In-store One-to-one Marketing

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With the proliferation of electronic media, one-to-one marketing has become more accessible and it is moving toward widespread adoption. It is particularly important for retailers, where several forms of one-to-one marketing are performed either before or after a shopping experience. One-to-one marketing during the shopping experience is still elusive, however, with recent technological advances it could soon become reality. We show how it can be carried out by using either personal digital assistance devices and wireless communication, or radio frequency identification. The main concept is based on providing coupons during a shopping experience and then routing the customer within the facility to possibly redeem them. The novel approach of selecting the coupons based on the already purchased goods enables one-to-one marketing during the actual shopping trip. Several models are presented based on the underlying technology and the option of a loyalty card. The concepts are computationally evaluated based on data obtained from a grocery store. They allude to substantially increased revenue by the store.

1. Introduction

In one-to-one marketing, marketing material is targeted and customized for a particular customer and it therefore takes into account his or her particular individual needs. As such it focuses on economies of scope rather than scale. While selected forms, e.g. mail-in catalogs, of one-to-one marketing date back many years, it is in the past few years that it gained much traction due to modern information technology. Customer tailored email marketing, see e.g., Byron (2005), and cross selling through customized web sites, (Amazon.com is considered a pioneer in this area) are now established marketing practices.

In its infancy are one-to-one marketing opportunities exploring the near field communication (NFC) protocol, which enables secure short range communication among devices such as cellular phones and terminals. So-called contactless smart cards (e.g., payments are made by simply waiving the card) are slowly penetrating the market. In particular, cellular phones are well suited for performing one-to-one marketing tasks. Consider, for example, a payment made by using an NFC enabled cellular phone. During the payment transaction, the vendor's NFC enabled terminal can easily pass along a web site link with promotional material. Trials have also been performed on establishing communication between a billboard and a passing of a customer carrying a smart phone. Other applications are listed in O'Connor (2006).

Another, well established and more traditional form of one-to-one marketing, used by high-low pricing retailers, are the coupons. We are not referring to manufacturer coupons (e.g., peel-off or in-box coupons, or coupons distributed by newspapers or magazines), but coupons distributed by the retailers. Using scan or point-of-sale data, retailers can target coupons to individual customers. A big limitation of such a strategy is the fact that the coupons are distributed to a customer either before the actual shopping experience (mail-in coupons), or after during the check-out process. So far, one-to-one marketing during the actual shopping experience is elusive. The potential revenue increase can be substantial since approximately 60% of the purchasing decisions by customers in grocery stores are made in the store, Kahn and McAlister (1997).

The main purpose of this research is to provide the modeling and algorithmic framework for coupon distribution during a shopping trip. By using real world data from a grocery store we also quantify potential revenue implications. Our framework is based on a deployment of two nascent technologies: wireless personal mobile devices (e.g., smart phones or personal digital assistants) and radio frequency identification (RFID). The former technology allows the exchange of information between the device and a store server. We have explicitly in mind a potential shopping list. The latter technology enables real time tracking of every individual item by affixing a small tag or transponder to every item. In particular, interrogators mounted on shelves (called also smart shelves) can query the items already purchased by a customer that are in the shopping cart. Basic facts on RFID are given later in this section.

Under the first scenario, we assume that shoppers enter a retail store with a personal mobile device preloaded with the shopping list. The list is next beamed to a central store server, which then computes a shopping path or route and communicates it back to the customer. The novel idea is to build into the route locations with promoted items. These locations are computed based on the shopping list and/or based on the historical purchasing habits of the customer (e.g., if a loyalty card program is in effect). The basic model finds a route that maximizes the store's expected revenue based on the likelihood of the customer purchasing items on promotion subject to the customer's aggregated utility over the route above a given threshold. The expected revenue is modeled based on discrete choice models. In the second scenario, which requires item level tagging and smart shelves, it is assumed that an interrogator, which is part of smart shelves, reads the already purchased items of the customer by interrogating the tags attached to these items in the shopping cart. Based on current basket information, a different device can then issue coupons to the customer and shows him or her a good route in order to redeem the coupons. As in the previous scenario, we use discrete choice modeling and we maximize the store's expected revenue. The new component here is the addition of a market basket analysis at modeling the expected revenue. Clearly, in a potential implementation of this strategy, only selected locations in the store should have the coupon issuing capability.

Given the store's expected revenue of an impulse purchase via coupon redemption, the underlying model for computing the route is the selective traveling salesman problem with time windows. The objective is to find a tour maximizing the store's expected revenue subject to the customer's aggregated utility on the route above a predefined value. Time windows model, for example, the fact that frozen food should not be present early in the route.

In addition to the novel concept and modeling, we also conduct a computational study by using a major grocery store. The store layout and customer historical purchases were obtained from the store, while promotions were simulated. The computational study shows large potential improvements in revenue.

To summarize, the main contributions of this study are as follows.

- By using two technologies, we develop concepts for in-store one-to-one marketing. The most important fact here is that marketing is performed during the shopping trip, and not before or after as is currently the case.
- Based on these concepts, we use both the standard logit model and a market basket model to show how to apply discrete choice modeling in computing the expected value of coupon redemption. When discussing the various scenarios, we consider two possible alternatives: the presence of a loyalty card program, and the ability to track shopping carts in the store.
- We show how to use the selective traveling salesman problem in order to compute a favorable shopping route of a customer.
- The computational study based on real world data reveals substantial potential revenue improvements.

The importance and relevance of our work has also recently been addressed in the Business Week (December 2007), where importance for in-store one-to-one marketing during a shopping experience is stressed. On the online portal www.shopbloom.com of Food Lion LLC, customers can create personalized shopping lists and obtain a printout of the aisles they need to visit. While this is convenient for the shopper, it decreases the revenue to the store since knowing where to go, shoppers would buy less on impulse. By using our approach this is circumvented since shoppers are deliberately routed to certain locations and thus impulse buying is encouraged.

The document is structured as follows. In Section 2 we provide the general framework, including all studied scenarios. All models are described in Section 3. This section also gives the underlying solution methodologies and algorithms. Section 4 is devoted to the computational experiments. We conclude the introduction with a quick tutorial on RFID and a literature overview.

1.1. Literature Review

The discrete choice models have been of interest to researchers and practitioners for a long time due to their applications. They are used in our work to compute the probabilities of buying products. An important approach to model customer's discrete choices is the multinomial logit (MNL) model, Boztug and Hildebrandt (2007) and Li (2007). In multinomial logit models, random utility maximization is applied to pick the best alternative among all available alternatives. Multinomial logit models are a generalization of the binary logit model, in which customers have only two alternatives, Cox (1972). On the other hand, if the utility follows the normal distribution, multinomial probit models are used. While the normal distribution is attractive in practice, it does not provide a closed form solution, McCulloch and Rossi (1994). An alternative modeling approach to MNL is the nested logit model, which allows correlations among alternatives in the process within a group or nest, Guadagni and Little (1998). Customers make multi-category choices during each shopping trip. We study the multi-category decision-making process, in which alternatives in different categories are correlated. Multi-category choice models are the extension of traditional single category models, Chiang (1991), Chintaguta (1993), Chong et al. (2001). Among multi-category models, Mehta (2007) treats purchase incidence and brand choice as distinct decision stages. A detailed state-of-the-art overview of multi-category models is provided in Seetharaman et al. (2005).

The concept of promotions is the driving force behind our work. There are many reasons that retailers run promotions, such as rewarding brand loyal customers and meeting short-term sales targets, Cutler (2000). As expected, a retail promotion with respect to a specific brand accordingly increases sales either through store substitutions across available stores and/or a brand substitution within a store, Kumar and Leone (1988). Issuing coupons is an important approach for price promotion. Traditional coupons such as those distributed by newspapers and magazines are appealing to manufacturers while in-store “surprise” coupons catch retailer attention because of many benefits, such as a subsequently increased basket size by unplanned purchases and better prediction of the frequency and type of impulse buying, Heilman et al. (2002). The impacts of coupons on customer's behavior in services such as repeated purchases and purchase timing are studied in Taylor (2001). From the standpoint of a retail store, there are at least three levels that need to be considered in a promotion decomposition model when evaluating a promotion: cross-brand, cross-period, and category expansion effects, Van Heerde et al. (2004). The common thread of all these works is that promotions in terms of coupons are effectively and frequently used in retailing. Customers' motivations for impulse buying are studied in Hausman (2000). Some impulse buying is unnecessary, but often such buying is rewarding to the customer. Relationship between store price promotions and customer purchases is investigated in Mulhern et al. (1995). Increasing customers' exposure to categories by extending shopping times and thus dwell time in the store also increases the probability of making impulse buying, Hui et. al (2007). As shown by our work, the effect of impulse buying can be even more pronounced in one-to-one marketing.

2. Framework

We consider two main scenarios: (1) the store does not have an RFID deployment, or (2) the store has an RFID deployment at item level as shown in Figure 1. If RFID is not deployed, then in order to perform one-to-one marketing a different technological setting is assumed. With a personal digital assistant or any similar device having a wireless capability and text editing features, the customer in the first scenario preloads her shopping list and is willing to share it with information systems in the store. The main idea is to improve the shopping experience by guiding the shopper through the store. The loyalty card is an additional possible distinctive component in this scenario. The store can better predict shopper's needs and habits, subsequently better serve the shopper by using her past purchases recorded through the loyalty program. In the second scenario, the store is RFID deployed with smart shelves and item level tagging is used. We also assume that certain locations in the store have coupon issuing capabilities. The concept here is that with the help of RFID, the on-shelf interrogator would detect the already purchased items in the shopping cart and then coupons would be distributed to the customer on the spot through the coupon issuing device. The on-shelf system can also recommend a route pass the locations with recommended coupons. Besides the functionality of smart shelves, which enables us to recommend promotional products and display the route, the ability of tracking shopping carts is beneficial in this scenario for preventing from frequently issuing coupons to the same shopper during the same trip. Similarly, the loyalty card program is a plus here. The goal in both scenarios is to entice impulse buying. We next discuss in greater details these options.

2.1. Shopping Lists

There are different types of shopping lists, Newcomb et al. (2003). The shopping list can be created by the store based on shopper's past purchases. If a shopper frequents the store, the store’s information system could be able to predict her needs. On the other hand, a shopper can create the shopping list by herself. It can also be possible to combine the two strategies. We focus here on the case where the customer creates the personal shopping list by herself. The other case does not require major changes to our models and concepts. Upon entering the store with a preloaded shopping list on a personal digital assistant that has wireless capabilities, the list is beamed to the store's information system. The information system receives the shopping list and

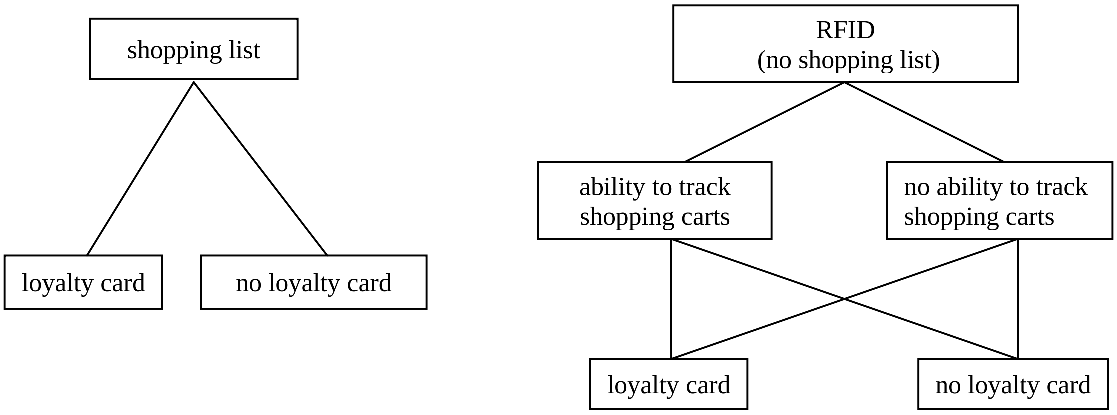

Figure 1: Scenarios based on various technologies

based on it computes a favorable route through the store. Furthermore, stores run promotions on a regular basis and thus the customer can deliberately be routed to pass selected locations with products on promotion (or, e.g., tasting booths). The ultimate goal is to induce impulsive buying.

The objective of the proposed route is to maximize the store's expected revenue, which is defined as the probability of buying promotional items multiplied by the price of the products. Clearly, the generated route would potentially create a negative impact on the customer if her anticipated shopping time is substantially increased. It is for this reason that we impose the maximum travel time on the proposed route. In addition, it is desirable that selected items are towards the end of the shopping experience, e.g., frozen food. At the end, the recommended computed route is sent back to the shopper's device and appropriately displayed. The entire concept is shown in Figure 2.

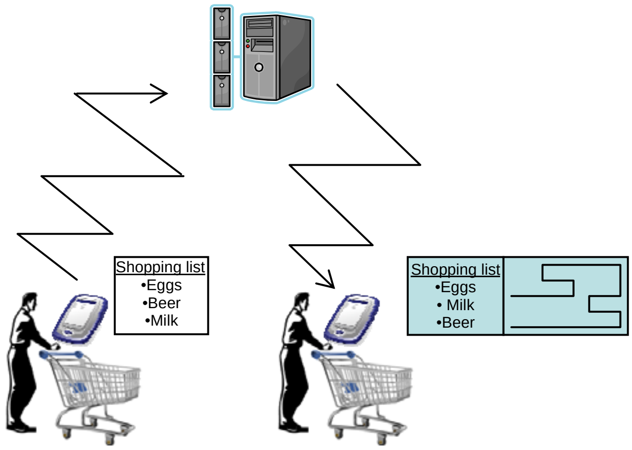

Figure 2: Store entrance with a shopping list

2.2. Smart Shelves and Radio Frequency Identification

In a smart shelf system, products are tagged by RFID transponders to give them a unique identification. Selected shelves are equipped with an antenna system and interrogator unit, which are connected to an information system. Every interrogator has the ability to detect transponders within a certain range and read their identifications. Through the signal strength, an interrogator can also conclude if the items are on a shelf or in a shopping cart. Besides smart shelves, we also assume that selected locations within the store are mounted with coupon issuing devices and user friendly displays. Let us consider a customer with a shopping cart located near a point with such devices. The customer has already purchased selected items and these can be identified by smart shelves. This information can then be communicated to an information system. In the next step, by considering the already purchased items and current promotions, a path can be computed that routes the customer towards selected promotional items. In the final step, the selected coupons would be issued by the device and the recommended route displayed. Similar to the previous concept, the goal is to maximize the expected revenue. In this case, the probability of the customer buying a promotional item is based on the market basket analysis, i.e., it takes into account already purchased items. The recommended route travel time is bounded above by a number.

2.3. Presence of Loyalty Cards

A loyalty program is commonly used in retailing to enhance the overall value-proposition and to improve customer loyalty. It is supposed to motivate buyers to make next purchases through discounts and potential faster service. A loyalty program also allows the store to track shopping patterns and habits of individual customers.

In our context, loyalty cards play a role in probability estimations. In presence of a loyalty program and the participation of the customer in such a program, discrete choice models presented in Section 3.1 are applicable. As a result, accurate probabilities can be derived. In absence of a loyalty program, on the other hand, a customer has to be considered as "generic" and thus indistinguishable. Discrete choice can still be used but its accuracy decreases.

2.4. Ability to Track Shopping Carts

Besides smart shelves, RFID has other potential benefits in retailing. We are interested in so-called smart shopping carts. A smart shopping cart resembles the normal one except that it is equipped with a tracking device. Such carts can be tracked throughout the store and thus routes of individual shoppers can be identified. This device can either be transparent to the shopper or it can offer a display. Additionally, each shopping cart is tagged with a unique identifier.

There are two alternatives for tracking shopping carts. The first one is the installation of a fixed number of interrogators into the floor, Larson et al. (2005). Shopping carts equipped with transponders and moving within the store can then be detected and the relevant information is communicated to an information system, which can then reconstruct the entire route for a customer at any point in time. The second alternative is the establishment of a real-time locator system. These systems use tagged objects (shopping carts in our case) and the well-known triangulation technique to establish the location of objects. Real-time locator systems have been recently installed in several industries, e.g., hospitals, Sokol (2005), and ports, Cho (2006).

In our context, shopping cart tracking would be beneficial in conjunction to the smart shelf setting. Consider two locations equipped with coupon issuing devices as shown in Figure 3.

Without the ability to track shopping carts, duplicate coupons could be issued to the same customer. This can clearly be annoying to the customer. On the other hand, with the shopping cart tracking ability, at the second location the information system can account for only the items purchased between the first and the second location and thus coupons can be issued only based on these items.

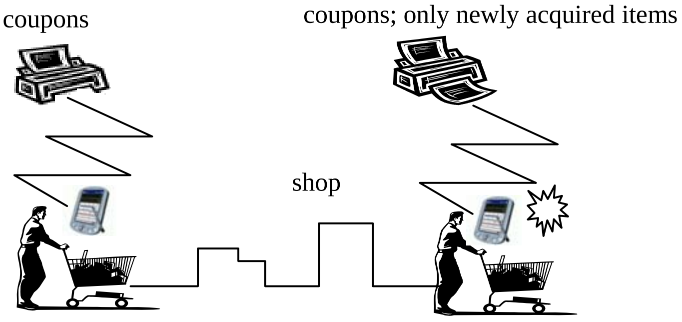

Figure 3: Coupon issuing under shopping cart tracking

3. Models

In this section, we provide the models. We give the framework and then point out the differences between various scenarios discussed in Section 2. An important component of our models is the discrete choice model. We need to model the probability of a potential customer buying a given product in a category. More importantly, we study the interdependency among product choice decisions. We also incorporate the current given basket of categories of a customer into the model.

3.1. Models

Prior models address either single-category brand choice or joint-category purchase incidence. On the one hand, single-category models ignore cross-category interdependence by independently maximizing utilities over individual categories. On the other hand, the standard multi-category choice models, e.g., Chib et al. (2002), address joint-category purchase incidence within a shopping trip at the level of categories. The brand selection decisions are omitted in basket analyses. Depending on a specific context of a choice problem, the multiple category decision problem can be perceived as either a collective choice or a sequence of choices (categories) in some order. Harlam and Lodish (1995) is of particular interest since it is a sequential model and it includes variables to reflect the dependencies among choices of items within the same shopping trip. We normally observe the final outcome of consumer's choices and not the partial steps. As a result a full holistic model would be very hard to calibrate. Instead, we apply the idea of sequential choice decisions and model the customer's overall choice process by two separate stages that are connected by conditional probabilities. In each stage, we apply the multinomial logit model and derive the conditional probabilities.

We consider a customer's decision process as a tree-structure where the brand choice is nested in category purchase, Figure 4. First, customer *k* determines if she makes a purchase from a category given she currently has a basket of categories $\widetilde{bc}_k$. This is followed by the decision of selecting products[1] corresponding to the chosen category. We denote by i a category and by $j\,|\,i$ a brand *j* in category *i*. We denote by *C(i,k,t)* the event of customer *k* considering a purchase from category *i* at time *t*. Notation *C(i,k,t)=1* encodes that such a purchase is made.

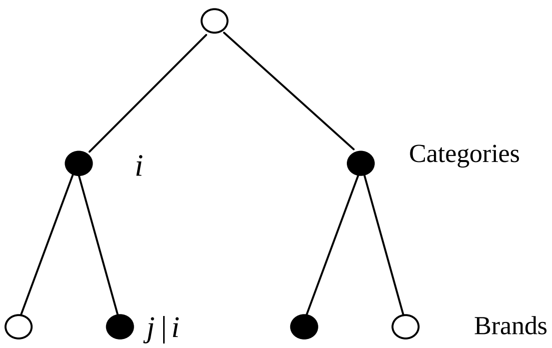

Figure 4: Hierarchical Decision Process

Given product *j* from category *i*, the choice probability is written as

$$prob(k, j\,|\,\widetilde{bc}_k) = P(k, j\,|\,C(i,k,t)=1)\cdot P\{C(i,k,t)=1\,|\,C(i',k,t)=1,\ i'\in\widetilde{bc}_k, i'\neq i\}. \quad (1)$$

In (1), $prob(k, j\,|\,\widetilde{bc}_k)$ represents the conditional probability of customer *k* buying brand *j* given current basket $\widetilde{bc}_k$. In addition, $P\{C(i,k,t)=1\,|\,C(i',k,t)=1, i'\in\widetilde{bc}_k, i'\neq i\}$ is the conditional probability of selecting category i given basket $\widetilde{bc}_k$ and $P(k, j\,|\,C(i,k,t)=1)$ is the conditional probability of picking product *j* from category *i*. We next study these conditional probabilities.

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[1]We use products, brands and items interchangeably.

Market Basket Selection

Russell and Peterson (2000) propose a multivariate logistic distribution model for the market basket selection problem. The market basket selection problem is modeled as a joint distribution of stochastic variables where each of the variables represent the selection of a single category. We borrow the conditional utility concepts to model the category selections. The error terms are assumed to be i.i.d Gumbel with parameter μ. Assuming the symmetric property of the choice variables, the probability of selecting category *i* by customer *k* at time *t*, given known purchases from other categories i' in the basket is formulated as

$$P\{C(i,k,t)=1 \mid C(i',k,t)=1 \text{ for } i' \in \widetilde{bc}_k, i' \neq i\} = \frac{\exp(\mu V(i,k,t))}{\sum_{i' \notin \widetilde{bc}_k} \exp(\mu V(i',k,t))}, \tag{2}$$

where *V* is the deterministic part of the utility function of customer *k* with respect to category *i* at time *t*. The deterministic utility $V(i,k,t)$ in (2) is defined as

$$V(i,k,t) = \beta_i + HH_{ikt} + MIX_{ikt} + \sum_{i' \in \widetilde{bc}_k, i' \neq i} \theta_{ii'k} C(i',k,t), \tag{3}$$

where β_i represents the utility level term with respect to category *i*. Quantity HH_{ikt} in (3) captures household characteristics, and it is expressed as

$$HH_{ikt} = \delta_1 Ln(Time_{ikt} + 1) + \delta_2 Loyal_{ik},$$

where $Time_{ikt}$ is the time since the last purchase of customer *k* and $Loyal_{ik}$ is the loyalty variable characterizing customer *k*'s long-term propensity to buy from category *i*. Both δ_1 and δ_2 are expected to be positive. Quantity MIX_{ikt} in (3) captures variables defining the marketing mix, and it is defined as

$$MIX_{ikt} = \nu_i Ln(Price_{ikt}),$$

where $Price_{ikt}$ is the average of products in category *i* at time *t* as encountered by customer *k*. Weight ν_i is expected to be negative. Quantity $\theta_{ii'k}$ in (3) captures the correlation between two categories. The symmetric assumption implies that $\theta_{ii'k} = \theta_{i'ik}$. These effects are modeled as

$$\theta_{ii'k} = \delta_{ii'} + \varepsilon \cdot Size_k .$$

Quantity $Size_k$ is the average number of categories per trip by customer *k*. It is expected ε to be positive and $\delta_{ii'}$ symmetric with respect to i and i'.

The Brand Choice Model

Chong et al. (2001) introduce a hierarchy modeling framework to study customer's shopping behaviors. It captures both the probability of making a purchase from a category and the probability of brand selection during a trip. However, it investigates the purchase incidence in a single-category context. We focus on the brand selection in a multi-category context. We assume that the error terms of random utilities given selected category *i* are i.i.d Gumbel with parameter μ_i . The conditional probability $P(k, j \mid C(i,k,t)=1)$ that customer *k* selects product *j* in category *i* to maximize his/her utility is

$$P(k, j \mid C(i,k,t)=1) = \frac{\exp(\mu_i V(k, j,t))}{\sum_{j' \in J(t)} \exp(\mu_i V(k, j',t))} \tag{4}$$

In (4), $J(t)$ denotes the set of all products in the category and $V(k, j,t)$ represents the deterministic part of the utility function. Furthermore, this deterministic portion of the utility function is modeled as

$$V(k, j,t) = \alpha_j + \beta_L L_{kj}(t) + \beta_p P_j(t),$$

where α_j is the level term of the utility function with respect to product *j*, which is assumed to be stable over time and constant across all customers. Quantity $L_{kj}(t)$ represents customer *k*'s purchase experience with respect to product *j* before trip *t* and β_L is the corresponding weight. This purchase experience corresponds to brand loyalty and can be expressed as

$$L_{kj}(t) = \nu \cdot L_{kj}(t-1) + \begin{cases} 1-\nu & \text{if product } j \text{ was purchased during trip } t\text{-1}, \\ 0 & \text{otherwise.} \end{cases}$$

Quantity $L_{kj}(t-1)$ is customer *k*'s loyalty to product *j* in time (trip) *t*-1 and ν is a smoothing constant between 0 and 1. Next, $P_j(t)$ represents price with respect to product *j* at trip *t* and β_p are the corresponding weights.

3.2. Modeling Framework

We assume that the store layout and planogram are provided. Customers travel from a category to a category. Based on a typical walking speed, the planogram, and layout, the anticipated walking time to go from one category to another can be computed. We first describe a general expected revenue maximization problem. We then discuss two special cases, namely the shopping list and RFID scenarios.

Suppose we have categories $N = \{1,\ldots,n\}$ in the store. Customer k's route Q can be described as an ordered sequence of categories. If required, we can add fictitious categories corresponding to checkout locations and point of entries. Customer k at time t enters the store with a shopping list consisting of categories $S_{tk} \subseteq N$. We allow $S_{tk} = \varnothing$, e.g., in the RFID scenario. Let $t_{ii'}$ denote the travel time from category i to category i', which is symmetric. Customers desire to purchase certain categories $\bar{N} \subseteq N$, such as frozen food and meat, towards the end of the shopping route, therefore we assign a fixed time u such that all items in categories from $\bar{N}$ must be purchased in the last u minutes of the route. Every category $i \in N$ has a set C_i of brand names or items. At time t, the store runs a set of promotions (and possibly tasting booths) consisting of items $\widetilde{C}_t$. By definition, $\widetilde{C}_t \subseteq \bigcup_{i \in N} C_i$. Let also $\widetilde{C}_{ti} = \widetilde{C}_t \bigcap C_i$ be the set of all items on promotion at time t in category i. The set of all categories with promotional items at time t is denoted by $\widehat{C}_t = \{i \in N \mid \widetilde{C}_{ti} \neq \varnothing\}$.

Let us construct the following complete graph $G_{tk} = (N, A)$. The cost of each edge (i, i') corresponds to travel time $t_{ii'}$. Both scenarios presented in Section 2 are aimed to maximize the total expected revenue generated from impulse purchasing based on promotions. We can model them as a generalization of the orienteering problem, Kantor (1992). The goal is to visit a subset of the nodes, i.e., categories, with maximum expected revenue while maintaining a certain level of the customer's aggregated utility function. In addition, nodes have time windows and some nodes must be included in the selection. Formally, let s and t be two special nodes. For $Q = \{s, i_1, \cdots, i_k, t\}$ we define $W_{i_j}(Q) = \sum_{v=1}^{j} t_{i_v, i_{v+1}} + t_{s, i_1}$ for $j = 1, \cdots, k$ based on a set of categories Q.

We denote by $\widetilde{bc}_k$ the basket of categories that customer k has at time t during the shopping trip. Let $R(Q \mid \widetilde{bc}_k) = \sum_{i \in Q \bigcap \widehat{C}_t \setminus \{s,t\}} \sum_{j \in \widetilde{C}_{ti}} prob(k, j \mid \widetilde{bc}_k) \cdot price_{t,j}$ be the expected revenue corresponding to shopping route Q given basket $\widetilde{bc}_k$. The store's manager wants to maximize the store's expected revenue. The generalized orienteering problem reads

$$\max_{Q \subseteq N} \quad R(Q \setminus C \mid \widetilde{bc}_k)$$
$$\text{subject to: } u_k(Q) \geq \alpha_k$$
$$l_{i_j} \leq W_{i_j}(Q) \leq u_{i_j} \qquad j = 1, \cdots, k$$
$$C \subseteq Q,$$

where C is a set of nodes that must be visited, u_k is the customer k's aggregated utility function with α_k the baseline utility vector, and $[l_i, u_i]$ the time window associated with node i. We note that both u_k and α_k are vectors. The recommended subset of categories $Q \setminus C$ with the maximum expected revenue provides marketing targets to distribute coupons. We assume that there are only a few promotional items within each category. Thus it is conceivable to offer coupons to all such items in the category.

Examples of possible aggregated utility functions: We list three conceivable aggregated utility functions for which retailers should have sufficient data to capture them. Let $u_k(Q) = (u_k^1(Q), u_k^2(Q), u_k^3(Q))$ and $\alpha_k = (\alpha_k^1, \alpha_k^2, \alpha_k^3)$. Utility u_k^1 captures the general preference for short shopping time, u_k^2 limits customers' budgets, and u_k^3 maximizes potential savings. Let $AP_{t,i}$, $AP'_{t,i}$ be the average price of products in category i at time t before and after promotion, respectively. We define $\bar{u}_k^1(Q) = \sum_{j=1}^{k-1} t_{i_j, i_{j+1}} + t_{s,i_1} + t_{i_k,t}$ to be the travel time corresponding to route Q. In addition, we define $\bar{u}_k^2(Q) = \sum_{i \in Q \setminus \{s,t\}} AP'_{t,i}$ to be the total expenditure and $u_k^3(Q) = \sum_{i \in Q \setminus \{s,t\}} (AP_{t,i} - AP'_{t,i})$ to be the total average savings along route Q. If B_k is the budget of customer k and T_k the maximum tolerable travel time, then the travel time utility constraint reads $u_k^1(Q) = T_k - \bar{u}_k^1(Q)$ and the consumption utility is $u_k^2(Q) = B_k - \bar{u}_k^2(Q)$. The three utility constraints can then be stated as

$$\bar{u}_k^1(Q) \leq \bar{\alpha}_k^1 = T_k - \alpha_k^1,$$
$$\bar{u}_k^2(Q) \leq \bar{\alpha}_k^2 = B_k - \alpha_k^2,$$
$$u_k^3(Q) \geq \alpha_k^3.$$

The first one imposes an upper bound on the travel time, the second one the tolerable budget, and the last one the minimum acceptable savings.

We next elaborate on these aspects, including setting $\overline{\alpha}_k^1$, $\overline{\alpha}_k^2$ and α_k^3, and provide details on the two scenarios considered.

Model with Shopping Lists

In this section we specify all data pertaining to this scenario with respect to the generalized orienteering problem. We define *s* to be the location corresponding to the checkout counters and *t* corresponding to the store entrance. For the initial basket we assume $\widetilde{bc}_k = \emptyset$ since there is no way to identify and track customers' baskets in this scenario. The route is conceptually constructed backwards. Frozen food and other highly perishable categories in $\overline{N}$ that should be purchased at the end of the trip have a time window $[0, u]$, which means that these categories should be in the shopping cart in the last *u* time units of the trip. Other categories have a time window of $[0, \infty]$, or no time window, because they could be purchased at any time during the trip. For example, suppose a customer needs to purchase milk, crackers, chips, fruit, and meat. Milk and meat have a time window of $[0, u]$, while crackers, chips and fruit have no time window because they can be purchased anytime during the trip.

Next, we discuss $\overline{\alpha}_k^1$. Assume customer k enters the store at time t with the shopping list including items from categories in S_{tk}. To determine $\overline{\alpha}_k^1$, we first solve the traveling salesman problem (TSP) with time windows on the sub-graph of G_{tk} defined by S_{tk}. The travel time v_{tk} is the time the shopper would spend in the store under an optimal route. We set $\overline{\alpha}_k^1 = v_{tk}(1+\overline{\alpha}_{tk})$, where $\overline{\alpha}_{tk}$ is the travel time tolerance with respect to customer *k* at time *t*. To determine $\overline{\alpha}_{tk}$, every time the customer visits the store, we record her shopping list. At checkout we link the point-of-sale data with the specific shopping list. Let

$$\lambda_{tk} = \frac{\text{the number of promoted items purchased that are not on the shopping list}}{\text{the total number of items purchased}}.$$

We take the average of λ_{tk} over all previous visits of the customer. If the loyalty card is not available, then we suggest to set $\lambda_{tk} = \lambda_t$, where

$$\lambda_t = \max(1 - \frac{\text{optimal route time with respect to the shopping list}}{\text{optimal route time with respect to point-of-sale}}, 0)$$

is the average over sample representative customers. In either case, we set $\bar{\alpha}_{tk} = \rho \cdot \lambda_{tk}$, where ρ is a scale factor.

The remaining two parameters $\overline{\alpha}_k^2$ and α_k^3 can be computed in a similar fashion by considering past purchasing power of customer *k* and the underlying savings.

The nodes of G_{tk} are defined as $S_{tk} \bigcup \widehat{C}_t$ since other categories need not be considered, and $C = S_{tk}$. Let $prob_{tkij}$ be the probability that during the shopping trip at time t customer k buys item j from category i where $j \in \widetilde{C}_{ti}$. Let $price_{tj}$ be the selling price of item j in time t. This is the promotional price of the item (or the reduced selling price of the item at a tasting booth). The store's expected revenue with respect to node (category) *i* is thus $R_{ti}^k = \sum_{j \in \widetilde{C}_{ti}} prob_{tkij} \cdot price_{tj}$ and it is considered as a node weight in G_{tk}. We denote by $\overline{Q} = (Q \setminus S_{tk}) \setminus \{s, t\}$ the subset of categories that are on promotion, but not on the shopping list. The objective function is specified as

$$\begin{aligned} R(Q \setminus S_{tk}) &= \sum_{i \in \overline{Q}} \sum_{j \in \widetilde{C}_{ti}} prob_{tkij} \cdot price_{tj} \\ &= \sum_{i \in \overline{Q}} R_{ti}^k. \end{aligned}$$

As seen above in the modeling framework, the goal in this scenario is to maximize the sum of the node weights based on maximizing the store's expected revenue.

Clearly, the route solving the generalized orienteering problem is the resulting recommendation. For example, suppose customer k enters the store with a shopping list, which includes milk, crackers, chips, fruit, and meat. Let us assume that it takes 30 minutes (v_{tk}=30) to visit every category on the shopping list based on an optimal route, and we calculate the time tolerance with respect to customer k to be 0.2 (we estimate that customer *k* is only willing to spend 20% more time of the actual minimum shopping time). It means that the proposed route with respect to the first utility component should not exceed 36 minutes if $\rho = 1$ and it must include every category on the shopping list.

In order to compute the expected revenue with respect to shopping route *Q*, we need to calculate $prob_{tkij}$. We first assume that customer *k* has a loyalty card. Then we have

$$prob_{tkij} = \frac{\exp[\mu V(i,k,t)]}{\sum_{i' \in \widehat{C}_t} \exp[\mu V(i',k,t)]} \frac{\exp(\mu_i V(k,j,t))}{\sum_{j' \in J(t)} \exp(\mu_i V(k,j',t))}. \tag{5}$$

based on (1). The first term in (5) denotes the purchase incidence probability of category *i*. The second term in (5) follows the standard multinomial logit probability for selecting products within category *i*. All parameters can be obtained by the maximum likelihood method, Ben-Akiva and Lerman (1985).

If the loyalty card is not available, we follow the same concepts except that index k is neglected. In this case, we take the average over sample representative customers when computing the probabilities by using the utility expression.

Model with Radio Frequency Identification

In this scenario, the shopping list is not available. The store is, however, deployed with RFID. Namely, smart shelves enable identifying items which are in the shopping carts and close enough to an interrogator. Hence, the store's information system can identify the current purchases of a customer up to a certain point and recommend promotional items with the goal to maximize the store's total expected revenue. Notice that without tracking shopping carts we can only record the sequence of purchases up to a certain point. The sequence is updated and recorded several times during the shopping trip; every time the customer passes a coupon issuing device. Consider a customer in front of a smart shelf equipped with a coupon issuing device. Let $\widetilde{bc}_k$ be the set or basket of categories that are already in customer *k*'s shopping cart at time *t*, which is the time when the customer is in front of the smart shelf, and let $bc_k^{'}$ be the set of categories that were in the shopping cart the last time customer *k* was in front of such a smart shelf. We denote by $\widehat{bc}_k = \widetilde{bc}_k \setminus bc_k^{'}$ the added categories to the shopping cart after customer *k* was in front of such a smart shelf the last time. Note that during a shopping trip the customer may pass by such shelves several times (assuming there are many of such shelves in the store).

The graph nodes in this case correspond to the subgraph of G_{tk} defined by $\widehat{C}_t$. The set *C* is empty and there are no time windows. The source node *s* equals to the node corresponding to the category of the current shelf. The sink node *t* is a new fictitious node and $t_{it} = 0$ for every category $i \in \widehat{C}_t$. We compute $prob(k, j \mid \widetilde{bc}_k)$ the probability of customer *k* purchasing product *j* given categories $\widetilde{bc}_k$ in the shopping cart in time t. We first assume that customer k has a loyalty card. We obtain

$$prob(k, j \mid \widetilde{bc}_k) = \frac{\exp[\mu V(i,k,t)]}{\sum_{i' \in \widehat{C}_t \setminus \widetilde{bc}_k} \exp[\mu V(i',k,t)]} \frac{\exp(\mu_i V(k, j,t))}{\sum_{j' \in J(t)} \exp(\mu_i V(k, j',t))}. \tag{6}$$

The difference between (6) and (5) is in the fact that in the denominator we sum over categories in $\widehat{C}_t \setminus \widetilde{bc}_k$.

Without the loyalty card it is the same concept except that index k is neglected and we take the average over sample representative customers.

Similar to the shopping list scenario, the proposed route of categories with items on promotion should be less than or equal to $\overline{\alpha}_k^1 = v_{tk}(1+\overline{\alpha}_{tk})$, where v_{tk} is the optimal travel time to visit categories in $\widetilde{bc}_k$. The total travel time limit is based on the point-of-sale data, instead of the shopping list. Additional inaccuracy here comes from the fact that a customer might have bought a promoted item that she intended to buy anyway. Under the loyalty program, we propose

$$\lambda_{tk} = \frac{\text{the number of promoted items purchased based on POS}}{\text{the number of total purchased items based on POS}}.$$

We take the average of λ_{tk} over all previous visits of the customer. If the customer is not enrolled in the loyalty program, then we average λ_{tk} over sample representative customers. We set $\overline{\alpha}_{tk} = \rho \cdot \lambda_{tk}$, where ρ is a scale factor.

The remaining two parameters $\overline{\alpha}_k^2$ and α_k^3 can be computed based on the same principles.

In addition, we can distinguish between the store being able to track the shopping carts or not. Suppose first that shopping cart tracking is not available. An issue in this case is that we do not want to hand out identical coupons to the same customer or issue coupons too frequently. We offer a solution as follows. We recommend to pick a small subset of categories that are in high traffic areas and are located far from the entry point. The latter implies that customers arrive at the location supposedly with some items in the carts and the former reflects the fact that many customers should pass by such a smart shelf. The coupon issuing devices are installed within the area of a subset of categories recommended above.

In the other case, the shopping carts can be tracked (see Section 2.4 for a discussion). We can now better control not giving the same coupons to a customer and when to deliver coupons. In case they can be delivered at several store locations, it would be annoying for the customer to receive them too frequently. To circumvent this, we propose the following strategy. We replace $\widetilde{bc}_k$ by $\widehat{bc}_k$ and thus use $prob(k, j \mid \widehat{bc}_k)$ in $R(Q \mid \widehat{bc}_k)$. Consider $M_{tk} = \max_{j \in \widetilde{C}_t \setminus \widetilde{bc}_k} prob(k, j \mid \widehat{bc}_k)$, which is the maximum conditional probability customer k would buy a promotional item based on added items to the shopping cart after the coupons were offered last time. If $M_{tk} \geq \overline{M}_{tk}$ for a threshold $\overline{M}_{tk}$, then consider giving the coupons. We can estimate $\overline{M}_{tk}$ as follows. Let $\widetilde{S} \subseteq \widetilde{C}_t$ be the set of promotional categories that have already been bought. Let S be the set of categories that have already been bought, but are not on promotion. We offer two alternatives to compute $\overline{M}_{tk}$. Let $q_{kj} = prob(k, j \mid S)$ be based on S for every $j \in \widetilde{S}$. We also define

$$\varepsilon_k = \min_{j \in \widetilde{S}} q_{kj} \quad \text{or}$$

$$\varepsilon_k = \frac{\sum_{j \in \widetilde{S}} q_{kj}}{|\widetilde{S}|}.$$

We set $\overline{M}_{tk} = \overline{\rho} \cdot \varepsilon_k$, where $\overline{\rho}$ is a scale factor.

3.3. Algorithms

In the shopping list scenario, we need to solve the TSP problem to compute the baseline travel time. On the other hand, in the second scenario, we also need to compute the baseline travel time to acquire all items in the current shopping cart $\widetilde{bc}_k$ with respect to customer k. Since the TSP needs to be solved in real-time, a fast heuristic is required. The Lin-Kernighan heuristic is a very efficient and quick heuristic for solving TSPs, Helsgaun (2000). Other heuristics can be employed, Gutin and Punnen (2002). The shopping list and current basket $\widetilde{bc}_k$ are respectively the input and the baseline travel time is the output.

The ultimate route in either scenario is obtained by solving the generalized orienteering problem. The standard orienteering problem does not include time windows and the predefined set of nodes C. This problem also needs to be solved by fast heuristics. Efficient heuristics for the orienteering problem exist, Chao et al. (1996), Ramesh and Kathleen (1991). These heuristics can easily be extended to accommodate all of our requirements. We point out that in our setting these are not large-scale problems (the number of nodes equals to the number of categories, which is within hundreds). Due to the limited size, branch-and-cut algorithms could also be used, Fischetti et al. (1998).

4. Numerical Experiments

In this section, we apply the model with shopping list, i.e., the first scenario to a real-world case of a major grocery store. Only the travel time utility component is considered. The store layout and the complete planogram were given and therefore, the distances between any two categories can accordingly be computed. The store holds from 200 to 250 categories and 35,000 to 50,000 different products.

Our information system was developed in VBA within Microsoft Excel. Parameters in the utility functions were computed by the maximum likelihood method with What's Best from Lindo Systems as the optimization solver. All TSP instances were solved by using the Lin-Kernighan routine of the branch-and-cut solver Concorde. The generalized orienteering problem was solved with the branch-and-cut solver from Fischetti et al. (1998).

The unit selling price for each product during a period of time is available. The only data not available were the current (future) promotions. For this reason we randomly generated them in the following way. First, we randomly generated a subset of brand names (these were selected from UPCs). In the second step, for each selected brand name we randomly generated a subset of items running a promotion. We considered several levels of promotion: less than 1%, 3% and 6% products on promotion. We stress that even the most aggressive level of 6% is below a typical level of 10% employed by this store (the number conveyed to us by the store manager). The price of a promotional item is reduced in a range of 20% to 30% (randomly in this range).

The store keeps point-of-sale data of each customer enrolled in the loyalty program. We focus our study on five representative customers. Each of these customers purchases on average 30 to 50 items during each shopping trip. Within the scope of our study, a customer on average visited the store 7 times during the time period. As a result, all data points in this section are the accumulated sum over 7 shopping trips. Additional point-of-sale data from the source customers were used to derive all of the parameters related to the discrete choice models.

Given a shopping list, we compute four different baseline cases. Baseline up-and-down ("BUD") represents the case where a customer travels along each aisle one by one from one end of the aisle to the other end and never turns around in the same aisle. She only visits the aisles where she has something to buy from. Adjusted baseline ("AB") represents a similar case, but when the customer reaches the last required category in one aisle she takes the shortest route to the next aisle she must visit. Larson et al. (2005) show that the "AB" strategy is commonly used by shoppers. On the other hand, the same authors argue that the 'BUD' strategy is not. We use 'BUD' as an additional benchmarking strategy. They are depicted in Figure 5, where the bigger dot represents the store entrance and checkout location, and small dots represent products from the shopping list. The solid line with arrows represents BUD and the dotted line with arrows represents AB. In the remaining two cases, we compute the baseline route by the Lin-Kernighan algorithm ("LK") or an optimal TSP solution ("OPT"). In Table 1, we summarize the baseline characteristics with respect to the travel time. We report the total travel time reduction over all shopping trips.

The baseline travel times are compared among the baseline cases of interest, where we compute the relative reduction of travel times between the two cases. For example, the travel time in the LK case is reduced by 8.74% compared to the adjusted baseline case. In most of the cases the TSP strategies yield significant time reduction (with the exception of customer 2) in the range form 5% to 11%. This clearly indicates that with respect to the shopping time the current wisdom can be substantially improved by using information systems (see also further discussion in Section 5). We also observe that the LK strategy almost always yields an optimal solution with the exception of customer 5.

We have already discussed random promotion generation. We apply three promotional levels: low, medium, and high. In the low promotional level, 0.7% of products are on promotion. There are 2.5% products on promotion in the medium promotional level, and 6.0% products in the high promotional level. We compare the differences of expected revenues among all four baseline cases and optimized cases. The time tolerance factor is fixed at 5%, i.e., $\overline{\alpha}_k^{-1} = v_{tk}(1+0.05)$.

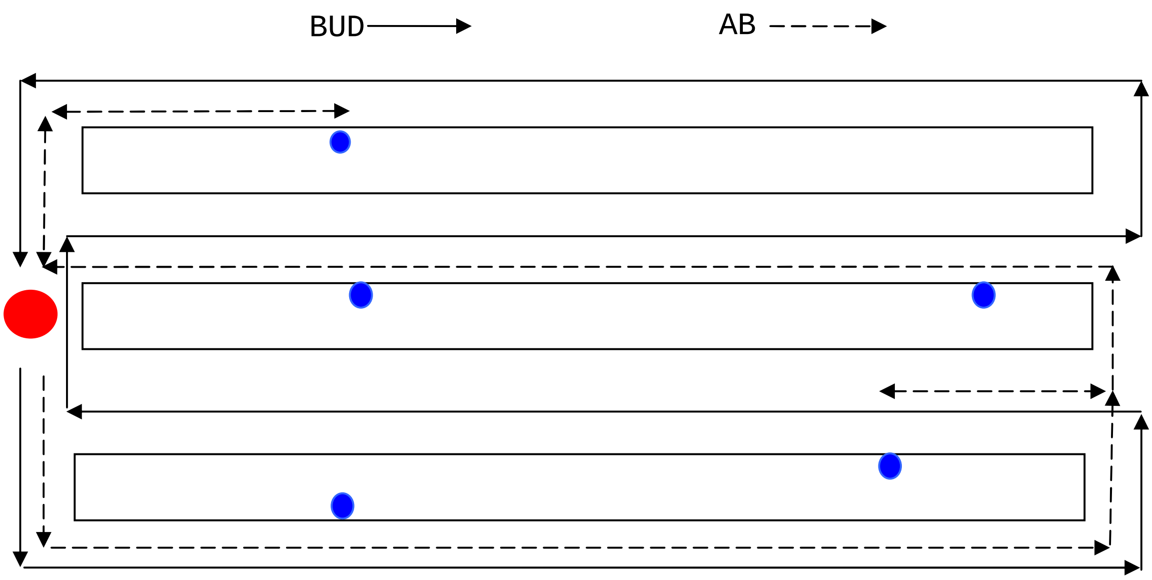

Figure 5: The BUD and AB strategies

Table 1: Baseline travel times

	AB/LK (%)	AB/OPT (%)	BUD/LK (%)	BUD/OPT (%)
customer 1	8.74	8.74	10.42	10.42
customer 2	0.79	0.79	1.53	1.53
customer 3	5.29	5.29	9.11	9.11
customer 4	7.74	7.74	8.27	8.27
customer 5	8.25	8.62	10.14	10.50

Figure 6, Figure 7, and Figure 8 show the expected revenue for all five customers and for all three promotional levels, respectively. The baseline case shows the revenue based on the underlying baseline route. As the customer follows the baseline route, she passes by promotions and the expected revenue is calculated accordingly based on R_{ti}^{k}. The optimal solutions vary since the travel time of the corresponding baseline route is different. For example, in Figure 7, customer 1, the adjusted baseline case shows revenue $5.75, which means that if this customer follows the adjusted baseline strategy in the store, she is expected to purchase $5.75 of promotional products that are not on her shopping list. On the other hand, if each time she follows the recommended optimized route, under identical promotions, she is expected to buy $11.99 of promotional items not on her shopping list. As the promotional level increases, more expected revenue is created, e.g., under the AB case with respect to customer 1, the revenue increases from $2.27 at the low promotional level to \$5.75 at the medium promotional level, to \$9.82 at the high promotional level. The improvement of expected revenue between the baseline and optimized cases decreases across BUD, AB, LK and OPT, as can be seen in Table 2, because the optimal travel time decreases. In Table 2, we report the improvement of expected revenue for all five customers. It is surprising that in most cases the medium promotional level yields less expected revenue than the low promotional level. It seems that the expected revenue is relatively flat for low to medium promotional level and it jumps substantially as the promotional level is increased from 3% to 6%.

Table 2: Improvement of expected revenue between baseline and optimized cases

	BUD	AB	LK	OPT
Low	\$18.07	\$17.97	\$15.94	\$15.91
Medium	\$18.13	\$17.13	\$11.11	\$10.93
High	\$43.49	\$43.41	\$33.21	\$33.17

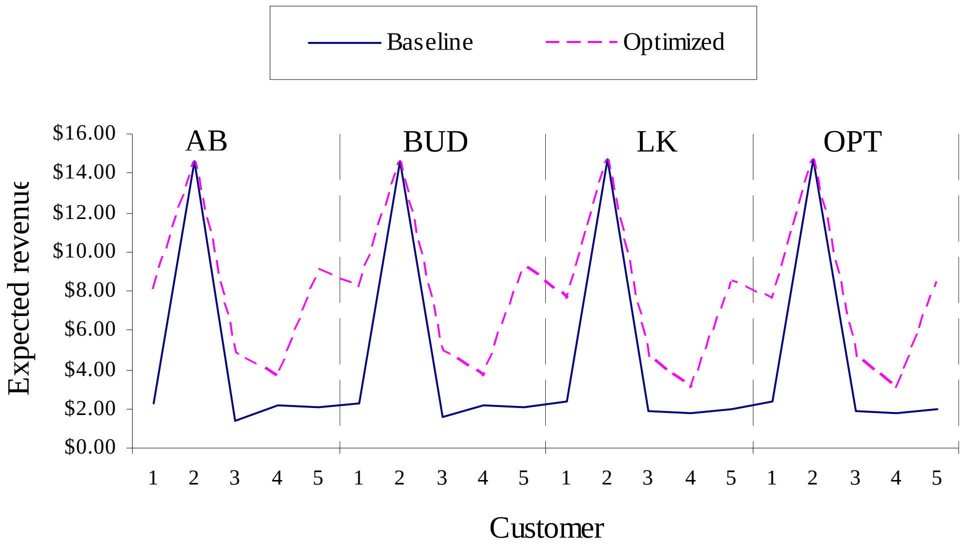

Figure 6: Expected revenue at the low promotional level

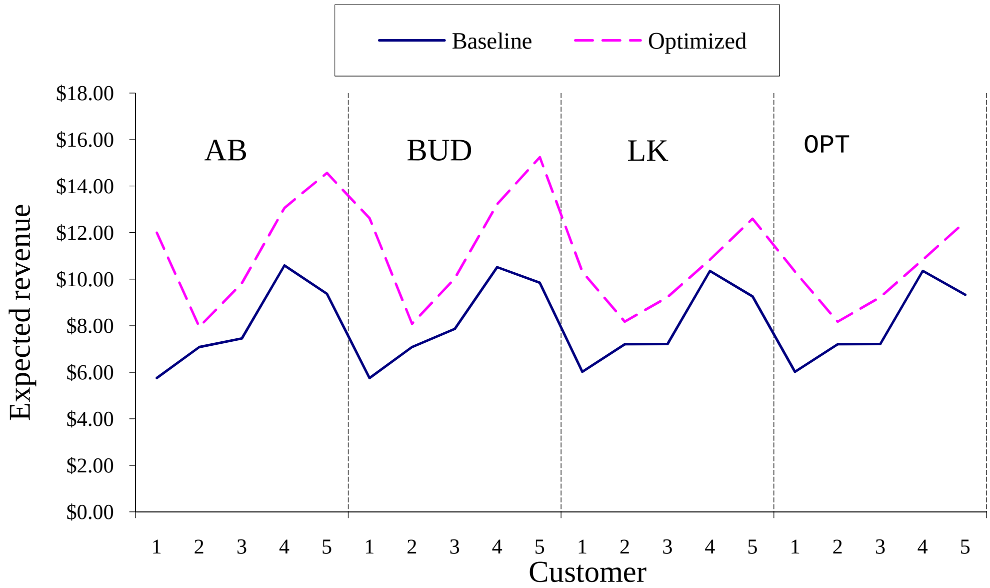

Figure 7: Expected revenue at the medium promotional level

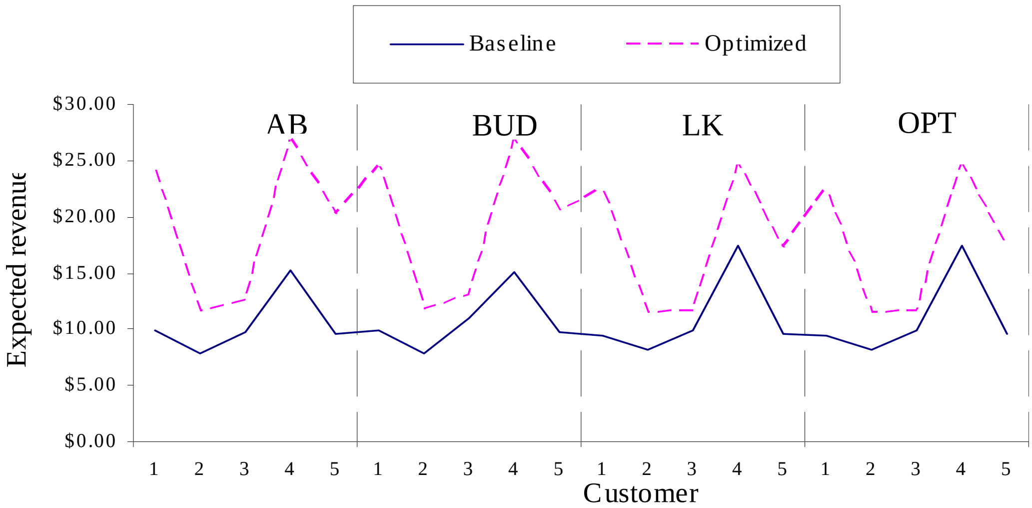

Figure 8: Expected revenue at the high promotional level

The expected revenue also varies with respect to the time tolerance factor. In Figure 9, we compute the expected revenue across all customers as the time tolerance factor is set to 5%, 10%, 15%, and 20%. Clearly, as expected, the revenue increases. The most notable increase is from 5% to 10%.

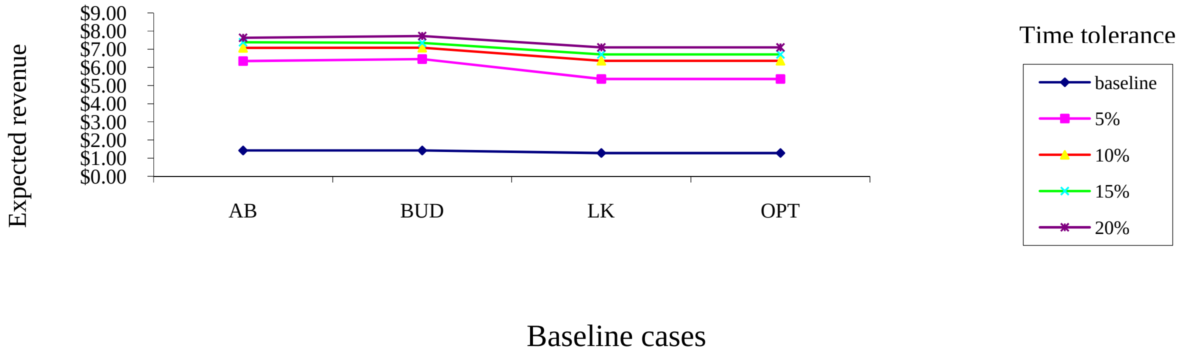

Figure 9: Sensitivity analysis of expected revenue with respect to the time tolerance factor

Based on the average number of customers per day for this store and the LK baseline strategy (the most conservative) with the highest promotional level (which is significantly lower than an average level of this store) it is estimated that an increased annual revenue of $500,000 is expected. Considering that this value applies to a single store, the revenue increase for an entire chain could be remarkable.

5. Conclusions and Remarks

One-to-one marketing is recently gaining attraction. There have been many experiments involving mobile phones. In retailing the most elusive concept is one-to-one marketing during a shopping experience and not as currently done at the checkout counter, which is after the shopping experience. By using recent technologies, we lay down models and concepts that would enable such a marketing principle. In-store one-to-one marketing models based on discrete choices provide promotion targets for individual customer. The in-store coupon distribution is personalized in our setting. At the same time, the recommended route is to maximize the store's expected revenue. Based on our models, the retail stores can issue promotion coupons that are tailored to specific customers. By using real-world data we show that substantial additional revenue is possible. We are convinced that it is only a matter of time before retailers start using this form of marketing. It will probably take longer to employ the RFID technology, but PDAs or smart phones already have high penetration and thus the first discussed concept of shopping lists is in our belief deployable in the short term future. Indeed, there are already web sites[1] that let visitors create shopping lists online and possibly send them to a store (or, in our context, downloadable to a

PDA). A system called Easi-Order, Electronics Times (1999), is a home-based shopping service through which customers generate their shopping lists at home and communicate them back to the grocery stores for picking up at a predetermined time. HighPoint Systems has deployed a similar concept for the online grocer[2] Peapod, LLC.

Regarding RFID, a few years ago a prototype future store has been built by Metro AG in Rheinberg, Germany[3]. The store uses RFID at the item level and it also features displays at shelves. These displays can be easily adopted to serve the purpose of our work. Nevertheless, this is only a prototype store and at present the cost of an RFID deployment at this scale is still prohibitive. There are also early implementations of smart shopping carts with mounted displays, Embedded star (2004), Gizmag (2005), USA Today (2003). The Klever-Kart system, Embedded star (2004), is different from previous intelligent carts since a Fujitsu mobile computer is permanently attached to a standard cart. The devices can be used to demonstrate electronic ads and promotions. On the other hand, the displays can also be used to track the current total charge by scanning each item before putting it in the cart and also to recommend promotions. In our work, we provide analytical models for such recommendations. We push this a step further, by also providing a store route leading past promoted items. Such technology combined with tracking of shopping carts can also serve our purpose (instead of presumably more costly RFID implementations).

Finally, we would like to comment on an important observation from our numerical study. In Table 1 we report the deviation in terms of the travel time of the estimated shopping path to an optimal shopping route. A similar study has recently been conducted by Hui et al. (2007). Their conclusion is that this deviation is around 20%, which is substantially higher than our observations. By replicating our approach, their value would be even larger (we find an optimal TSP tour while they use simulated annealing, which can yield suboptimal tours). Based on these facts it follows that this deviation is not standard across the stores but it can vary significantly.

Based on the discussion in Section 4, an important managerial insight is derived. The computational experiments show that the added revenue of our personalized coupon distribution is relatively flat up to a certain promotional level. Beyond this threshold, it increases substantially. As a

[1]http://www.commissaries.com/log_in/html/list_fr.cfm, http://www.shopbloom.com/
[2]http://www.peapod.com/
[3]http://www.future-store.org/servlet/PB/menu/1007054/index.html

result, the store manager should find out this threshold and then promote slightly above it, if possible.

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