The Implementation Challenge of Pricing Decision Support Systems for Retail Managers

Alan L. Montgomery

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Alan L. Montgomery (e-mail: alan.montgomery@cmu.edu, phone: 1(412)268-4562, fax 1(412)268-7357) is an Associate Professor at the Graduate School of Industrial Administration, Carnegie Mellon University, 5000 Forbes Ave., Pittsburgh, PA 15213.

Abstract:

There has been an explosion in the availability of data and computing ability in retail management that has led to a new desire on the part of managers to implement demand based management. Demand based management uses statistical models to predict consumer price response using historical information. These models can be used to construct pricing decision support systems for retail managers. Currently, many firms have begun offering software to perform price optimization. This article considers how recent advances in academic research can contribute to the implementation of these systems, and in turn consider the new questions likely to be posed by the developers and users of these new systems.

Keywords: Marketing, Decision Support System, Retailing, Scanner Data, Price Optimization

1. Introduction

The introduction of computerized technology into the retail environment over the past two decades has resulted in new opportunities for retailer managers [1]. For example, demand based management uses statistical models to predict consumer price response using historical information. The most prevalent type of information in retail markets is transaction data collected using optical bar code scanners which track every item purchased by a consumer at the point-of-sale. This data could potentially contain a wealth of information about how consumers respond to price and promotions. The promise is that this information can be used to recommend optimal pricing and promotional strategies.

The purpose of this article is to consider practical and research challenges for developing pricing decision support systems (PDSS) for retailers using transaction data. Although PDSS is relevant for any retailer, we focus on grocery retailers due to the prevalence of academic research in this area [2]. This places our PDSS in a fast and large decision space, which places some unique requirements on PDSS. Most supermarket chains carry over 35,000 items in 400 categories, operate scores of stores, constantly adjust prices on a weekly basis due to changes in demand, supply, and competition, and may manage wholesale and retail operations. We foresee that these PDSS are meant to help managers make decisions, but they also serve to help automate decision making [3]. Although we still see an important role for the manager in making subjective decisions for which a PDSS is not well suited.

2. The Genesis of Pricing Decision Support Systems

Little [4] proposed a set of requirements for decision support systems (DSS). Namely that for a decision model to be used by a manager it must be "simple, robust, easy to control, adaptive, as complete as possible, and easy to communicate with". Translating this decision model into a usable DSS for non-technically oriented managers can be quite challenging. The first concern of many managers is whether they are going to be replaced by a machine. Adoption of a DSS requires support from inside the company [5]. Its subsequent success depends upon other factors such as direction interaction with the user ([6], [7]). Past research has shown that the quantitative strengths of DSS can complement the qualitative expertise of managers ([8], [9]). It can also make them less susceptible to their perceptual biases such as anchoring and adjustment heuristics ([10]). In summary, we have learned a good deal in the two decades since Little [11] discussed DSS for marketing managers.

A natural question is why should we consider PDSS for supermarket retailers now? I believe there are two important reasons. First it appears that the market is ready for such a system ([12], [13]), although widespread adoption has not happened yet [14]. Many retailers have now come to recognize the potential of their data as indicated by the large number of PDSS software suppliers listed in Table 1. Notice that most of these companies have been started only within the past five years. There is good deal of diversity in the focus and comprehensive of these software solutions.

Company	**Location**	**Website**	**Founded**
ACNielsen	New York, NY	Acnielsen.com	1923, 1995*
Applied Predictive Technologies	Arlington, VA	predictivetechnologies.com	1999
DemandTec	San Carlos, CA	Demandtec.com	1999
i2	Dallas, TX	i2.com	1988
Evant	San Francisco, CA	nonstop.com	1994
KhiMetrics	Scottsdale, AZ	khimetrics.com	1993, 2000*
Knowledge Support Systems (KSS)	Florham Park, NJ	kssg.com	1993
Manugistics	Rockville, MD	Manugistics.com	2001*
Marketmax	Wakefield, MA	marketmax.com	2003*
Maxager Technology	San Rafael, CA	maxager.com	
Metreo	Palo Alto, CA	metreo.com	2000
ProfitLogic	Cambridge, MA	profitlogic.com	1984, 2001*
Retek	Minneapolis, MN	retek.com	1986, 1996*
Zilliant	Austin, TX	zilliant.com	1998

Table 1. Companies offering price optimization software for retailers. Note: * denotes the date that the first price optimization software for retail management was released, instead of the founding of the company. All web address should be prefixed by http://www.

It should be noted that the original impetus for collecting this data was not to optimize the demand side, but to control the supply side of the retail business. The largest single cost for the vast majority of retailers is the cost of goods sold, which brings the management of the supply channel to the forefront. Hence it is natural that many of companies, such as i2, have entered the market for price optimization software because their customers are demanding integrated supply and demand systems. Many other companies like Comergent, 4R Systems, IMI Americas, JDA Software Groups, OpenPricer, PriceWorks, ProfitScience, Pros Revenue Management, QL2, Revenue Technologies, Rapt, SAP, SAS, Selectica, SmartOps, Strategic Pricing Group, Vendavo, and Trilogy appear poised for introducing new price optimization software for retailers. Although this new market is not without risk, as illustrated by new entrants like Optivo (founded 2000 in Palo Alto, CA) that have already disappeared.

Second, there have been many advances in the academic literature concerning modeling and estimation [15]. Some of these advances have made their way into practice, although many have not. Additionally, studying PDSS could have a positive impact on research. Many researchers focus narrowly on an individual problem, without considering how it interacts with other components. A primary benefit from studying PDSS is that it is an integrative experience, which may help in developing more universal theories of pricing and retailing.

The plethora of research and companies offering PDSS illustrates not their simplicity but their complexity. There are a myriad of decisions that must be made to implement a PDSS that range from bold strategic decisions (e.g., corporate adoption of PDSS) to minute tactical ones (e.g., what to do about an incorrectly signed parameter). We do not claim that a complete PDSS exists either in theory or practice. In fact, only 12% of retailers are even using markdown optimization software, although 53% plan to use it in the next two years [16]. These figures show that widespread implementation is lacking—but at the same time widely anticipated. To help prepare for the implementation of PDSS we articulate its requirements, review what is known about these systems, and anticipate future research that will be necessary to fully deliver on their promise.

3. Requirements of a DSS for Supermarket Retailing

There is quite a bit of diversity in what the software developers in Table 1 classify as a PDSS. Hence part of the purpose is to codify our definition of a PDSS. The basic requirements of a pricing DSS as used in this article include the following:

- *Forecast movement, revenue, profit in real-time.* The core of a pricing DSS is the ability to predict sales as a function of prices and other input variables like feature and display advertising (e.g., out-of-store and in-store advertising).
- *Produce weekly forecasts at the chain, zone, and store level.* A unique requirement of the retailing environment is that the user needs to be able to manipulate prices for the chain, zone, or store together. Since most retailers have scores of stores it is critical that a manager be able to have changes percolate throughout the chain automatically and perhaps deviate from these strategies on an individual basis. For example, one store may choose to aggressively promote a specific product due to competitive conditions.
- *Manipulate price, feature, display, and wholesale cost in an interactive environment.* To become a useful decision aid the user must be able to interactively set "what-if" pricing scenarios.
- *Change prices for groups of products.* Most products do not exist in isolation but belong to a family of products, for example, Jello has a variety of flavors. The manager should be able to manipulate sets of prices as a whole as well as individually. Again, there needs to be quite a bit of flexibility in defining these groups and deviations from these family strategies.
- *Provide a multi-week planning horizon in order to manage promotional calendars.* Price promotions are inherently dynamic, and managers need to be able to set prices for not just a single week, but multiple weeks. Additionally, many stores may have seasonal cycles in which certain items will be promoted as certain times (e.g., turkeys at Thanksgiving), but other weekly promotions may not be known months in advance. Hence, the PDSS needs to be able to anticipate the likelihood of promotions from manufacturers and wholesalers.
- *Work with incomplete information.* Most retailers are able to track promotional prices at competitors quite well since they are widely advertised, however complete information about competitive everyday prices are costly to collect and tend to be incomplete.

- *Coordination across categories and stores.* Categories and stores are not independent of one another, but must be coordinated. The PDSS needs to aid the manager in setting and maintaining a consistent image across categories and stores.
- *Integrate information from many sources.* The PDSS must be able to extract data from current sources and export its data into a compatible format. An ideal system would promise total integration, although this is quite demanding given the disparate systems that most retailers have in place. For example, many inventory systems are not integrated with retail pricing systems.
- *Scalability.* The PDSS must be scalable to assist a retailer with a one category in a single store or one with hundreds of categories in thousands of stores. We note that many current estimation techniques, like Monte Carlo Markov Chain (MCMC), may not scale well.
- *Recommend price strategies.* A price DSS needs to be able to recommend prices, perhaps optimal strategies. However, optimization cannot naively mean recommending a single price vector, but must reflect the uncertainty inherent in statistical models. Most demand models have enough uncertainty in the parameter estimates that confidence intervals of the optimal price vector may be quite large, and the DSS needs to reflect this uncertainty to the user. Alternatively, the model should be able to suggest directions for improved pricing strategies given the proposed pricing strategy. Furthermore, the DSS needs to be able to caution users against bad pricing strategies.

The DSS is meant to aid a category manager in setting price and promotional policies for the retailer. The largest problem facing the user is how to manage the large number of possible pricing decisions. A typical category may have 400 SKUs, which for a regional retailer with 100 stores could mean up to 40,000 pricing decisions each week in a single category, while a national retail could be face thousands of stores with hundreds of thousands of decisions. A DSS for the entire store with more than 35,000 SKUs could easily result in millions of pricing decisions each week. To reduce the dimensionality of this problem, stores are typically grouped into zones and prices are identical within a zone. Additionally, the focus tends to be upon setting the everyday prices for multiple weeks or even months and optimizing promotional prices given everyday prices.

Although divorcing the everyday and promotional pricing policies is a common in practice to reduce the complexity of the decision, this decomposition is suboptimal. In general the selection of an everyday and promotional pricing policy represents a joint optimization problem. Obviously this makes the optimization considerably more complex and it is the tradeoff between optimization complexity and tractability that lies at the heart of a practical consideration in creating a PDSS.

While these reductions can reduce the decision space they do not alter the size of the dataset used to estimate the parameters of the model that underlies the PDSS. For example, if the retailer in our initial example has three years of weekly, store level available with five measures (price, movement, feature, display, and cost) this would result in a dataset of about 240 megabytes for a single category, while data at an individual transaction level could be hundreds of times larger.

The flow of information to support this decision support system will be crucial. There are likely to be at least three major areas where data is processed. The first is in the store environment, where purchase is recorded and tabulated for each transaction and moved into a data warehouse. Many systems may have a lag between collection in the field and collection at a data warehouse (e.g., all transactions are transferred at the end of the day or week). The key fields in this dataset are likely to be UPC, week, and store identifier.

The next step is processing this dataset to specify and create the model that underlies the PDSS. Preparing the data can require cleaning up the data, flagging weeks or items with suspicious activity, or reconciling data from disparate systems. For example, many retailers set their promotional strategies for a weekly cycle that begins on Thursday while everyday price changes may be set on a weekly cycle that begins on Sunday. In addition to the retail data the PDSS must also have access to information about inventory and purchasing. Inventory data is needed to assess current assortments, the value of promotions to clear out unexpectedly low demand, and potential stockouts. Purchasing information supplies the wholesale costs needed for predicting profits.

A difficult data problem arises at this stage, since the key fields of a purchasing system are likely to be product or case code and supplier. There is not necessarily a one-to-one correspondence between a product code and UPC. For example, a retailer could have multiple suppliers for a single UPC, there may be several UPCs that essentially identical or highly substitutable (10.1 oz versus 10.2 oz; or regular versus special package design), there may be multiple case sizes for a single UPC each with different prices, the marginal cost may depend upon the quantity purchased, and cases may actually contain a mixture of UPCs (e.g., the manufacturer bundles three flavors together in a single carton). These problems may account for only a fraction of the items sold, but the PDSS must be designed to handle each of them if the system is to meet its challenge of usability. In summary, a PDSS needs to be able to translate between buying decisions at a carton level to a shelf-price for a single unit.

The last major flow of information is moving the data from the analysis phase to the price staging area where the information is transmitted back to the store and shelf prices are physically set. Often the modeling is performed by an analyst or statistician who may work in conjunction with the category manager who makes the pricing decisions. An added complication comes from retailers who have franchisees who can make independent decisions which override the PDSS. Additionally, the price optimization is likely an independent system from the price staging. It is this stage where prices are moved from the PDSS into the store databases where shelf tags are printed and distributed. Again this may seem trivial but can be complex due to the data translations that may occur from one system to the next.

4. Research Advances and their Contributions to PDSS

Currently, the two leading vendors of PDSS, DemandTec and KhiMetrics, would meet most (if not all) the requirements proposed in the previous section. There are many differences in each firm's approach to data cleansing, modeling, and optimization to implement a PDSS. Our purpose is not to debate the relative merits of each approach, but to point out that there is quite a bit of diversity in how a PDSS can be constructed. Although the requirements of a pricing PDSS may seem straightforward—albeit a complex undertaking—its implementation raises many interesting research questions. In this section we discuss the potential contributions of recent academic research which can aid in the development of a PDSS. These contributions also reflect weaknesses in the current set of PDSS packages and identify challenging problems for researchers (both within industry and academia) to solve.

Modeling price response using transaction data. The fundamental problem in PDSS is to relate past price and promotional changes to sales. Guadagni and Little [17] were one of the first to show how household level transaction data can be used to solve this problem. Since that time there has been a huge growth of research in this area that is beyond the scope of this paper to review. We refer the interested reader to [18], [19], and [20]. It would appear that both industry practioners and academic researchers would agree on the value of these models for modeling own-price response, coupons, market structure analysis, and shelfspace management [21]. But certainly there is room for newer models that better incorporate consumer behavior and the psychology of price response.

Many of the recent advances in methodology focus upon new Bayesian methods for estimation using Monte Carlo Markov Chain (MCMC) and Gibbs Sampling [22]. For example, [23] and [24] show how response can be measured at an individual or store-level, respectively. These techniques introduce hierarchical models, in which the parameters of one model become the input for another model or a hierarchy of models. The advantage of these techniques is that they effectively average or "shrink" less stable, individual-level estimates towards more stable, pooled estimates [25]. On the other hand these techniques can require an estimation procedure to be simulated thousands of times making them impractical for some applications. Moreover, practitioners must often rely upon commercial statistical software (such as SAS's PROC MIXED) that do not efficiently estimate these models [26]. It would appear that approximate, but very fast techniques for estimation may work well in hierarchical models [27]. A challenge for academic researchers is to improve the scalability of their models which use MCMC techniques, since scalability is an important consideration in real-time PDSS.

Integrating household and store data. Instead of treating household and store transaction logs as incompatible datasets, researchers have considered how macro and micro datasets can be reconciled. [28] show that price elasticities estimated from market share models at the store level and choice models estimated with household level data are similar in magnitude. More generally, one can think of combining the forecasts of quite different models together to yield a superior consensus forecast [29].

Product-level modeling. A traditional approach in marketing is to analyze only the top items in a category (see [30], [31]) or aggregate data to the brand-level (see [17], [21]). The usual argument is that this provides a reasonable measurement of sales in the category. However, this is inadequate for a pricing DSS. Every item and even potential items must be included. In fact the highest selling products are typically the ones that receive the most managerial attention, which suggests that a PDSS may disproportionately increase the profitability of items with smaller shares.

One approach to this problem is to assume that demand for individual products is a function of their attributes ([32],[33]). This can dramatically reduce the dimensionality of the demand system. Additionally, it can solve the problem of new items. Since, the attributes are observed it is always possible to make inferences about new products, which is critical for a PDSS. An added advantage of attribute based models is that they can also be used in optimizing assortments, which brings out another fruitful area of research ([34],[35]). A PDSS cannot take assortment as fixed, but must understand how assortment influences demand [36].

Another alternative would be to enforce restrictions in the substitution matrix of a demand system [37]. Montgomery [38] proposes an integrated procedure for identifying and estimating the market structure and shows the importance of carrying over the uncertainty when demand is unknown. Due to the high dimensionality of this problem, an analyst's assumptions can have substantial impact in pricing decisions. This identifies another potential problem for PDSS, namely that good fitting models do not necessarily lead to good inferences. For example, imagine that prices are always set to a high or a low value. A linear regression model may fit the model really well, but if uncertainty about the functional form is incorporated then inferences can be substantively different ([39], [40]). Most retailers do not continuously experiment and vary prices but often cluster prices around odd price endings, yet results about the importance of these effects are mixed ([41],[42]). In summary, these results suggest that the process of statistical inference is just as important as estimation. Yet, the primary emphasis on modeling has been on the former and not the latter, which identifies another direction for future research.

Promotional response and cross-category effects. Research concerning promotions has been an especially active area, see [43] for a review. Creating DSS for manufacturers using scanner data has been considered both in practice and research ([44],[45],[46]). Promotional DSS for retailers have received less effort, although [47] proposed a system for markdown promotions at a department store. Although the problems of creating promotional schedules for manufacturers and retailers show some similarities, there are also some basic differences. Namely, that the retailer is being offered a palette of possible promotions by the manufacturers and must decide which of these offers to accept [48]. Unfortunately, this is one area where typically retailers have very poor records. Generally retailers keep excellent records on the manufacturer offers that are adopted since reimbursement for a promotion depends upon the number of units sold, as with scanbacks [49]. However the offers received from a manufacturer often end up in the bottom of the category manager's desk drawer. But if a PDSS is to work optimally it must have information about what potential promotional offers exist, and even more than that must be able to generate expectations about the frequency and number of promotions.

The effects of promotions are generally larger than a single category and may influence a store's overall price image ([50], [51]). Most retailers subscribe to the theory that their price image is driven by some set of high-volume products [52]. In practice, this means that many Hi-Lo retailers are using price promotions to drive their price image. This suggests that promotions must be taken holistically and not on a category by category basis. However, this is an area where academic research is underdeveloped, one exception is [53] who show consumers may have similar response to feature promotions in different categories. Understanding promotions generally requires information about multiple categories, which substantially increases the dimension of the problem, and competitive prices, which often are unknown. This identifies another area for future research in understanding the effects of promotions across categories.

Pricing in information poor environments. A consistent theme up to this point has been the overwhelming amount of information that is available to retailers. However, there are many times where retailers have very little information, such as with new products or new stores. Unfortunately, traditional approaches to estimating models may not work. This is one of the advantages of Bayesian techniques that allow for incorporating prior empirical or subjective information. Hierarchical techniques as employed by Montgomery [24] allow a retailer to predict response at a new store location without any historical information at those locations by borrowing information from other stores. Beyond retailing there are many examples of using hierarchical models to predict demand with little or even no information [54]. Using a new technique developed by Montgomery and Rossi [55], analysts can leverage economic models which are often very parsimonious but also place potentially rigid restrictions on cross-substitution matrices. Effectively their approach shrinks estimates towards a restricted model, but is adaptive in that as more information is added the estimates look very much like unrestricted estimates. These techniques work well with very little information and allow analysts to incorporate prior information. In summary, PDDS need to be robust and work in both information rich and poor environments.

More flexible optimization strategies. It has long been recognized that groceries tend to be price inelastic. This implies that broad price increases may increase the profitability of grocery retailers ([56], [57]). However, retailers are hesitant to engage in broad price increases. One possible explanation is that our models are inadequate [40]. One suggestion to overcoming this problem is to constrain prices to some region ([58], [24]). For example, [24] constrains the average price or total revenue to equal the same value before the store introduced. These constrained optimization strategies have become popular in practice. Unfortunately, the constraints can end up driving the optimization strategy and may result in infeasible solutions. These problems point to a need for a better understanding of what drives these constraints: do they reflect inadequacies in our models or useful proxies for unknown information?

5. Practical Challenges for Pricing Decision Support Systems

There are many research and practical questions that must be addressed to create a DSS for retail managers. These challenges are not an exhaustive set but one that reflects the experiences (and biases) of the author. We briefly discuss some of these:

Better access to data. For all the investment in data warehouses, many of these systems lack easy access to usable data for managers. One of the requirements of PDSS is that they require clean datasets to feed into their analytical engines, a byproduct of this is a clean, consolidated dataset. Surprisingly, this may be the first time that many managers have had such easy access to their own datasets. Hence, the adoption of PDSS may require expensive changes in the way that data is stored, but also promote the use of this data for both reporting and decision making. At the same time the huge quantities of data point to better systems for visualizing data for non-statistically oriented users.

Better user interface to models. Many category managers in retailing do not have an analytical or statistical background, yet they are the ones that must use these very quantitative systems to improve their decision making. Again one possibility is to use visual techniques to interface with the PDSS.

Better insight into optimal price recommendations. Optimization tends to be treated as a black box to the user. Unless the model can provide some intuition in understanding why this new strategy is better, users are more apt to reject it. One possibility is to decompose the current pricing strategy and the recommended optimal pricing strategy into a series of moves, where the user can understand each of these moves. Instead of treating optimization as a black box process, the PDSS could break down the price change into a series of steps. For example the most profitable step is to increase all prices, the second step is to increase the price gap between national brands and private labels, and the final step would be to add a small premium to best selling product. Perhaps by decomposing the solution into a series of simpler moves the user could better understand the pricing recommendations.

The need to experiment. As retailers start to adopt price optimization software on a widescale basis, this adoption could also introduce endogeneity into the pricing solution. If retailers gain confidence in a PDSS, they could become reluctant to deviate from the "optimal" recommendations. In turn the price recommendations from one week would become the data fed into the DSS to understand price relationships, this results in an endogenous relationship between the observed data and the DSS. It is possible that prices—or more likely—the relationships between prices could be kept in a narrow range, and prevents the PDSS from ever detecting problems within the system. For example, suppose a PDSS predicts that an item is elastic and subsequently the price is always kept low. Unfortunately, the PDSS can not detect the true relationship due to a lack of price variation, and the DSS would perpetuate its errors. This points out a need to explicitly understand the value of price variation in order to ensure that DSS have adequate experimental information to make good recommendations. Unfortunately, we need to better understand how to value price experiments before they are run. In summary, PDSS need to also be able to aid in the design of price experiments and help anticipate the need to experiment.

The reliance on historical information. A PDSS as outlined in this article focuses largely on forecasting demand using historical information. However, historical information may not be predictive of the future when structural changes occur, for example the introduction of a new competitor or substitute, or if there is inadequate variation in past prices to reliably estimate demand. Furthermore there is also the possibility that no historical data exists, as is common with new operations. Potentially, Bayesian techniques could be employed [55], cross-sectional data could be exploited [59], or subjective judgments could be incorporated [60], but at the heart of the PDSS described in this article is a reliance on historical information and the willingness of the analyst to believe that at some level the market is stable.

Measuring and monitoring competitive response. Most retailers believe there businesses to be strongly influenced by competitive strategy. However, few retailers actually have much information about their competitors available. First, to collect competitive prices supermarket retailers generally have to physically visit their competitors and record prices just as a consumer would. This is time consuming and expensive, so many retailers work with only small samples of competitive prices. Advertised promotions are monitored diligently, but most prices are not advertised. Second, even if past competitive prices are known, the key task for a PDSS is to predict future prices and competitive response to proposed pricing levels. Given the granularity of the decisions made in a PDSS this represents a challenging problem that has not been considered within either industry or the academic community.

Integrating supply and demand decisions into a single environment. Many vendors of inventory and supply management software are designing price optimizers because their customers as asking for such integrated systems. A future direction for both industry and academics is to better integrate inventory, purchasing, and pricing into a single problem.

6. Conclusions

Retail managers appear to be ready for PDSS. Many such systems are now appearing in practice. These systems draw either directly or indirectly upon academic marketing research. There are many practical issues to address and wide-spread implementation of these systems may be years away. However, these new systems have the potential to change how prices are set, data collected, and the types of questions managers will ask, which opens up many potential directions for new research that we have discussed in this paper. It is our hope that this article will help educate practioners about the wealth of research upon which to draw, and researchers to the better understand the realities facing retailers in a real-time, information intense environment.

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