A Decision Support System for Vendor Managed Inventory

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Recently, vendors and retailers have begun to forge cooperative agreements to manage inventory, which requires sharing demand information and setting mutually agreed upon performance targets for the supply chain. This paper describes the market forecasting and inventory management components of a Vendor Managed Inventory (VMI) decision support system and how this system was implemented by a major apparel manufacturer and over 30 of its retail partners. The DSS also helped the vendor and retailers arrive at jointly agreed upon customer service level and inventory turnover targets. As a result of implementing this VMI system, customer service levels improved dramatically, often coupled with a significant improvement in inventory turnover. The VMI performance results relative to the existing system and related insights for supply chain coordination are discussed.

Vendor Managed Inventory (VMI) systems have been initiated by certain manufacturers to improve both retail customer service levels and inventory turnover. VMI systems achieve these goals through more accurate sales forecasting methods and more effective distribution of inventory in the supply chain. The VMI system allows the retailer to expand the assortment of the vendor’s products that can be offered within a given retail space. This improves the profitability of the vendor’s brand for both the retailer and the vendor. Retailers working alone are generally not able to achieve the same productivity increases because the vendor is the one able to provide a more responsive replenishment system based on more precise demand information.

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The VMI system we describe uses a decision support system (DSS) to develop a specific model for each retailer that provides weekly sales forecasts (even in difficult promotional retail environments). The DSS further assists the user with decision methods for inventory management and models for measuring and improving system performance. Under the VMI agreement, the retailer provides seasonal promotional plans and sales data to the vendor. The vendor then produces the sales forecasts and supplies the inventory to meet agreed upon customer service levels and inventory turnover targets. The DSS also helps the vendor and each retail partner to jointly set customer service levels and inventory turnover targets by evaluating alternative inventory level and replenishment decisions and identifying achievable system performance levels.

The DSS described here has been implemented by a major apparel manufacturer in conjunction with over 30 of its key retail accounts. The VMI system has been highly successful. Over a three-year period, service levels have improved dramatically, with minor increases in the retailers’ inventory levels. In many cases, the participating retailers’ buyers have found that the VMI system’s forecasts are more accurate than their own and they now rely on these forecasts for merchandise planning.

One of the vendor’s primary objectives in this VMI system was to increase customer service level through better forecasts and more effective use of inventory. This would lead to a higher availability of sizes and color choices, thus making this vendor’s brand relatively more attractive and therefore achieve increased sales. In principle, one could argue that it might be difficult to persuade the retailers to increase their service levels, as opposed to simply using the VMI’s improved inventory management to increase their inventory turnover. However, in this instance, the participating retailers had set high goals for customer service level, but were failing to meet them because of inaccurate sales forecasting and/or suboptimal inventory allocation. Thus, when the VMI system caused the customer service level to increase with a relatively small amount of additional inventory investment, both the vendor and the retailers experienced improved results.

Related Supply Chain Literature

VMI can be viewed as an example of channel coordination, which has been studied by both marketing and supply chain researchers. The supply chain literature, recently surveyed by Tsay et al. (1998), develops an economic rationale for why retailers and vendors may choose different levels of inventory investment. In particular, Narayan and Raman (1997) and Cachon (1997) study the coordination of inventory levels when the retail price is fixed and develop models for the effects of VMI on service level and channel profits. They argue that the vendor may have a higher perceived cost of stockouts than the retailer. This may occur because the retailer’s profit margin per unit is lower than the vendor’s, or because a customer may simply substitute a different brand at the same store when a stockout occurs. This clearly results in a shortage cost that is larger for the vendor than for the retailer. These cost differences can cause retailers to select a lower customer service level than the manufacturer would prefer.

The marketing models, beginning with the seminal paper by Jeuland and Shugan
(1983), compare both the prices and the “level of channel effort” that retailers choose, versus those the vendor would choose, to optimize the complete channel. For our VMI application, retail prices were fixed, due to legal considerations. Thus, the VMI channel coordination problem in this paper more closely resembles the situation studied by Desiraju and Moorthy (1997). They consider the case of demand uncertainty and propose jointly set performance requirements as a means of coordinating channel effort among the retailers. In the VMI context, the retailer’s inventory investment and the corresponding customer service level can be viewed as an example of “channel effort” that has a decreasing marginal impact on demand. The conclusion of the related marketing literature is again that without channel coordination retailers will tend to provide a lower level of “effort” than is needed to maximize channel profits.

Collaborative, forecasting, planning and replenishment, or CPFR\(^1\), systems also improve sales forecasts through information sharing between retailers and vendors. CPFR agreements typically go further than this paper’s VMI system in that they develop joint business plans with specified financial remedies when targets are not met. On the other hand, a CPFR system need not include a vendor managed DSS for sales forecasting, inventory management and performance analysis. A CPFR approach to sales forecasting may not lead to the same improvements in accuracy as VMI, since they are typically collaborative subjective forecasting efforts. Quick Response (Q/R) systems, which have also been implemented by a number of vendors, focus on reducing the lead time for replenishment, which in turn reduces the need for safety stock and thus improves inventory turnover. A VMI system can potentially achieve these same objectives.

This paper makes the following contributions to retailing research in supply chain management. It:

- Combines promotion response and parameter updating models developed in the marketing and forecasting literature with inventory management and system performance models developed in the management science literature. This is a novel integration of these individual models into a single decision support system.
- Describes a major multicompany implementation of a VMI decision support system and the resulting improvements in supply chain performance.
- Provides an example of how certain incentive incompatibilities in retail supply chain management can be resolved and discusses the relationship to channel coordination theory.

**VMI BACKGROUND AND BENEFITS**

A key business motivation for developing VMI replenishment systems is to develop a deeper partnership between the vendor and key retail accounts. Some of the specific goals cited for this system were to: (1) give the retailers’ customers the best opportunity to purchase the vendor’s products, (2) help the retailers manage their inventory more effectively, and (3) assist the vendor in production scheduling\(^2\).

To understand the importance of enhancing the vendor/retailer relationship, it is useful
to consider the typical retail decision-making environment for forecasting and inventory management. Buyers for department store chains are responsible for 20 to 40 product categories, which may include thousands of individual SKUs at the style-color-size level. For example, a product category might be Levi 501 stone washed denim jeans. Buyers generate an aggregate (chainwide or regional level) forecast and use historical ratios to forecast sales allocations among the individual SKUs and stores (e.g., 40% of past sales were medium size, 2.2% of sales in the Eastridge store).

Buyers are also responsible for planning and executing temporary price promotions that include newspaper, radio, or TV support. Many of the phenomena that affect sales in a category are observable only infrequently (e.g., Father’s Day coupled with a radio ad). Thus, the opportunities for the buyer to learn from previous decisions are limited and perplexing. At the same time, buyers monitor sales trends on a weekly basis and correspondingly adjust their forecasts. These forecast updates are often made intuitively based on ad hoc rules.

Specifically VMI offers the following benefits. For the retailer:

- More effective inventory management and less uncertainty regarding inventory turnover and customer service levels. The VMI system provides a way to set and achieve performance targets for both these goals.
- A cost-effective way to obtain sales forecasting and inventory management services. As the vendor’s analysts implemented the system across many retailers, economies of scale were achieved in both the development and the customization of the models. This lead to a VMI forecasting system that was more accurate and developed at a lower cost than could be realized by any individual retailer.

For the vendor:

- VMI provides a method for the vendor to increase the availability of their brand in stores, relative to competitors’ brands, and still meet the retailers’ budgetary open-to-buy constraints.
- Retailers’ orders are often misleading data for production planning. Orders do not provide accurate information about which merchandise sells more rapidly and which styles stocks out in midseason, for example. Furthermore, less popular styles and colors are typically sold eventually through markdowns. Relying on actual sales data also prevents the “bullwhip effect” (Lee, Padmanabhan, and Whang, 1997), that occurs when time lags, coupled with batch orders from the retailer, tend to amplify demand fluctuations as they go up the supply chain.
- VMI also reduces the opportunity and incentives for gaming, for example, retailers sometimes intentionally inflate orders when product supplies are limited and proportionally allocated by the vendor.

In this paper, we first describe the forecasting, inventory management and systems performance models, followed by an overview of the decision support system for implementing the VMI. We then discuss the implementation of the VMI system by a major
apparel vendor and the benefits achieved. We conclude with insights for future implementations and research.

MODEL DEVELOPMENT

An overview of the models developed for the VMI system is shown in Figure 1. The forecasting model provides the weekly forecasts at the product level for a specific retailer and an estimate for the standard error of the demand, which are required as inputs for the inventory decision model. The product sales forecast is also used by the vendor for production planning and by the participating retailers for merchandise planning. The parameter estimation provides initial values for the parameters of the forecasting model and the updating model then smooths them each week to adjust for changes in sales patterns over time. The inventory decision model determines the appropriate stock levels for each SKU at each store in each week of the season, depending on the forecasted demand and the choice of inventory management policy. These models also offer the
capability to do “what if?” analyses by simulating the performance results that can be obtained with different choices of inventory management policies.

**The Inventory Decision Model**

Retailers tend to replenish the inventory of each product category on a fixed schedule (once a week is typical). In this context, the classical “news vendor” inventory model provides a good approximation for the inventory replenishment decision (Nahmias and Smith, 1994). Conceptually, the target inventory level at the beginning of the cycle for each SKU at each store has the form:

\[ s = \text{Forecasted Demand} + \text{Safety Stock}, \]

where the time period for the forecast is the inventory “cycle time” between replenishments.

We adopt the common assumption that the demand per cycle is normally distributed. In this case, the safety stock for any particular SKU can be expressed as:

\[ \text{Safety Stock} = z* \sigma(t), \]

where \( \sigma(t) \) is the standard deviation of the sales forecast error in week \( t \) and \( z \) is chosen such that \( P\{\text{demand} \leq s\} = \text{target service level} \). Estimates of \( \sigma(t) \) are computed by the forecasting model in the VMI system, as we discuss later in the paper.

We use a “top down” model that allocates the total forecasted sales for each product at each retailer across the product’s SKUs and the retailer’s stores. This is preferable to a “bottom up” forecasting model for this application because the low weekly sales rates at the store and SKU level generate extremely noisy estimates of demand.

Thus, for a given retailer, we have that:

\[ F_{in}(t) = \text{forecasted sales of SKU } i \text{ at store } n \text{ in week } t \text{ is given by} \]

\[ F_{in}(t) = f_{in} F(t). \quad (1) \]

where:

\[ F(t) = \text{total forecasted product sales at this retailer in week } t \]

\[ f_{in} = \text{fraction of sales of SKU } i \text{ occurring at store } n. \]

If the retailer has micromarketing data that forecast the individual SKU and store selling rates, the fractions \( f_{in} \) can be estimated directly. In our application, no micromarketing data
were available, and consequently separate store and SKU proportions were determined independently.

Because the vendor can observe the proportional selling patterns for each size and color of a particular product across all its retail customers, the SKU selling proportions can be defined as:

\[ f_i = \text{fraction of product sales coming from SKU } i. \]

Similarly, each retailer can estimate the expected proportion of sales for each store in the chain for a product of this kind. This defines:

\[ g_n = \text{historical proportion of product sales coming from store } n. \]

This leads to a first order approximation \( f_n = f_i g_n \) that uses readily available data.

The allocated forecast \( F_n(t) = f_i g_n F(t) \) from (1) then combines the vendor’s knowledge of proportional selling patterns for SKUs obtained across all retailers with each retailer’s knowledge of the stores’ selling proportions within that chain.

If we define:

\[ \sigma^2_{in}(t) = \text{the variance of demand for SKU } i \text{ at store } n, \]

then the target stock levels:

\[ s_n(t) = \text{stock level for SKU } i \text{ at store } n \text{ in week } t \]

can be determined from the safety stock formula discussed previously:

\[ s_n(t) = F_n(t) + z * \sigma_{in}(t). \quad (2) \]

The \( z \) value is determined by the customer service level target, that is,

\[ \Phi(z) = P\{\text{the SKU is in stock for the entire cycle time}\}. \]

with \( \Phi(z) \) = the cumulative of the standard normal distribution.

In some cases, the desired service level \( \Phi(z) \) is set by corporate policy, for example, 95%. Service level can also be chosen to minimize the sum of expected shortage and inventory costs by using the “critical ratio” formula (see, e.g., Nahmias, 1997, p. 275)

\[ \Phi(z) = c_u / (c_u + c_e), \quad (3) \]

where \( c_u = \text{the cost per unit of inventory shortage} \)

\[ c_e = \text{the holding cost per unit of excess inventory}. \]
Clearly, service level increases with $c_e$ and decreases with $c_u$. When the retailer and the vendor have different values for these costs channel distortions can result, as noted previously.

A simple approximation for $\sigma_{in}(t)$ can be obtained by allocating the total variance $\sigma^2(t)$ proportionally to each SKU/store combination, that is, let $\sigma^2_{in}(t) = f_{in} \sigma^2(t)$. In the likely case that the SKU/store sales are positively correlated for a given product, this becomes a conservative approximation because $\sigma^2(t)$ is larger than the sum of the individual variances when there is positive correlation.

Improving the forecast accuracy reduces the safety stock by reducing $\sigma(t)$. More frequent inventory replenishments, offered by Quick Response and VMI, reduce both the forecasted demand and the safety stock, since both depend directly on the cycle time.

**Using the Inventory Decision Models to Set Performance Targets**

An essential part of the VMI system was developing jointly agreed upon performance targets for each retailer. Each retailer had a number of goals and constraints, which included:

1. Minimum total inventory levels for each SKU for presentation purposes.
2. Initial total season open-to-buy budgets for each product.
3. Inventory turnover requirements.
4. Customer service level.

Clearly, some of these objectives are conflicting and some combinations of constraints may be infeasible. The inventory decision models were used as part of the VMI DSS to understand the tradeoffs between the constraints and the system performance for each retailer.

Minimum store inventory constraints can be expressed as:

$$s_{in}(t) \geq m_{in} \text{ for all } i, n, \text{ and } t, \quad (4)$$

where $m_{in}$ is the minimum presentation inventory required for SKU $i$ at store $n$. The initial open-to-buy (OTB) budget can be expressed as:

$$\sum_{i,n,t} c_i s_{in}(t) \leq B, \quad (5)$$

where $c_i$ = the standard unit cost for SKU $i$ and $B$ is the retailer’s OTB budget.

The forecasted annual inventory turnover for a product at a particular retailer can be predicted from the total annualized sales forecast divided by the average target inventory over the season:
Retailer’s Annualized Inventory Turnover

\[
\text{Retailer’s Annualized Inventory Turnover} = \frac{52 \times \sum_{t} F(t) / W}{\sum_{t \in \mathcal{T}} s_{i}(t) / W}.
\]  

(6)

where \( W \) = length of the season in weeks. (Note that \( W \) cancels out of this ratio.)

For normally distributed demand, the service level:

\[
\alpha_{i}(t) = P\{\text{SKU } i \text{ is in stock at store } n \text{ for the complete inventory cycle}\}
\]

can be predicted for any particular choice of \( s_{i}(t) \). The weighted average system service level \( \alpha \) can then be defined as shown below:

\[
\alpha_{i}(t) = \Phi\left(\frac{s_{i}(t) - F_{i}(t)}{\sigma_{i}(t)}\right)
\]

(7)

\[
\alpha = \frac{\sum_{i \in \mathcal{T}} \alpha_{i}(t) F_{i}(t)}{\sum_{t} F(t)}.
\]

(8)

These formulas thus provide the basis for determining the tradeoffs between inventory investment and service level for each specific retailer.

The Sales Forecasting Model

The sales forecasts generated by the model must meet three specific goals:

1. Provide the forecasted weekly demand and the forecast error inputs for the inventory decision model,
2. Provide the long-term aggregate forecasts for the vendor’s production planning; and
3. Provide weekly promotion response forecasts for buyers for use in their merchandise planning.

Because the forecasting model is used for many different retailers, it must be flexible and customizable. We specified a general class of models that includes several functional forms for sales response that have previously been applied successfully by marketing researchers.

Forecasted sales \( F(t) \) for a product in any given week \( t \) of the season are expressed as a product of Baseline Sales \( S_{b} \), Seasonal Effects \( V(t) \) and Merchandising Effects \( M(x) \), as shown in (9):
Managing Inventory

Sales = \[ \text{Baseline Sales} \times \text{Seasonal Effect} \times \text{Mechandising Effects} \],

or \( F(t) = S_n V(t) M(x) \).

The weekly sales forecast in (9) corresponds to the total sales of all sizes of the given product. If merchandising decisions are made at the corporate level, the forecast corresponds to the sum of sales across all stores. However, if merchandising decisions are made at a regional or zone level, the same model can be applied to these forecasts as well. As noted previously, while the sales model could also be applied at the individual SKU/store level, the weekly unit sales rates are too low for reliable parameter estimation.

Baseline sales are sometimes referred to as “normal” sales or “de-promoted” sales. The seasonal effect captures the periodic seasonal variations in sales that are due to factors such as holidays and back-to-school. Merchandising effects include all factors affecting sales that are controllable by the retailer, such as price, advertising and in-store presentation. The settings of these variables are specified each week by the retailer as represented by the vector \( x = x_1, x_2, \ldots, x_m \), which is set by the retailer.

We also use a multiplicatively separable model to combine the individual merchandising effects. The general form is:

\[
M(x) = \prod_{i=1}^{m} [\psi_i(x_i / x_i^0)]^{v_i},
\]

where \( x_i \) = the setting for the marketing variable \( i \)

\( x_i^0 \) = a normalizing value for variable \( i \)

\( v_i \) = the elasticity or sensitivity parameter for variable \( i \).

The function \( \psi_i(x_i / x_i^0) \) in (10) takes one of three forms, which can be tested to determine the best functional form for each merchandising effect:

1. \( \psi_i(x_i / x_i^0) = x_i / x_i^0 \) constant elasticity \( \text{(11)} \)
2. \( \psi_i(x_i / x_i^0) = e^{1-x_i/x_i^0} \), where \( x_i < x_i^0 \) exponential \( \text{(12)} \)
3. \( \psi_i(x_i / x_i^0) = e^{v_i} \), where \( x_i = 0 \) or 1. simple multiplier \( \text{(13)} \)

All three forms have the advantage that taking a natural logarithm of Equation (10) results in a linear function of the parameters \{\( v_i \}\}, which allows these parameters to be estimated by linear regression.

The multiplicative sales response model presented in Equations (9) through (13) builds
on several studies that have found multiplicative (nonlinear) models to be better than additive ones (See the review in Kalyanam, 1996). However, there is less of a consensus regarding the exact nonlinear functional form that is most appropriate for an individual merchandising effect. Some studies have used the exponential form (12) to model price sensitivity when periodic promotions are used (Blattberg and Wisniewski, 1989). This functional form can be written as $e^{-wp}$ or $e^{\eta(1-p/p_0)}$, where $p_0$ is the regular price and $p$ is the temporary markdown price. Others (e.g., Achabal et al., 1990) have used the constant elasticity form (11) written as $(p_0/p)^\gamma$ for modeling response to temporary price promotions. This form is similar to the Cobb–Douglas models used in the economics literature for modeling sensitivity to permanent price changes. Both forms provide similar forecast accuracy (Kalyanam, 1996).

The following equation illustrates one example specification of the forecasting model that was used for several retailers. For other retailers, fewer effects or different model forms were determined to be more appropriate.

$$M(p,A,L,T,d) = \left(\frac{p_0}{p}\right)^{\gamma} \left(\frac{A}{A_0}\right)^{\alpha} \left(\frac{L}{7}\right)^{\gamma} \left(\frac{p_0}{p}\right)^{\beta(1-1/T)} \prod_i e^{\mu(k)d(k,t)}$$

where:

- $p_0$ = the regular price
- $p$ = the current (possibly markdown) price
- $T$ = time (in weeks) since the previous promotional markdown on this product
- $A$ = feature advertising space for this product in percentage of a page
- $A_0$ = smallest ad size (typically a line list, which is 10% of a page)
- $L$ = length of time, in days, that the promotional price will run during the week
- $\gamma$ = elasticity of sales with respect to markdown price
- $\beta$ = elasticity of sales with respect to promotional frequency
- $\alpha$ = elasticity of sales with respect to ad size
- $\tau$ = elasticity of sales with respect to promotion length
- $\mu(k)$ = parameter for store-wide-event type $k$
- $d(k,t)$ = indicator variable for “store-wide event” $k$ in week $t$; that is, $d(k,t) = 1$ if event $k$ occurs in week $t$, 0 otherwise.

Two timing effects are considered in (14). The increase in weekly sales from a temporary price reduction depends upon the length $L$ in days of the price reduction. This is captured by using the constant elasticity functional form $(L/T)^\gamma$, (corresponding to $x_1 = L$ and $x_1^0 = 7$ days.) This function is set equal to 1 when there is no price markdown. With $\tau < 1$, the function provides a concave correction factor for promotions that are less than 7 days. The other timing effect is captured by $(p_0/p)^{\beta(1-1/T)}$. This effect implies that a longer interval $T$ between promotions contributes increasing amounts to the price elasticity with respect to the markdown price $p$. This form of the timing effect was developed and tested in Achabal et al. (1990).

A number of retailers we studied use free-standing-inserts in the Sunday newspaper to
advertise temporary price markdowns. This advertising typically features selected products with large full page or half page photos in the insert, and uses smaller ads or simply line lists to announce the markdowns on other products that are also part of the weekly promotion. In our experience, markdowns without any type of ad are rare and are often contrary to corporate policy. Experimentation with various functional forms found that the constant elasticity form \((A/A_0)^\alpha\) performed well for the historical sales data from a large number of retailers, where \(A\) is the size of the ad, and \(A_0\) is a normalizing factor, which can be set equal to the smallest ad size. The elasticity \(\alpha\) is less than one, which implies that ads make decreasing marginal contributions to sales as size increases.

Retailers use a variety of storewide events such as “white sales,” Super-Saturday, and so forth, whose effects can be captured by the simple multiplier form (10). Each of these effects has an indicator variable \(d(k,t)\) that specifies whether an event \(k\) occurs in week \(t\).

Parameter Estimation by Linear Regression

By taking the natural logarithm of the multiplicative model (14), we obtain a linear relationship that allows the parameters \(\gamma\), \(\alpha\), \(\tau\), \(\beta\), and \(\mu(k)\) to be estimated by OLS regression. For each regression run, a minimum of 104 weeks of sales data were used so that all seasonal variations were observed at least twice. Stepwise regression was then applied so that only those coefficient values that had significant sales impacts were retained in the model. Also, pooling was used to include products that were promoted on different schedules to reduce the collinearity between the estimates of the promotion responses and the estimation of the seasonal coefficients. Pooling is particularly important for estimating parameters for the elements of the model that are observed only infrequently, in particular, the weekly seasonality values \(V(t)\).

Product pooling choices were made subjectively, by selecting products that are expected to appeal to similar customers (such as men’s and women’s products). At the same time, it is important to select enough products for pooling to obtain a sufficient number of observations of seasonal effects and promotion response. In general, pooling four to ten products within the same subcategory seemed to work the best (for instance, eight different styles of men’s casual pants of the same type). However, when fewer distinct products were available, it was sometimes necessary to combine products from different subcategories. The approach of pooling products that appeal to similar customers was successful in yielding high \(R^2\) values.

Sales forecasts were conducted on a weekly basis for all retailers on the VMI DSS. This time period was selected because retailers typically retain sales data and promotion information on a weekly basis. Promotions sometimes run for less than one week, but this can be handled by the correction factor and parameter \(\tau\) shown in (14), where the parameter \(\tau\) is determined as part of the regression.

Aggregating sales data across retailers was specifically avoided because this would require adding together sales that occurred under different promotional environments. For any given retailer, the promotion response model could be developed either for the total chain sales or for total regional sales. The preferred approach was to conform to the
retailer’s current practice of chainwide or regional forecasting. A good rule of thumb is that weekly product sales forecasts should average at least several hundred units at the chosen level of aggregation. Table 1 summarizes typical ranges of parameter values and the Adj.-R² values observed over all participating retailers.

Parameter Updating

Despite the fact the Adjusted R² values in Table 1 were considered quite good, we found that the weekly sales forecast accuracy during the season could be improved significantly by updating certain parameters. This might be due to the fact that the parameters estimated by regression on the previous season’s sales data failed to reflect changes in market conditions or promotional strategy for the current season, for example. Furthermore, in the case of new products, the regression estimates were often based on sales of similar, but not identical, products in the previous season.

A variety of methods has been used for parameter updating in retail sales forecasting systems. Exponential smoothing, originally developed for inventory management by Brown (1962), is the basis for parameter updating in IBM’s INFORMEM inventory management system, which is used by a number of retailers. For a more recent treatment of exponential smoothing, see Nahmias (1997, Chapter 2).

Smith et al. (1994) developed a discounted least squares method for simultaneous updating of multiple model parameters and tested it in a retail sales forecasting application. This method reduces to exponential smoothing in the one-dimensional case. Nahmias (1997, p. 294) also summarizes Brown’s method for using exponential smoothing to obtain updated estimates σ(t), the standard deviation of the forecast error.

Both discounted least squares and simple exponential smoothing methods were tested on the historical data in a number of our applications. Although discounted least squares adapts to parameter changes more quickly and provides more accurate forecasts, it also tends to cause greater fluctuations in the parameter values and requires a matrix inversion.

Table 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Range of Values</th>
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<tr>
<td>Elasticity Parameters</td>
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<tr>
<td>Markdown Price</td>
<td>γ</td>
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<td>Promotion Spacing</td>
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<td>Ad Size</td>
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<td>Promotion Length</td>
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<tr>
<td>Event Type</td>
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<td>Small</td>
<td>S</td>
<td>0.00 to 0.50</td>
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<tr>
<td>Medium</td>
<td>M</td>
<td>0.00 to 1.30</td>
</tr>
<tr>
<td>Large</td>
<td>L</td>
<td>0.00 to 2.00</td>
</tr>
<tr>
<td>Adj. R² values</td>
<td></td>
<td>0.75 to 0.93</td>
</tr>
</tbody>
</table>
for implementation. In the VMI application, the current parameter values are used to provide a 60 week forecast for the vendor’s production planning. Because this requires stable parameter estimates, we chose exponential smoothing methods for parameter updating rather than discounted least squares.

The choice of which parameters to update was based on which parameters were the most significant explanatory variables. In the table below, as indicated, each product has its own Base Sales parameter $S_0$. Common seasonal effects $V(t)$ and elasticities $v_i$ are used for all products pooled in the regression. However, the price response parameter $g$ in (14) is updated separately for each product, due to its significance. Since the regression estimates of price response may suffer somewhat due to pooling, parameter updating through exponential smoothing reduces the averaging effects of pooling and mimics, in some respects, the results of using shrinkage estimators (Blattberg and George, 1992).

<table>
<thead>
<tr>
<th>Parameter Estimation</th>
<th>Parameter Updating</th>
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<td>Base Sales</td>
<td>Different by product</td>
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<tr>
<td>Price Response</td>
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<tr>
<td>Factors Other than Price</td>
<td>Same for all pooled products</td>
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</table>

### THE VMI DECISION SUPPORT SYSTEM

The DSS for the VMI system was designed to support three user activities: (1) selecting and fitting a forecasting model to historical data; (2) sales forecasting and parameter updating; (3) performance analysis. Working with a team of buyers and database designers, the authors designed the user interface and developed the software for the first two functions. The vendor’s analysts, on a separate system, implemented the third function of performance analysis.

Operationally, the VMI DSS was used to generate revised sales forecasts each week, as actual sales data are observed by updating the base sales value $S_0$ and the promotion elasticity parameter $g$ for each product. This is illustrated schematically in Figure 1. Estimates of the MAD (Mean Absolute Deviation) of the one-week ahead, four-weeks ahead and sixty-weeks ahead sales forecasts are also updated by exponential smoothing. Users can then review the results displayed by the DSS, as shown in Figure 2.

Figure 2 features a unified user view with several panels on one screen: a forecast statistics panel, a graphical panel, and a database panel. The forecast statistics panel allows the user to see the 1, 4, 8, and 60 week ahead forecasts for each given product, for a given customer account. The graphical panel contains a chart of forecasted versus actual unit sales over a historical time frame so that the user can visually assess the system’s performance. The database panel contains a “snapshot window” that
displays the important promotion and inventory data that the analyst can use to review the results of the forecasting model. Based on an analysis of the information contained in the snapshot window, the user has the option to drop a particular week from the learning process, thus treating it as an outlier. The VMI DSS also offered the ability to automatically drop outliers that exceeded a certain percentage error tolerance.

Using the graph in Figure 2, the user can view the forecasted versus actual sales for any specified time period. Based on the user specified outlier tolerances, the resulting outlier points are highlighted by the circles on the x-axis shown on this screen. In some cases, outliers may be caused by data integrity problems (e.g., unrecorded promotions). The Data Snapshot Window at the bottom of the screen allows the user to view all the supporting details for “suspicious” weeks. This helps the analyst detect and correct the data integrity problems and leads to a more accurate regression estimation of the parameters.
Determining the Forecasting Model and Updating the Parameters

For each new retailer, the first step is to specify the form of the response model (14) and determine the initial model parameters by linear regression. The user first selects the products to be pooled for the analysis and the promotional factors (e.g., newspaper ad size, radio or TV time) to be included. A functional form for each promotional factor is selected from the three choices listed in (11) through (13). The VMI DSS simplified the task of selecting alternative choices of products for pooling together. By trial and error, the user tests different combinations and compares their R-square values in the regression until a satisfactory model is developed. Once the final form of the model is decided upon, the promotional factors and their model forms are stored in a parameter data table. This allows the different models for each retailer’s set of products to be stored as data, without any reprogramming.

Setting Inventory Performance Targets

The vendor’s analysts worked with merchandising managers at each retail company to set specific performance targets. Using Equations (4) through (8), the DSS forecasted the effects of different inventory decisions to determine the performance tradeoffs available to a specific retailer. When the open-to-buy budget or inventory turnover constraints in (5) and (6) were not met with the selected stock levels, the inventory levels \( s_n(t) \) were adjusted downward until targets were met. If the resulting decrease in service level (8) was too great, the retailer was often persuaded to relax the budget constraints. After the system operated for some time, the observed inventory turnover and service levels could be used to fine-tune the system.

These trial and error experiments were performed jointly by team members from the vendor and the retailer. Thus, the retailers’ team members learned what tradeoffs were possible and whether or not certain combinations of constraints were feasible. The mutual understanding that evolved from this interactive process was an added benefit of the VMI system and was essential to its satisfactory implementation.

The Implementation Process

A proof of concept study was undertaken with two retailers in 1995 to validate the forecasting models and to train the vendor’s analysts in the use of the DSS. For six additional retailers, the authors and the analysts worked together to develop an appropriate forecasting model for each retailer. After that, the vendor’s analysts performed more of the modeling themselves, with assistance from the authors. Roughly half the retailer models were developed without the authors’ assistance. The first four to six retailers each took several days of runs and experimentation with the model to achieve satisfactory forecasts. By the time the vendor’s analysts took over the model development, the estimation process was reduced to four to six hours. Thus, there was a significant “learning curve”
ASSESSING THE BENEFITS

Figures 3 and 4 show the changes in the annual inventory turnover and the customer service level that occurred over the first four years of the VMI system’s operation. The companies shown here are two of the nation’s largest department store chains that consist of a total of 15 separate retail divisions. They have the longest history on the system, representing roughly half of the total VMI sales volume by the end of 1997. Merchandise Categories 1 and 2 were also the first ones on the system and represent over 75% of sales for the products on the VMI system. Figure 3 shows that the inventory turnover declined slightly, stabilizing around 4.0 for Company 1 and around 3.0 for Company 2, whereas Figure 4 shows that service levels increased dramatically, particularly for Company 2. Service level was measured as the average

**FIGURE 3**

Annual Inventory Turnover for VMI Companies
percentage of SKUs in stock at the end of the inventory cycle, which is computed automatically by the system. The expected value of this observed service level corresponds to the formulas given in (7) and (8), but individual observations may differ.

These results show that the service level increased substantially after the system’s introduction, with only a modest decrease in annual inventory turnover. Figures 3 and 4 show that for Merchandise Category 1, the service level and inventory turnover improved simultaneously in some instances for both retailers. This was possible because the available inventory was allocated across the stores and SKUs more effectively than before. From one retailer’s perspective, the increase in service level achieved by the VMI system represents “the difference between night and day.”

Calculating the Incremental Improvement

Although these performance results are impressive, they do not provide an incremental quantitative measure of the VMI system’s contributions, as compared to the retailers’ previous inventory management methods. Specifically, a comparison of the performance of the retailers’ systems in 1995 with the VMI system’s performance in subsequent years should take into account the fact that the service levels increased significantly between 1995 and 1998. This direct comparison requires some further assumptions and analysis.

We used the target stock level formula (2) to compute the change in inventory that
would be required to support the observed service level improvement between 1995 and 1998. Multiplying the 1995 inventory turnover by the corresponding inventory factor projects the inventory turnover that would have been required in 1998 using the 1995 inventory management system. Figure 5 illustrates this approach. Using (2), the optimal inventory level can be written as \( m + \sigma^* z \), where \( m \) is the mean demand per cycle and \( \sigma \) is the standard deviation of the demand. Our calculation is based on the coefficient of variation ratio \( \sigma/m \) for the “average” SKU stocked. For the “average” SKU we used a coefficient of variation \( \sigma/m = 2.0 \) at the single SKU and store level, which has been found to be typical for merchandise in this category (Agrawal and Smith, 1997).

We can now compute the ratio \( r_{12} \) for the change in the target inventory of the “average” SKU that is required to change the service level from \( F(z_1) \) to \( F(z_2) \) as follows:

\[
r_{12} = \frac{m_1 + \sigma_1^* z_1}{m_1 + \sigma_1^* z_2} \frac{1 + 2z_1}{1 + 2z_2},
\]

(15)

where \( z_1 \) and \( z_2 \) are selected from Table 2 below for 1995 and 1998, respectively. The predicted turnover in 1998 is determined by \( r_{12} \times (1995 \text{ Turnover}) \) in each case. The computed values are presented in Table 3.

Comparing the predicted values to the actual values, we see substantial improvements in all four instances. The largest improvement of 76% is for Company 2, in Category 1.
The difference in inventory turnover can then be used to compute the corresponding savings in the value of the on-hand inventory required for the reported 1998 sales. These savings are reported in the last column of Table 3 and are, as in the case of inventory turnover, quite substantial.

It is natural to wonder whether some of this improvement occurred due to a general improvement in inventory management effectiveness across all retailers. For example, it is well known that sales volume increases lead to improved economies of scale in inventory management and thus to improved inventory turnover. However, during this period, sales for Category 1 declined while Category 2 increased, and total unit sales remained relatively flat. As further evidence, Figure 6 compares the annual inventory turnover of the retailers who participated in the VMI system during 1996 to 1998 to those who did not. Despite the vendor’s goal of having the VMI retailers increase their service levels, which in turn requires more inventory, the non-VMI retailers still had lower inventory turnovers in both categories during this same time period. (Service levels at non-VMI retailers were not available.) This implies that the non-VMI retailers did not achieve significant inventory efficiency improvements for these two product categories during this same time period because they lacked the support from the improved system.

Thus, we can infer that the VMI system allowed these two multidivision companies to improve service levels significantly at all their retail chains, with only a modest increase in inventory investment and a substantial improvement in the efficiency of the inventory management system. The corresponding inventory dollar savings are substantial, particularly if a VMI system were rolled-out to achieve similar savings for other product lines at these companies.

### Table 2

<table>
<thead>
<tr>
<th>Service Level Changes and Ratio Calculations</th>
<th>1995</th>
<th>1998</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company 1 Service Level</td>
<td>77%</td>
<td>91%</td>
</tr>
<tr>
<td>Z value</td>
<td>0.74</td>
<td>1.34</td>
</tr>
<tr>
<td>r_{12} value</td>
<td>0.67</td>
<td></td>
</tr>
<tr>
<td>Company 2 Service Level</td>
<td>69%</td>
<td>94%</td>
</tr>
<tr>
<td>Z value</td>
<td>0.50</td>
<td>1.56</td>
</tr>
<tr>
<td>r_{12} value</td>
<td>0.49</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3

<table>
<thead>
<tr>
<th>Predicted and Actual Inventory Turnover in 1998</th>
<th>Without VMI (Predicted)</th>
<th>With VMI (Actual)</th>
<th>Improvement</th>
<th>Inventory Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company 1 Category 1</td>
<td>3.4</td>
<td>4.0</td>
<td>18%</td>
<td>$1.1M</td>
</tr>
<tr>
<td>Category 2</td>
<td>3.0</td>
<td>4.0</td>
<td>33%</td>
<td>$1.7M</td>
</tr>
<tr>
<td>Company 2 Category 1</td>
<td>1.7</td>
<td>3.0</td>
<td>76%</td>
<td>$6.5M</td>
</tr>
<tr>
<td>Category 2</td>
<td>2.2</td>
<td>3.1</td>
<td>41%</td>
<td>$1.5M</td>
</tr>
</tbody>
</table>
Estimating the Benefits to the Vendor

The increase in service level resulting from the VMI system is an important benefit from the vendor’s perspective as well. One of the vendor’s goals for the VMI system was to improve customer service level. This enhances the competitive position of the vendor’s products by making them more readily available to customers. One quantitative measure of this benefit is the reduction in lost sales shown in Table 4 for these two companies. These lost sales percentages are determined from the partial expectation of the normal distribution for the given service levels. Using this estimate assumes that all SKUs and stores are stocked at precisely their target service levels and that the demand is normally distributed, so that unfilled demand can be estimated. In one respect, this is a conservative

<table>
<thead>
<tr>
<th>Company</th>
<th>1995 Lost Sales</th>
<th>1998 Lost Sales</th>
<th>$ Values of Change in 1998</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company 1</td>
<td>13%</td>
<td>9%</td>
<td>$720,000</td>
</tr>
<tr>
<td>Company 2</td>
<td>30%</td>
<td>6%</td>
<td>$2,440,000</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>$3,160,000</td>
</tr>
</tbody>
</table>

Figure 6

Annual Inventory Turnover for VMI and non-VMI Retailers
assumption in that if the same total inventory were suboptimally distributed, lost sales would necessarily be higher. These reductions in lost sales represent roughly $3.2 million in additional annual revenue for the vendor from just these two retailers, based on 1998 unit sales. Thus the vendor also achieved direct financial benefits from the VMI system.

CONCLUSIONS

This VMI decision support system combines inventory optimization methods from management science and promotional response models from marketing. We believe that this is the first time that these individual models have been integrated together in a retailing DSS application and implemented in a field setting. This implementation of the VMI system at over 30 major retailers demonstrates that service levels can be improved dramatically with a nominal increase in inventory investment using such a system. The joint development of the DSS by the authors and the vendor’s analysts proved to be a critical step in achieving acceptance and effective implementation of these marketing and management science models across multiple organizations. The vendor and the retailers use of the VMI system led to greater inventory management effectiveness and more realistic expectations for system performance than could have been achieved by either individually. Based on the benefits calculations, discussed previously, retailers who did not participate in the system did not achieve comparable performance improvements during the same time period with the same products.

The development and implementation of this system offers several important insights for retail supply chain researchers and practitioners. It demonstrates that a vendor managed sales forecasting and inventory replenishment system can achieve effective retail supply chain coordination that is viewed as beneficial by both the vendor and the retailers. In particular, the VMI system achieved the vendor’s goal of better product availability, both in terms of the breadth of the vendor’s product line offered by the retailers and in the customer service levels that were achieved, even with the broader assortment. At the same time, the retailers received improved sales forecasts and more effective inventory management that benefited their financial performance.

It is important to note how the theory was modified to allow the models to work in practice. For example, even when the regression was successful in fitting the sales forecasting model to the previous years’ sales data, updating of certain model parameters improved the forecast by adapting to the changing sales rates in the current year. Storing each component of the model (both its form specification and parameters) as data in a large relational database allowed the DSS to manage literally hundreds of econometric models. Parameter updating occurred automatically each week, subject to review by the vendor’s analysts. The DSS software automated much of the econometric work and then interacted with the analysts on a continual, but “exception oriented” basis as new data arrived and new forecasts were generated. This allowed the system to scale well to serve many accounts.

There are significant “learning curve” effects in the design of sales forecasting models across multiple retailers for the same categories of products. This provided
economies of scale in the vendor’s implementation of the VMI forecasting system. There were further economies of scale in resources for software development and analytically skilled personnel that also benefited the vendor, which made the system cost effective to implement. Although the authors assisted with the first few implementations, the vendor’s analysts’ cumulative experience with the DSS allowed them to assume full responsibility for implementing the system at over half of the retailers.

There are a number of insights that resulted from fitting these sales forecasting models across a spectrum of retail accounts that we believe can be applied to other retail forecasting and VMI applications. These include:

1. Updating certain key parameters noticeably improved the accuracy of the weekly sales forecasts, even when the regression fit was quite good. Base sales and price response were the most important parameters to update in our experience;
2. Increasing the number of response factors in the forecasting model beyond two or three tended to provide higher adjusted R-square values in the parameter estimation phase, but less accurate sales forecasts in future periods. This is another demonstration of the superiority of “parsimonious” forecasting models that use as few parameters as possible;
3. Problems due to the collinearity of promotional activities were successfully managed by requiring at least two years of data and by pooling data from products that were on different promotion schedules; and
4. It is important to aggregate sales to the level where there are at least approximately 100 units sold per week to achieve stable forecasts. These aggregate forecasts can then be allocated to the stores and SKUs based on their historical fractions of sales. Our experience has shown this to be a better approach than trying to do individual forecasts at the SKU-store-week level.

In some instances, the implementation of a VMI system leads to a “reengineering” of the retailer’s underlying decision making processes. For example, retailers on the VMI system were induced to improve their promotional planning systems and to maintain more appropriate databases. Often retailers are unsure what data should be retained in a data warehouse. A forecasting model helps define the key data requirements including (1) what data elements to keep, (2) at what aggregation level, and (3) over what timeframe.

In the future, more detailed market information offers some potential opportunities for improving retail sales forecasting models, which could then be integrated into a VMI system. Micromarketing data can provide the basis for more accurate store level sales forecasting and consequently more effective inventory management. As retailers’ databases begin to tie purchases to specific customers, there may be opportunities for forecasting models and decision support systems that build on the behavior of identifiable customer segments. Experimental promotions, which are being undertaken by some retailers across subsets of stores, can also provide more diverse data sets for fitting the forecasting model.
NOTES

1. For additional information see www.cpfr.org.
2. Interviews with Tom Fanoe, President, Joe Boxer; Ralph Briskin, former Director, Levi Link Services (currently Director e.commerce The Mens Wearhouse); and Sandy Golden, Manager, Retail Replenishment–Levi Strauss & Company.
3. Apparel buyers typically work on initial markups that allow promotional markdowns to be profitable with little if any support from the vendor. As a result, apparel buyers generally plan and execute their promotions independently of the vendor. This is in contrast to packaged goods promotions that are typically initiated by vendors.
4. These forms are equivalent, except that the second is expressed in terms of percentage markdown $1 - \frac{p}{p_0}$.
5. Interview with Howard Gross, Chairman–Miller’s Outpost/Anchor Blue.
6. This partial expectation is tabulated, for example, in Nahmias (1997, pp. 835–41).

REFERENCES
