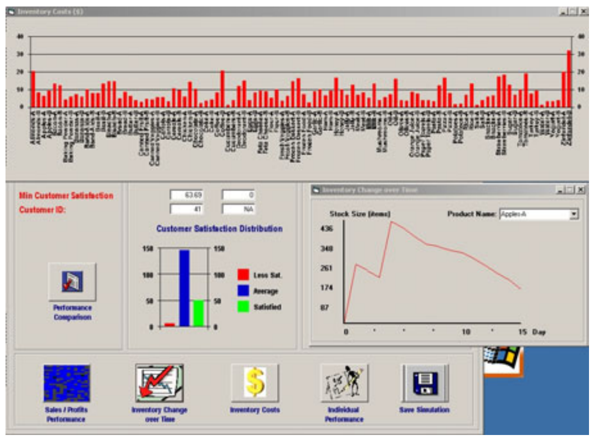

Figure 4: Detailed Results Screen

For each customer:

- Discounted products and discount amounts.
- Average satisfaction level.
- Change in average spending compared to the one before discounts.
- Percent change in average satisfaction.
- Average quantity bought from each product.

3 CASE STUDIES

In order to compare the two approaches, we have built a sample database consists of 200 customers models with 100 products from a major grocery store's transaction data and investigated the performance difference against same allowance on promotion spending.

Let us assume that as a promotion strategy for two weeks, we would like to spend $1,150 on the discounts and want to maximize the customer satisfaction. One possible approach is using a traditional approach such as giving 10% discount on top-10 favorite products. Another approach is by following the personalized pricing strategy, giving 10 coupons to each individual at the store entrance with different discount levels on different products.

Both approaches were simulated using the developed environment and Fig.5 shows the results.

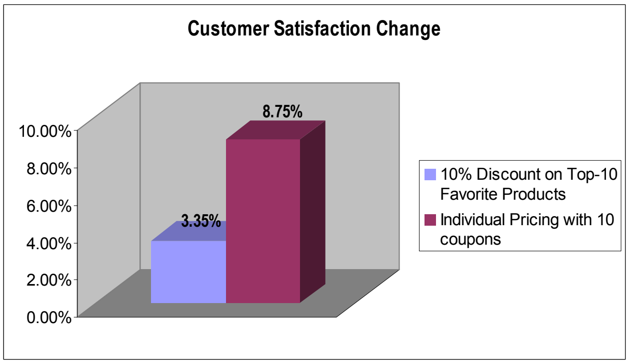

Figure 5: Results of the 1st Case Study

It was observed that individual pricing outperforms the traditional approach significantly by increasing the customer satisfaction by 8.75%.

In the second case study, we have compared the amount needed on promotions for the same change in customer satisfaction. Now the question is: "As a store manager, if I want to increase the overall customer satisfaction by 3.35% how much should I spend on discounts?"

We know from previous caser that using traditional approach, such as giving 10% discount on top 10 popular products, it costs $1,150. However, with the individual pricing approach, the optimization results showed that same amount of change can be achieved by giving 5 coupons this time and spending less than 1/3 of the traditional approach. The following figure shows the results.

Figure 6: Results of the 2nd Case Study

These case studies showed that personalized pricing outperforms the traditional product-centric approach significantly by increasing customer satisfaction and profits.

Although the numerical results on customer satisfaction and profits depend on the nature of the shopping behavior of the customer population, we believe that for other cases personalized pricing will again outperform the traditional approach since it optimizes the store performance by looking at each customer's shopping behavior.

4 DISCUSSIONS AND CONCLUSION

The continuously increasing competition in retail industry pushes companies into a position of searching better ways to communicate with their customers. Grocery retail is one of these sectors which have tight profit margins. Currently, most of the grocery stores provide a type of loyalty program which provides same discounts to subscribed customers. However this product-centered approach is efficient up to some level since customers are being divided into several segments and treated as a part of the segment rather than an individual. We believe that a more determined approach, such as personalized pricing will enable grocery stores to increase their customer satisfaction levels without sacrificing too much of the profits.

Our discussed approach is based on agent-based modeling and simulation, which models each customer's shopping behavior to simulate the store performance. First, each customer is modeled using the available transaction data. Then based on a given store strategy, simulations are performed to optimize the store performance by giving individual discounts.

We have developed a system to simulate the shopping behavior and optimize the store performance. We have conducted several case studies using this environment and compared the performance of two approaches. The results showed that personalized pricing outperforms the traditional product-centered approach significantly. It is believed that the successful implementation of the discussed research will impact the grocery retail significantly by increasing the customer satisfaction, sales volume and profits.

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