RC22986 (W0311-079) November 12, 2003
Mathematics

IBM Research Report

Product Pricing in the E-business Era

Aliza Heching, Ying Tat Leung
IBM Research Division
Thomas J. Watson Research Center
P.O. Box 218
Yorktown Heights, NY 10598

Product Pricing in the e-Business Era

Aliza Heching and Ying Tat Leung

IBM Research Division, Thomas J. Watson Research Center, Yorktown Heights, NY 10598

ahechi@us.ibm.com, ytl@us.ibm.com

Abstract

Product pricing has slowly evolved from pure intuition-based decisions to a mix of art and science. This is due in no small part to the availability of historical sales and other data which are now routinely collected by enterprise information systems. We review recent trends in pricing products in the retail (business to consumers) and wholesale (business to business) industries and elaborate on factors that lead to such trends. The research literature on approaches to help price a product is examined. We also introduce common concepts behind commercially available software systems that provide pricing decision support, and discuss the business benefits of using such a system.

Introduction

Product pricing has evolved from simple list pricing, punctuated with an occasional sale or price markdown, to sophisticated pricing mechanisms including auctions, reverse auctions, dynamic pricing, and differentiated pricing based upon factors such as type of consumer and sales channel. The birth of these more sophisticated pricing mechanisms can perhaps be traced back to the time of airline deregulation. Airlines, faced with stiff competition, high costs, and differentiated classes of customers, turned to more sophisticated pricing mechanisms as a means for financial survival.

The rise in e-business is leading to increased interest by retailers in sophisticated pricing mechanisms. Successful implementation of a pricing mechanism requires a significant amount of data about customers and their buying habits. Traditional (bricks and mortar) retailers collect numerous data types everyday, including point-of-sale purchase data, store traffic data, and logs of customer service calls. In addition to these data types, Web-based retailers ("e-retailers") have access to click-stream data. Click-stream data provides e-retailers with a rich source of information, allowing them to track customers' decision processes as they browse catalogs and make purchase decisions on the Web. Thus, the rise of e-business has brought with it the possibility and profitability of more sophisticated pricing mechanisms in the retail sector. In addition, e-business allows for lower cost and more frequent (if needed) price changes as well as relatively low-cost price testing to gain a better understanding of true market demand.

The growing interest in the use and successful implementation of pricing mechanisms brings with it an increasing need and desire to explore the effectiveness of such mechanisms. Product pricing is now a consistent theme of retail trade shows and conferences. Further, an entire industry aimed at providing advanced pricing software solutions has been born, attracting high-tech start-up firms and veterans in supply chain management and enterprise resource planning alike. The general press has dedicated detailed articles to this subject; see, e.g., McWilliams (2001), Merrick (2001), Tedechi (2002). A recently published industry study (Marn, Roegner, and Zawada (2003)) shows that product pricing is the most effective means for increasing profits among levers including sales volume, fixed costs, and variable costs.

Product pricing mechanisms can be broadly classified into three main categories: products sold through publicly posted prices, products sold through individually negotiated prices, and products sold through auction mechanisms. A fundamental distinguishing factor between these three mechanisms is the time at which the purchaser has knowledge of the final price that he will pay. In the first category, products sold through publicly posted prices, prices are posted and non-negotiable. Thus, at any time the purchaser has full-knowledge of the final price that he will pay. Most consumer retail stores in developed countries sell products using publicly posted prices. In the second category, products sold through individually negotiated prices, at the time that the purchaser initiates the buying activity he has no knowledge of the final price that he will pay. Prior to agreeing to purchase the item, the purchaser receives a firm price quote from the seller. At that time the purchaser decides whether or not to purchase the item. In the final category, products sold through auction mechanisms, the purchaser has no knowledge of the final price that he will pay at the time that he initiates purchasing activity. Depending upon the specific auction mechanism, the quantity of product the buyer procures as well as the price per item is revealed to the buyer only after he makes a purchase commitment. Products sold through responses to Requests for Quotes ("RFQs") put out by a business buyer are often sold using a combination of the second and third mechanisms. The RFQ process is an (reverse) auction; after the winner has been determined, amendments to the originally stated orders (and hence price) or other forms of negotiation may occur as a result of updated product offerings or changes in the buyer's needs.

In this chapter we focus on the first two classes of pricing mechanisms. We restrict our focus to pricing products that are physical or consumable, such as consumer goods or parts used for manufacturing. We do not consider pricing issues that relate to pricing financial products such as options, or one-of-a-kind artifacts such as antiques or fine art. Finally, we assume that the seller is always a business and do not consider the case of recreational selling of used items or collectibles by an individual.

Pricing in the e-Business Environment

The traditional bricks-and-mortar business environment is characterized by consumers who must physically enter a store in order to view merchandise and make purchasing decisions. Retailers face competition primarily from other retailers in close physical proximity. Price change decisions often entail costly advertising associated with publicizing the new prices. Further, price changes often necessitate a physical marking on each individual item to reflect the new prices. This process is both costly and time consuming. As a result, traditional retailers often limit themselves to a small number of price changes for any given item being sold.

However, the advent of e-business has brought with it some fundamental changes in traditional methods of conducting business. Due to the inherent automation that characterizes e-business, there is a low marginal cost associated with implementing a price change. Price changes can often be implemented via a change to a single database entry which will then trigger price label printouts at the retail stores. With the likely widespread future use of either liquid crystal display panels or electronic paper, this process will be further simplified. This low marginal cost allows the seller more flexibility with respect to the number of price changes that he can consider during any given time period.

An extreme form of e-business in retail, sometimes known as e-tailing, is where the retailer only has virtual stores on the Web and does not have any physical retail locations. e-tailing is characterized by the use of a website to display products for sale; one can view e-tailing as a business that publishes and distributes its catalog of products via the Web. e-tailing has grown in popularity over the years, as there are many factors that render sales over-the-Web an attractive option for sellers. Displaying products via a website allows e-retailers to build a catalog that is much larger than anything that could fit into a mailbox or into a retail store location. Further, e-tailing allows for significant, if not complete, automation of processes such as order-taking and customer service, thereby reducing transaction costs. Web sales are often characterized by larger purchases per transaction; sellers often display products complementary to those that the customer is viewing, to entice customers to purchase additional items. e-tailing also provides opportunity for richer interactions with customers, as the use of automated tools allows e-retailers to provide additional services (such as e-mail confirmation when orders are placed or shipped, or when new products of similar kinds are announced) at very low cost to the retailer.

The information technology that enables the existence of e-tailing brings with it changes which impact pricing strategies:(i) The low marginal cost of price changes, as discussed above, allows the seller unprecedented flexibility with respect to the number of price changes and durations of effective prices. Dell.com reports that weekly price changes are routine; in fact, prices can be changed as often as daily (McWilliams (2001)). (ii) e-tailing expands the geographic location of customers accessible by retailers. Whereas the reach of retail stores is limited (for the most part) to customers in close geographic proximity to the retail location, websites can be accessed globally by customers. Consequently, product life-cycles (or product shelf-lives) are longer as sellers are not constrained by the seasonal cycles of a single geographic region. The longer selling season will impact pricing decisions used by e-tailers, who will now consider the larger customer base and more varied customer demands when making pricing decisions. Further, this expanded reach brings with it a more fragmented market characterized by global competition, as consumers are exposed to websites of sellers from a wide range of geographic locations. e-tailers must now consider pricing actions taken by a potentially large number of competitors and decide whether and how to respond. (iii) e-business increases the number of sales channels via which a seller can reach his customers. The majority of traditional retailers use only in-store sales as a means to generate revenues. Some retailers also use catalogs as an additional means to access customers. The growth of e-business introduces new channels by which sellers can access customers, such as shopping from home, kiosks in public places, or even from one's cellular telephone. e-tailers will consider the role of each of these sales channels, as well as the interactions between them, when making pricing decisions.

Current Pricing Practice

One can distinguish the use of different pricing mechanisms into two categories, according to the target purchaser of the goods. These two categories are: business-to-consumer ("B2C") and business-to-business ("B2B"). B2C refers to a retailer or manufacturer selling directly to consumers; B2B refers to a retailer or manufacturer selling to other retailers or manufacturers. Table 1 provides a list of common pricing mechanisms.

If we consider this list of pricing mechanisms, B2B engagements are most typically paired with special bids (responses to RFQs), auctions, trade promotions, price discrimination in the forms of customized catalogs, quantity discounts, and annual rebates. Special bids can sometimes be viewed as a special case of a reverse auction where there is only one round of blind bidding. B2C engagements are most typically paired with everyday low pricing (“EDLP”), high-low or promotional pricing, end-of-season markdowns, bundling discounts, non-linear pricing, non-price promotions, price discrimination in the form of coupons, and early bird specials.

Pricing Mechanism	**Description**
Special bid	Customized price tailored for each RFQ.
Auction	In its simplest form, public selling of an item to the highest bidder. Many more sophisticated forms now exist.
Quantity discount	Price is lowered as a function of the total purchase volume.
Annual rebate	Rebate to purchaser at end of year; magnitude of rebate is determined according to the total purchase value over the entire year.
Contract pricing	Items sold over a given time period at a pre-negotiated price in a pre-specified volume range, possibly with multiple price-volume range pairs. Other conditions such as order or supply lead times also apply.
Trade promotion	Co-operative promotion to the end-consumer by two or more businesses (such as a manufacturer and a retailer).
Every day low pricing (“EDLP”)	Item is sold at a single, fixed price; this price does not change over time.
High-low pricing	Price of an item may change over time, e.g., initially assign high price to the item (to capture revenues of less price-sensitive customers); reduce price later in selling season.
End-of-season markdown	Common practice for seasonal items; reduce selling price at end-of-season in attempt to deplete excess inventories.

Bundling discount	Price reduction is offered if customer purchases a pre-specified group (bundle) of items.
Non-linear pricing	Different size packs are priced as separate items, not directly proportional to the pack size.
Non-price promotion	Non-price related incentive offered to induce purchase of item (such as positioning of item at prominent locations in a store).
Customer loyalty program	Selected items sold at a reduced price to customers participating in a loyalty program.
Early bird special	Price reduction offered if purchase item during specified time periods.

A business that wishes to successfully implement any pricing mechanism must engage in both strategic and tactical planning. Strategic planning is used to determine which pricing mechanism(s) to use on what product in which market. Once a pricing mechanism is selected, tactical planning is used to make decisions regarding proper implementation of the pricing mechanism selected during the strategic planning phase.

As an example of this dual-decision process, consider a B2C retailer faced with the strategic decision of whether to adopt an EDLP pricing strategy or a high-low pricing strategy. This decision is dependent upon the target market, the products sold, the long term brand image, and the retailer’s overall marketing and operational strategies. Typically, a medium-to-large retailer uses more than one pricing strategy for its different products and markets, and perhaps even for its different channels.

After the strategic decision is made, the retailer is faced with a set of tactical decisions. If the retailer adopts an EDLP pricing strategy, the buyer must determine the single selling price that will be used for the majority of the selling season. He is then faced with markdown decisions for seasonal items during the end-of-season clearance period and for discontinued items during the close-out period. If the retailer adopts a high-low pricing strategy, the buyer must determine, for each product, a set of prices that will be used during the selling season. In addition, the use of non-price promotions must also be determined, in coordination with pricing decisions. A survey of pricing strategies and pricing tactics typically used by retailers of consumer packaged goods can be found in Shankar and Bolton (2003).

One of the more challenging aspects of the tactical decision-making process is estimating how demand responds to changes in prices and promotions. The buyer often uses the retailer's historical demand and price data to help with this estimation. In most instances the buyer has electronic access to the business' historical data through the use of databases or, more likely, online analytical processing front-ends to databases. For some industries, the buyer may even have historical sales and price data at an aggregate level for a market or product category (e.g., A.C. Nielsen for the grocery industry or A&S for the personal computer industry). Some businesses perform analysis on promotion and markdown effects on their products' sales, most commonly using the estimation of "lift factors" corresponding to specific promotion types or markdown percentages used historically in the product family. A lift factor measures the change in sales resulting from a price change or promotion, and is computed by comparing the sales volumes between two or more historical time periods which are similar in all aspects except price or promotion type. Tables of lift factors corresponding to different markdowns and promotions can be produced using automated database queries. If more than one aspect of two historical time periods differ, linear regression is typically used to estimate the effect of each factor. Market information vendors (e.g., A.C. Nielsen) sell such analysis on commodity products in any given market (at the aggregate level) or for a specific store (with point-of-sale data provided by the customer).

These strategic and tactical decisions are often made manually or using ad-hoc methods, without the help of optimization tools.[1] For

[1] By the term "manual" we mean that the user makes decisions based upon his estimation. The user may (and most likely will) have access to sources of data, such as historical sales, but these sources simply display historical facts and do not provide predictive computation. We use the term "manual" independent of whether the overall procedure is in any way computerized.

example, buyers often use a spreadsheet to compute key performance measures such as total revenue, gross margin, or return on inventory investment for a product family or group of stores over a given time horizon. The buyer then performs “what-if analysis,” which measures the impact of implementing different pricing or promotion decisions on the key performance measures. The results of the what-if analysis are used to guide strategic and tactical decision-making. However, what-if analysis is time consuming and costly and the accuracy of the results depends heavily upon the accuracy of any measures estimated by each individual buyer.

In the case of a B2B transaction the same dual decision process is required, but the decisions that must be made are different in nature. For a B2B retailer, strategic decisions include determining criteria for a customer to be eligible for contract pricing, annual rebates or other quantity discounts, and target gross margins for products sold by sales representatives. (These target gross margins may be specified by market or by product family). The magnitude of contract or quantity discounts and the value of annual rebates as a fraction of the sales price are also strategic decisions. In the next stage, tactical decisions include the degree of control allowed to sales representatives or bid response teams. The degree of control can be expressed as a minimum gross margin, minimum gross profit per transaction, or both. Closely related to these decisions are the incentives offered to the sales teams, which will indirectly influence the ultimate selling price. Because these decisions are indirect levers of control, rigorous mathematical modeling is seldom used in practice. Sometimes a B2B retailer will perform empirical studies comparing different regions or experimenting with different degrees of price control, to gain valuable insight into optimizing such tactical decisions.

B2B retailers guide their wholesale pricing decisions by estimating how demand responds to changes in prices and promotions. In a B2B relationship, the B2B retailer (e.g., the wholesaler) will sell to the B2C retailer (e.g., the retailer) who in turn sells to the end consumer. However, the wholesaler’s attempt to measure end-consumer response to price and promotion decisions is complicated by the following two factors: (i) the retailer employs a pricing and promotion scheme which does not necessarily reflect that employed by the wholesaler and (ii)the retailer may not be willing to share end-consumer data with the wholesaler. Both of these factors make it more difficult for the wholesaler to measure demand response to different price and promotion schemes. To mitigate the impact of (i), wholesalers will often include clauses in contracts with the retailers that include guidelines with respect to the relationship between retail and wholesale prices. The impact of (ii) has been mitigated by the continued advent of cost effective information technology and the ever-increasing understanding of the value of information sharing along a supply chain (see, e.g., Gallego (2000)).

For medium-to-large sized B2B businesses, selling price decisions are often left to the sales or bid-response teams. The price for each product sold to each customer is determined based upon a large number of factors including, for example, the previously determined long-term sales strategy for the given customer, the total value of the transaction, the current inventory positions for all of the products in the transaction, and the probability of winning the bid for the transaction. The latter factor, i.e., the probability of winning the bid given a reasonable range of prices, must be predicted in a manner similar to that employed to predict total product demand given it's price.

The appropriateness of the pricing decisions made by the sales or bid-response teams is largely dependent upon the expertise of each individual pricer. These decisions are generally manually determined, using historical bid or sales data to predict the probability of winning the current bid. Prices offered in face-to-face negotiations (as opposed to RFQs) are even more difficult to determine as the pricer must, in general, determine the bid price in real time. Cases where the purchaser will provide a yes/no response after seeing the bid price can be viewed as a first-price sealed bid auction. (See, e.g., Riley and Samuelson (1981).) In practice, however, there are often multiple rounds of bidding, even with formal requests for quotes. This lack of fixed structure in the sales negotiation process complicates the optimal pricing analysis. The pricing decision relies heavily on the potential purchaser’s response to the price offered, forcing the practitioner to use a manual process for determining prices.

Thus, optimal pricing and promotion decisions both in the B2C and B2B arenas are difficult to determine. For the most part, these decisions are made using manual techniques, and the appropriateness of the decisions are largely based upon individual pricer expertise and the accuracy of estimates made by the buyers.

Research Literature

Pricing related issues have been addressed in the economics, marketing, and operations research and operations management literature. In this section we provide an overview of the research papers that can be used for decision support as opposed to papers whose primary contribution lies in describing the dynamics of optimal prices. We refer the reader to Elmaghabry and Keskinocak (2003), Yano and Gilbert (2003) and Chan et al. (2001) for more extensive surveys of existing pricing literature.

Much of the contribution of the economics literature to the pricing area is in providing high level models to analyze the various forms of price discrimination, both in B2B and B2C settings. See, for example, Wolfstetter (1999) for a discussion of pricing in a monopoly and an oligopoly. Riley and Zeckhauser (1983) provides an interesting argument describing the benefit to the seller of non-negotiable, posted pricing. Another major thrust of this literature is to understand the behavior of price in the presence of changing market conditions. In particular, the literature studies the phenomenon of price “stickiness,” where prices remain relatively stable in spite of changes in market conditions. See for example, Blinder (1982). Monroe and Della Bitta (1978) provides a survey on models for pricing decisions. Their paper contains the earliest call for researchers and practitioners to focus on model-based pricing. The economics literature also focuses on developing models that describe human purchasing behavior. The Bass diffusion model (Bass (1969)) is a well-known model for describing how consumers make purchasing decisions.

Extensions to this model as well as many additional models have been developed in the economics literature.

While the microeconomic models are elegant and insightful, for the most part they do not address operational rules or provide decision support capabilities. We now turn to the contributions of the marketing and operations literature.

B2C pricing has experienced a surge in research activity over the last decade. At the strategic planning level, Ho et al. (1998) study the conditions under which EDLP or high-low pricing is beneficial. In tactical pricing, Smith and Achabal (1998) is one of the first studies that garnered attention from retailers. There, the authors study the problem of pricing during the end-of-season clearance period. They consider a continuous time, continuous price setting with deterministic demand. This problem is extended in Heching et al. (2001) to the case of maximizing revenue or profit over the entire selling season for products with a more complex structure, such as bundled products or custom configured products.

Gallego and van Ryzin (1994) study the stochastic demand version of this model and analyze the problem using optimal control theory. They also extend the problem to cases where only a discrete set of prices is permitted, the initial inventory level is a decision variable, and inventory replenishments are possible (as opposed to a clearance setting where no new inventory will be ordered). Bitran and Mondschein (1997) consider a similar problem, and use dynamic programming to determine the optimal strategy. Tellis and Zufryden (1995) consider a more comprehensive demand model which includes the effects of brand loyalty, stockpiling, and customer segmentation. The profit maximization problem is formulated as a nonlinear integer program and is solved using the Solver optimization module in an Excel spreadsheet. While this approach can provide insight into the more general pricing problem, it is not a practical solution for a retailer with tens or hundreds of stores and possibly thousands of items in each store.

A general version of the problem of maximizing the revenue from a set of products over a finite horizon, assuming that the product demand follows a stochastic point process, is studied in Gallego and van Ryzin (1997). An interesting result derived there is that the solution to the deterministic version of the revenue maximization problem is asymptotically optimal in the stochastic case. Heching et al. (2002) report on an empirical study in which results from such optimization models are compared to the pricing decisions made by a retailer. Their results indicate that revenue can potentially increase by 4% or more when using model-based pricing schemes.

Sometimes, for each product, there exists a menu of fixed prices from which the planner can select. Such situations can arise when pricing and product planning functions are performed by different organization within a company. In this case, the planner must decide when to switch to a different price. Feng and Gallego (1995) study this problem under a Poisson demand assumption.

A closely related issue is the combined problem of determining price and inventory levels. Recent works in this area include Federgruen and Heching (1999), Petruzzi and Dada (1999), Van Mieghem and Dada (1999), and Subrahmanyan and Shoemaker (1996). Eliashberg and Steinberg (1991) provides a survey of problems that lie in the interface between marketing and production decisions. Also related is the problem of pricing products in conjunction with service-related decisions. See Hassin and Haviv (2003) for a survey of basic models in this literature. Extensions to more complicated situations have been suggested, for example, by Bernstein and Federgruen (2001) and Maglaris and Zeevi (2003).

Many of the papers referenced above consider a setting where sellers operate as monopolists. There has also been significant research interest focusing on pricing decisions in the face of horizontal or vertical competition. The assumption that sellers operate in a monopoly environment has been relaxed; sellers may be facing external competition and may also be managing a portfolio of competing products. See, e.g., Gallego and van Ryzin (1997), Tsay et al. (1999), Gilbert (2000), and Zhu (2002).

The B2B pricing research literature is not quite as active at present. Papaioannou and Cassaigne (2000) provides a recent review of statistical models in bid pricing in a request-for-quote environment. A basic assumption in these earlier models is that complete historical data on bids (including those submitted by competitors) are available. This assumption is satisfied for the purchaser, but not for the seller. To avoid this problem, Cassaigne and Papaioannou (2000) proposed an expert system approach to estimating the bid-win probability (i.e., the probability that a seller will win a bid). Similar in spirit, but using a data mining approach, Lawrence (2003) estimates the bid-win probability using only those data available to the seller. Cao et al. (2002) uses a machine learning approach to determine the win probabilities and to estimate missing win-loss information from historical bidding data. One could also use discrete-choice analysis to model buyer behavior and to estimate the bid-win probability. See, e.g., Ben-Akiva and Lerman (1985) for a discussion of discrete choice models. (Talluri and van Ryzin (2000) have used this approach in the context of airline revenue management.) Once the bid-win probability is estimated as a function of selling price (and other factors), the problem of maximizing the expected profit of that particular bid is relatively straightforward.

In a number of industries, manufacturers often plan promotions (both price and non-price related) in collaboration with retailers. In these cases the manufacturer typically contributes some money to an end-consumer promotion, for example, in the form of a direct payment or a price reduction to the retailer. The retailer may then decide to contribute his own money to boost the promotion, for example, in the form of a price reduction to the consumer. Alternatively, the retailer may decide to retain the entire promotion contribution from the manufacturer and take no action to promote the product to the consumer. The amount of contribution from the retailer given a manufacturer’s promotion, called the pass through rate, is a decision that can be optimized. Arjunji and Bass (1996) describes a model to optimize the pass through rate, retail promotion duration, and order quantity for a manufacturer-promoted product. Krishna and Kopalle (2003) investigates a similar situation in a multi-product environment. Silva-Risso et al. (1999) reports a decision support system for a manufacturer to determine an optimal promotion plan given a known and constant pass through rate. At a more strategic level, Neslin et al. (1995) investigates the relationship between retailer / consumer behavior and the optimal promotion plan the manufacturer should develop. Although the focus of the paper is on managerial insights, the optimization model there gives a strong flavor of a model that could be used for tactical decision support.

Commercial Systems

Though airlines have been profitably employing sophisticated pricing mechanisms (yield management) for over two decades, retailers have been slower in adopting these more advanced methods. Instead, retail pricing decisions have traditionally been left in the hands of buyers, who rely on a combination of intuition and spreadsheet calculations to make pricing decisions. Decisions are often driven by target margin objectives, frequently resulting in misalignment between consumer demand and retail prices. However, successful implementation of yield management in airline pricing as well as tougher economic conditions have convinced retailers that there may be merit to using mathematical models for optimizing pricing decisions. This growing recognition has brought with it a demand for solution providers to develop software that addresses the complexities associated with retail pricing optimization.

In response to this demand, a number of software tools have been developed with the objective of improving retailer profitability through price optimization. In this section we discuss the available commercial price optimization tools. We find that the majority of commercial systems at this time are designed for the B2C retail industry with publicly posted prices. Some of these commercial systems also have promotion optimization capability, e.g., maximize revenue or profit by determining an optimal set of (non-price related) promotions over time. For the sake of brevity, we use the term price optimization system with the understanding that the system may also provide promotion optimization capability (as well as simultaneous price and promotion optimization).

Most of the vendors who offer retail pricing optimization tools are new to the revenue management arena, and have not traditionally offered airline yield management tools. These include DemandTec, Khimetrics, KSS Group, ProfitLogic, and Rapt. O'Neill, Daggupaty, and Cauley (2003) and Elmaghabry and Keskinocak (2002) provide an overview of some of these vendors. Supply chain management vendors, such as i2 Technologies and Manugistics also provide offerings in the price optimization area.

The commercial offerings are all similar in user functionality: each provides a model for estimating a demand function (demand as a function of selling price and other factors). This demand function is used by the optimization model to maximize profit or revenue, while considering user-defined constraints such as business rules, current inventory levels, required service levels, and length of the selling season. The business rules constraints ensure that the computed solution is sensible from the end consumer's perspective and that specified business strategies and policies are observed. For example, the seller may constrain the system such that a larger package size of a product should be priced higher than a smaller package size of the same product, or that national brands should be priced at least as high as a house brand of the equivalent product. Other business rule constraints may include the number, magnitude, or frequency of allowable markdowns, or constraints requiring that groups of items must always be marked down simultaneously. An additional feature offered by these systems is to consider the multiple sales channels (and multiple store locations within the "bricks-and-mortar" sales channel) and provide optimal channel and location specific prices for each product.

Typically, each vendor has a proprietary method for modeling demand. The coefficients of the demand model are determined using historical sales and price data. Cost data, competitive actions, prevailing market conditions, cost of capital, salvage values, and inventory carrying costs are also important factors to be considered. Ideally, historical sales data are obtained from corporate databases or directly from point-of-sale systems. Methods for modeling demand include, for example, simple 'lift factor' calculations, traditional econometric models, and consumer choice models (commonly used in marketing). Some vendors determine the appropriate demand model for each product by using an “attribute management system.” Products with similar attributes are clustered together. A library of demand functions is maintained, and econometric modeling is used to find the demand function that fits best with each cluster of products.

Developing demand models and searching for a revenue or profit maximizing solution given these demand models (with estimated parameters) and the business constraints, are nontrivial tasks in terms of computational complexity and the quality of the solution. These two factors serve as technical differentiating factors in the business, which we discuss in more detail in the next section. To specify the constraints, most vendors provide a user-friendly interface. For example, a list of related constraints can be specified by using a ‘for’ loop, similar to a high level programming language. Managing these constraints is challenging since there is typically a fairly large set of constraints (often in the thousands) which need to be manually input and maintained. Even if one considers a simplified demand model where each product is modeled independently of other products, many business constraints (such as the relationship of the prices of the different pack sizes) will link products together, producing a large set of constraints.

The prices generated by the price optimization system are reviewed by the buyer. Buyers will often conduct “what-if” analysis to study the profitability of implementing the suggested pricing strategy under different scenarios. (What-if capability is offered by most of the commercial systems.) Once the buyer determines the final pricing strategy, the prices are input into price management systems. The retailer must then consider issues related to price implementation. Methods must be put in place for rolling prices out to store locations. The results of these prices must be measured and monitored as consumer response to retail prices is observed, to ensure that no modifications are required. The price optimization software may have functionality that allows the retailer to analyze and monitor the impact of pricing decisions on sales and margins. Price adjustments due to competitive actions and seasonal changes may require the retailer to use the price optimization system to revise the retail prices.

More recently, some systems have been developed to aid in B2B transactions. One of the first such systems was developed by Manugistics. The system analyzes a specific customer contract (for example, a contract proposed in the context of an RFQ) and recommends optimal prices for the set of products requested by the customer. The logic is fundamentally similar to that of a B2C system with the exception that each customer is classified into a specific market segment and historical data from that segment alone is used to estimate the demand model. In addition, a contract winning probability is estimated as a function of price and other factors.

Finally, in an ideal situation, the price optimization software will have a facility allowing for data exchange or integration with POS systems and with commonly available software in other areas such as inventory management. This allows for full integration between all the seller’s data systems so that, for example, POS systems immediately reflect changes in price and decisions made by the inventory management systems incorporate the impact of the new pricing scheme.

It should be noted that the terms “price or promotion optimization” or “price or promotion planning” have been used rather loosely in describing these commercial systems. In a number of cases the system does not provide any automatic optimization per se, but instead provides relevant information (such as historical sales reports) that help the user optimize prices or promotions. These systems do not have an underlying demand model or an optimization engine, and are instead focused on business data analysis, data management, and workflow. Such systems are clearly useful in their own right but are not the focus of this article.

Benefits of Price Optimization

As with revenue management systems used by airlines, it is difficult to accurately assess the monetary benefits of a retail price optimization system. The accuracy of this estimate depends largely upon the accuracy of the estimate of demand sensitivity to prices and promotions, which is difficult to measure. Typically, one of the following two approaches is adopted:

(i) The seller uses historical data to develop a demand model. The seller uses this demand model to simulate historical sales (and associated profits and revenues) assuming that the prices (and promotions) suggested by the price optimization system are adopted. The profit and revenues generated under this scenario are compared with the true historical profits and revenues. This gives an estimate of the profit and revenue improvement derived by using the price optimization system. This estimated profit and revenue improvement is then adjusted to account for inaccuracy in the demand model. The adjustment is commonly performed in one of two ways. (a) An estimate of inaccuracy in the demand model is obtained by comparing the demand predicted by the demand model using the historical price vector to the actual historical demand. This estimated inaccuracy is then used to adjust the estimated revenue improvement by adjusting the estimated revenue improvement according to the percentage error in the demand model. (b) An alternative method for determining an adjustment in the estimated improvement is to compare the demand predicted by the demand model using the historical price vector to the historical demand predicted by the demand model using the price vector suggested by the price optimization system. Again, the estimated inaccuracy is used to adjust the estimated revenue improvement. The intuition in this method is that the predicted differences in demand (when the prices are different) may be relatively accurate, even though the actual demand observed for any given price may not be.

(ii) A potentially more costly but perhaps more convincing method for measuring the benefit of price and promotion optimization is to conduct a pilot study. For example, a subset of retail locations in a retail store chain adopts the price and promotion strategy suggested by the price optimization tool. Profits generated by this subset of retail locations are compared with the profits generated by the control set of retail locations for which traditional pricing rules were applied, to measure the benefit of the price optimization system. The benefit of this approach is that it eliminates the direct dependence of the estimate of the benefit on the accuracy of the demand model. On the other hand, the difficulties with this approach lie in finding two comparable, representative, and sufficiently large sets of retail locations, and ensuring that there are no unusual factors or events that occur during the time of the experiment. Perhaps the biggest hurdle is that the retailer must have sufficient confidence in the price optimization system to conduct such an experiment in a significant number of stores over a reasonably long period of time.

Both approaches for estimating the benefit of the price optimization system are used in practice. As the price optimization industry matures and sellers are observing successful implementations of price optimization systems, more retailers are gaining enough confidence to adopt the second approach.

Because the retail price optimization industry is quite young, the long-term value of such price optimization systems has yet to be established. Further, the magnitude of the monetary benefit depends on the particular retail environment and the method of implementing the price optimization system. However, results of pilot studies are encouraging. Pilot implementations report improvements in revenue on the order of 1-5%. The associated improvement to the bottom line is generally significantly larger, as sales cost is not impacted by using the price optimization system. For example, Feldman (1990) reports that for an industry with a 1.6% profit margin, a 1% revenue improvement translates to a 60% increase in profits. Other quantifiable benefits include reduction in inventory levels (especially for seasonal products) or, equivalently, an increase in sell through, improvement in gross margin return on inventory investment, and reduction in labor costs due to a reduction in the number of unnecessary markdowns. See, e.g., Johnson, Allen, and Dash (2001), Girard (2002), and Scott (2003), for discussions of actual implementations of price optimization systems and the benefits observed in those cases.

A common question is how a mathematical model, relying primarily on historical sales data, can perform better than an experienced retail buyer and can produce such significant financial gains. There are two arguments to support this phenomenon.

First, a medium to large retailer (at present the target user of such systems) has many buyers with varying degrees of expertise. While the price optimization system may not outperform the more experienced buyers, it will be helpful to the less experienced buyers. In particular, not only will the price optimization system most likely outperform the less experienced buyers, but it can also serve to accelerate their learning curve. The retailer, as a whole, therefore benefits. This point should be noted when a retailer is selecting buyers for a feasibility or pilot study of a price optimization system. Some retailers may be inclined to select to include only the top buyers in this pilot study and therefore conclude that the price optimization system is not beneficial because it does not outperform the top buyers. The retailer should consider the broad range in expertise of his buyers when assessing the benefit of a price optimization system.

Second, even more experienced buyers have difficulty performing well at the store-product level. A medium to large sized retailer has a large number of store-product combinations, often each with very sparse historical data that can be used by the buyer to make good pricing decisions. Further, it requires a significant time commitment for the buyer to analyze every store-product combination to make good pricing decisions. As a result buyers are often forced, for example, to adopt common prices for a product over all store locations. However, processing a large number of items with detailed data is precisely the strength of computer-based models. The price optimization system can price each store (or region) differently, based upon the historical behavior observed at each store (or region). Thus, while a more experienced buyer may be able to more accurately predict aggregate behavior of a product family for the entire retail chain, the price optimization system is often more accurate in predicting behavior at the more detailed store-product level.

Both of these arguments support the concept that a decision support system such as a price optimization system complements the ability of its human user. For example, the buyer may be more accurate at determining the demand trend for a product family at the retail chain level, and the price optimization system can be used to compute the demand models at the store-product level, while taking into consideration the high-level demand trend specified by the buyer. Also, the buyer may be more accurate in predicting the demand trend for large product families or products that appeal to specific customer types. The buyer can be used to determine the pricing scheme for these products and the retailer can use the price optimization system to estimate the demand and determine prices for the other products. In these ways, the buyer’s time can be more efficiently utilized. The use of a price optimization system can allow the buyer more time to analyze other, more qualitative though equally important factors (such as fashion trends) or competitive behavior. By combining expert knowledge with a data-based optimization model, retailers can expect to see significant improvements in pricing performance and in overall retail profits.

References

R.V. Arjunji and F.M. Bass, “A Model of Retail Promotion,” manuscript, Yale School of Management, New Haven, CT, 1996.

F.M. Bass, “A New Product Growth Model for Consumer Durables,” *Management Science*, Vol. 15, No. 5, 215-226, 1969.

F. Bernstein and A. Federgruen, “Dynamic Inventory and Pricing Models for Competing Retailers,” conditionally accepted to *Naval Research Logistics,* 2001.

M. Ben-Akiva and S. Lerman, *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge, 1985.

G.R. Bitran and S.V. Mondschein, “Periodic Pricing of Seasonal Products in Retailing,” *Management Science*, Vol. 43, No. 1, 64-79, 1997.

A. Blinder, “Inventories and Sticky Prices: More on the Microfoundations of Macroeconomics,” *American Economic Review*, Vol. 72, 334-348, 1982.

L.M.A. Chan, Z.J.M. Shen, D. Simchi-Levi, and J. Swann, "Review of Dynamic and Online Pricing Research to Improve Supply Chain Performance,” chapter to appear in *Handbook on Supply Chain Analysis in the eBusiness Era*, Kluwer Academic Publishers, 2001.

H. Cao, R. Gung, R. Lawrence, Y. Jang, G. Lin and Y. Lu, “Bid Winning Probability Estimation and Pricing Modeling,” U.S. patent filed, 2002.

N. Cassaigne and V. Papaioannou, “Knowledge focused bid price setting process,” Proceedings of the 11th International Workshop on Database and Expert Systems Applications, 841–845, 2000.

J. Eliashberg and R. Steinberg, "Marketing-production joint decision making," in J. Eliashberg and J.D. Lilien (ed.), *Management Science in Marketing, Handbooks in Operations Research and Management Science*, Volume 5, North Holland, Amsterdam, 1991.

W. Elmaghabry and P. Keskinocak, “Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices, and Future Directions,” *Management Science* Vol. 49, No. 10, 1287-1309, 2003.

A. Federgruen and A. Heching, "Combined pricing and inventory control under uncertainty," *Operations Research* Vol. 47, No. 3, 454-475, 1999.

J.M. Feldman, “Fares: To Raise or Not to Raise,” *Air Transport World*, Vol. 27, No. 6, 58-59, 1990.

Y. Feng and G. Gallego, "Optimal starting times for end-of-season sales and optimal stopping times for promotional fares," *Management Science* Vol. 41, No. 8, 1371-1391, 1995.

G. Gallego, Y. Huang, K. Katircioglu, and Y.T. Leung, “When to share information in a simple supply chain,” submitted for publication, 2000.

G. Gallego and G.J. van Ryzin, “Optimal Dynamic Pricing of Inventories with Stochastic Demand over Finite Horizons,” *Management Science*, Vol. 40, No. 8, 999-1020, 1994.

G. Gallego and G.J. van Ryzin, "A multi-product dynamic pricing problem and its applications to network yield management," *Operations Research,* Vol. 45, No. 1, 24-41, 1997.

S.M. Gilbert, “Coordination of Pricing and Multiple-period Production across Multiple Constant Priced Goods,” *Management Science*, Vol. 46, No. 12, 1602-1616, 2000.

G. Girard, “Price optimization is hot, but it’s just the beginning,” AMR Research Report, August 2002.

R. Hassin and M. Haviv, *To Queue or Not to Queue: Equilibrium Behavior in Queueing Systems* (International Series in Operations Research & Management Science, 59), Kluwer Academic Publishers, 2003.

A. Heching, G. Gallego, G. van Ryzin , "Markdown pricing: An empirical analysis of policies and revenue potential at one apparel retailer," *Journal of Pricing and Revenue Management*, Vol. 1, No. 2, July 2002.

A. Heching, Y.T. Leung, M. Levanoni, G. Parija, “Optimal pricing and promotion decisions to maximize profit,” presented at the INFORMS Marketing Science Conference, Wiesbaden, Germany, July 2001.

T.H. Ho, C.S. Tang, D.R. Bell, “Rational Shopping Behavior and the Option Value of Variable Pricing,” *Management Science*, 44, 12, Part 2, S145-S160, 1998.

C.A. Johnson, L. Allen, A. Dash. "Retail Revenue Management," The Forrester Report, December 2001.

A. Krishna and P. Kopalle, "Retailers' Optimal Ordering and Pricing Decisions in a Multi-brand Trade-Dealing Environment," manuscript, University of Michigan Graduate School of Business, 2003.

R. D. Lawrence, "A Machine-Learning Approach to Optimal Bid Pricing", in *Computational Modeling and Problem Solving in the Networked World: Interfaces in Computer Science and Operations Research*, edited by H. K. Bhargava and N. Ye, Kluwer Academic Publishers, 2003.

C. Maglaris and A. Zeevi, "Pricing and design of differentiated services: Approximate analysis and structural insights," submitted for publication, 2003.

M.V. Marn, E.V. Roegner and C.C. Zawada, "The Power of Pricing," *McKinsey Quarterly*, 2003, Number 1.

G. McWilliams, "Lean Machine: How Dell Fine-Tunes its PC Pricing to Gain Edge in a Slow Market," *Wall Street Journal* (Eastern edition), June 8, 2001, pg. A1.

A. Merrick, "Priced to move: Retailers attempt to get a leg up on markdowns with new software," *Wall Street Journal*, August 7, 2001.

K.B. Monroe and A.J. Della Bitta, "Models for pricing decisions," *Journal of Marketing Research,* Vol. XV, August 1978, 413-28.

S.A. Neslin, S.G. Powell, and L.S. Stone, "The Effects of Retailer and Consumer Response on Optimal Manufacturer Advertising and Trade Promotion Strategies," *Management Science*, Vol. 41, No. 5, 749-766, 1995.

M. O'Neill, V. Daggupaty, C. Cauley. "Max margin, The role of price optimization systems," IDC Report Number 29704, Vol. 1, January 2003.

V. Papaioannou and N. Cassaigne, "A critical analysis of bid pricing models and support tool," 2000 IEEE International Conference on Systems, Man, and Cybernetics, 3, 2098–2103, 2000.

N. Petruzzi and M. Dada, "Pricing and the Newsvendor Problem: A Review with Extensions," *Operations Research*, Vol. 47, No. 2, 1999.

J. Riley and R. Zeckhauser, "Optimal selling strategies: When to haggle, when to hold firm," *The Quarterly Journal of Economics*, May 1983, 267-289.

J.G. Riley and W.F. Samuelson, "Optimal Auctions," *American Economic Review*, Vol. 71, 381-392, 1981.

K. Scott, "Driving demand profitability with pricing," AMR Research Report, January 2003.

V. Shankar and R. Bolton, "Determinants of retailer pricing strategy," to appear in Marketing Science, 2003.

J.M. Silva-Risso, R.E. Bucklin, D.G. Morrison, "A Decision Support System for Planning Manufacturers' Sales Promotion Calendars," *Marketing Science*, Vol. 18, No. 3, 274-300, 1999.

S.A. Smith, D.D. Achabal, “Clearance Pricing & Inventory Policies for Retail Chains,” *Management Science*, Vol. 44 , No. 3, 285-300, 1998.

S. Subrahmanyan and R. Shoemaker, "Developing optimal pricing and inventory policies for retailers who face uncertain demand," *Journal of Retailing*, Vol. 72, No. 1, 7-30, 1996.

K.T. Talluri and G.J. van Ryzin, “Revenue Management Under a General Discrete Choice Model of Demand,” conditionally accepted to *Management Science*, 2000.

B. Tedechi, “Scientifically priced retail goods,” The New York Times, September 2, 2002.

G.J. Tellis, F.S. Zufryden, “Tackling the Retailer Decision Maze: Which Brands to Discount, How Much, When and Why?,” *Marketing Science* Vol. 14, No. 3, Part 1, 271-299, 1995.

A.A. Tsay, S. Nahmias, and N. Agrawal, “Modeling Supply Chain Contracts: A Review,” in *Quantitative Models for Supply Chain Management*, edited by S. Tayur, R. Ganeshan and M. Magazine, Kluwer Academic Publishers, 1999.

J. Van Mieghan and M. Dada, “Price vs. Production Postponement: Capacity and Competition,” *Management Science*, Vol. 45, No. 12, 1631-1649, 1999.

E. Wolfstetter, “Topics in Microeconomics: Industrial organization, auctions, and incentives,” Cambridge University Press, 1999.

C. Yano and S.M. Gilbert, “Coordinated Pricing and Production / Procurement Decisions: A Review," in *Managing Business Interfaces: Marketing, Engineering, and Manufacturing Perspectives*, edited by Chakravarty and Eliashberg, Kluwer Academic Publishers, 2003.

K. Zhu and U.W. Thonemann, "Coordination of Pricing and Inventory Control Across Products,” Working Paper, University of Science and Technology Hong Kong and University of Munster, 2002 (under review).