Complete, Pareto, and No Inventory: Alternative Strategies for Retail Inventory

by

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Executive Summary

Retailers with slow inventory turnover are often perplexed in making the trade-off between inventory availability and carrying cost. To study this complex business problem, three alternative inventory strategies, referred to as complete, Pareto, and no inventory, are examined. There is an entire spectrum for retail inventory levels. One extreme represented by the complete inventory, is the traditional approach of stocking and displaying all items such that customer demands are immediately fulfilled. This is so-called "just in case" inventory. The other extreme, no inventory, refers to a display only inventory, where items are express shipped to customers directly from the organization’s central distribution center. Between the extremes lies the Pareto inventory, stocking only the best selling items. This strategy is based on the Pareto Principle that approximately 20 percent of the items account for approximately 80 percent of the sales. Items not stocked in the retail store are displayed and offered to customers in the same manner as the no inventory scenario, whereby the item is express shipped directly to the customer or store from the distribution center. Pareto and no inventory strategies are made viable by providing a cycle time of overnight or second day delivery. A model is developed for analyzing these alternatives, and computer simulation is used to determine the expected result of each inventory strategy. Pareto inventory is found to be advantageous with significant improvements in inventory turnover.

Introduction

Successfully selling upscale, low inventory-turnover products requires having the right inventory mix, while simultaneously keeping total inventory low. These objectives often conflict. Ensuring that items are in stock for immediate customer fulfillment helps sales but inflates inventory, which can be disastrous for inventory turnover and lead to large volumes of discontinued and obsolete inventory. Alternatively, keeping inventory low frequently can cause out-of-stock situations, hurting sales. Selecting the right inventory strategy can be a pivotal business decision.

This complex business problem is examined for a retailer of upscale men's shoes, which has retail stores nationwide. Sales volumes are relatively low, as compared to the average shoe store, while the number of stock keeping units (SKUs) carried is high as a result of the many combinations of pattern, color, size, and width. The distribution center (DC) carries approximately 10,000 active SKUs. Thus, it is not unusual for a particular retail store to not sell any of an individual SKU during the course of a year. Not surprisingly, this tends to lead to large volumes of discontinued and obsolete inventory, and low inventory turnover.
Retail Inventory Strategies

Three different retail inventory strategies, which together represent the spectrum of inventory stocking levels, are compared. One extreme is the traditional approach of stocking all items in the retail store for immediate customer fulfillment, termed the complete inventory. In this scenario, if items (where an "item" is defined as a particular SKU) are stocked in sufficiently large quantities, stock outs and special orders are a rarity. The other extreme, the "no inventory" scenario, refers to having a display-only inventory where customer demands are fulfilled by express special order from the DC. An express special order is defined to mean next day or perhaps second day delivery to the customer via air-freight. The intent here is to come as close as possible to providing the desired item when and where the customer wants, with "when" generally limited to no sooner than the following morning. However, "where" is virtually unlimited and could be left to the customer's discretion. For example the shoes could be shipped to the customer's home or office, or picked up at the store possibly after a high quality "spit shine." The particular shoes displayed could be selected to represent the entire size distribution, such that customers could try shoes on to check fit. (Size and fit are quite consistent between different patterns.) Thus it could be said "if the shoe fits - ship it."

Between these two extremes are varying degrees of stocking items in the retail store. The third strategy, the Pareto inventory approach, lies here. This involves displaying all stock numbers\(^1\), but stocking only the best selling SKUs. About 20 percent of the items often accounts for 80 percent of the sales, according to the Pareto Principle. Empirical data shows this holds true here. Thus by stocking only the top selling 20 percent of the items, the retail store should be able to fulfill approximately 80 percent of customer demand on the spot. The remaining 80 percent of items would be held at the DC, with the associated 20 percent of customer demands fulfilled by express special order, as in the no-inventory scenario. By increasing the percent of SKUs stocked, the percent of demands immediately fulfilled also increases.

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\(^1\) A stock number is a combination of pattern and color. If display space is limited, displaying at least one of each pattern would suffice, with the most popular color(s) chosen for each pattern.

We use a type of computer simulation, sometimes called Monte Carlo simulation, to evaluate the impact and desirability of the alternative strategies discussed above. Simulation offers a very effective method of answering "What if" questions. However, one question that cannot be answered via simulation is how will customer's behave? For example, how will customers react to the express special order as an alternative to immediate fulfillment and how will this affect demand? Only customers can answer such questions. In a related study, marketing research is being conducted to consider such issues (Morgan, Retzlaff-Roberts, and Nichols, forthcoming). However, simulation can accommodate uncertainty by representing an array of customer responses.

As is demonstrated in the analysis below, the Pareto strategy is recommended because of the significant improvement in inventory turnover. The display-only strategy may offer possibilities for some locations, such as airports where the certainty of delayed fulfillment is not a hindrance, but we do not consider it a very plausible replacement for the complete inventory shoe store located in a shopping mall.
Current Situation

As shown in Figure 1, shoes are manufactured and obtained from both domestic and overseas manufacturing sites, and shipped to a central DC. Then shoes are shipped from the DC directly to each of the retail stores. As previously mentioned, there are approximately 10,000 active SKUs at the DC. These represent approximately 300 stock numbers. The average stock number is available in approximately 33 size and width combinations, however, the actual size and width availability varies considerably by stock number with the most popular stock numbers being available in over 100 size and width combinations. There are up to seven widths ranging from 2A to 3E, and up to 20 sizes ranging from size 5 to size 16. Less popular stock numbers are available in considerably fewer sizes and widths.

To reduce inventory and improve inventory turnover, the retailer neither stocks, nor displays all 300 stock numbers. Rather they stock and display about 100 stock numbers. In addition, they carry a limited size selection. While no two stores are identical, the average retail store currently carries approximately 1,180 active SKUs, about 12 percent of the SKUs available at the DC. Thus, the average stock number is available in only about 11.8 sizes in the retail store. In other words, about one-third of the stock numbers are available in about one-third of the sizes, which makes about one-ninth of the SKUs available in the retail store.

The numbers describing the current situation have been based upon empirical data where possible. However, where exact data were unavailable, reasonable assumptions as determined by management were made. For example, retail data has been tracked by revenue, rather than by pairs of shoes as follows. The average number of pairs of shoes in inventory is about 1,800, with approximately 1,200

![Figure 1: Distribution Network](image-url)
Retail Inventory Strategies

pairs (67%) being from active SKUs, and approximately 600 pairs (33%) being from discontinued SKUs. For active inventory, having 1,200 pairs from 1,180 SKUs means the vast majority have a stock-up-to level of one. Only a handful are stocked two deep, meaning two pairs per SKU, which is the maximum. Based on average sales of nine pairs per day (net of returns), and a 360 day year, the average annual inventory turn is based on sales of 3,240 pairs and inventory of 1,800 pairs, for an inventory turns ratio of 1.8.

Sales of discontinued shoes (about three pairs per day) account for approximately one-third of retail sales. The remaining six pairs per day represent sales from active inventory, which means that turn on active inventory is also about 1.8 (based on inventory of about 1,200). However, as a result of the low stock-up-to levels for active items, the desired item is sometimes out of stock. In such a situation a special order is offered to the customer, where the desired pair of shoes will be shipped directly to the customer from the DC. Special orders are generally not available for discontinued inventory. In addition, special orders are offered for some non-stocked items, such as when a customer wants a size or color of a stocked pattern, which is not stocked. This means that more than the stocked 1,180 SKUs are actually being sold from the retail store. A special order currently takes five to seven days, so it is not an express special order. Special orders are estimated to account for approximately 1.5 pairs per day, leaving 4.5 pairs per day being sold from active in-store inventory.

When a special order is offered, approximately 45 percent of customers accept with the remaining 55 percent representing lost sales. So, the 1.5 special orders per day currently being realized in sales is only 45 percent of the demand for out-of-stock and non-stocked active SKUs. This means approximately 3.3 pairs per day are actually being demanded from active inventory that is not available for immediate fulfillment. Combined with the average 4.5 pairs per day being sold from active in-store inventory, this indicates the overall demand from active inventory is approximately 7.8 pairs per day. If the discontinued sales are also included, total demand for the average retail store is about 10.8 pairs per day.

Comparison Of Traditional Versus Pareto Stocking Policies

In the traditional approach, as a result of the large number of SKUs and relatively low sales volume, some stores may never sell a particular SKU all year. The shoes have been placed in the retail stores in anticipation of a demand that never occurs. The very low probabilities of selling for many of the SKUs, means that a large gamble is being taken for a large number of shoes. This is the "just in case" approach to retail inventory. As a result, the retail stores have large inventories and low inventory turns, which have traditionally led to markdowns and obsolete shoes.

By using the Pareto inventory approach, some portion of the SKUs, say 20 percent, would be held at the retail store with the remaining 80 percent held only at the DC. This means that for less popular items the risk of placing shoes where they will not sell is greatly reduced. In addition, it may be that fewer of the less popular items need be manufactured, since one pair is not needed for every retail store. Thus retail inventories are reduced and inventory turnover increased considerably. This should also lead to considerably less obsolete and discontinued inventory in the long run.

Making Special Orders Attractive

Success of the Pareto as well as the no-inventory strategy hinges on improving the acceptance rate on special orders. Providing the shoes when and where the customer wants
leads to satisfied customers. In the case of special orders, the lower bound on "when" will, in most cases, be the following morning. Shipping the shoes overnight or second day, rather than the current five to seven day fulfillment, would increase costs but it should also improve acceptance rates. Where to ship is easily solved by simply asking the customer. If the customer is concerned about fit and comfort and does not mind returning to the store, he may prefer the shoes be shipped to the store. In this case the store could give the shoes a high quality shine as an added customer service. However, many customers would likely prefer having the shoes shipped to their home or office and thus avoid the return trip to the store.

There also might be incentives offered that encourage future purchases. For example, "with your special order here's a coupon for $10 off your next purchase." This sort of incentive might be used in conjunction with shipping time to tailor the scenario to what the customer wants. For example, "We could have the shoes to you tomorrow, or if you don't mind waiting, we could have those shoes to you in about five days and offer you a coupon for $10 off your next purchase." As indicated earlier, marketing research is being conducted to determine which strategies will work best (Morgan, Retzlaff-Roberts, and Nichols, forthcoming).

The Inventory Decision Model

To further clarify the current situation, empirical data were used to develop a representative demand distribution for 1,140 SKUs. A size distribution was first developed, including both size and width, based on what portion of sales each size represents in the empirical data. Similarly, a stock number distribution was developed based on what portion of sales each stock number represents. These respectively produce probabilities of customer size and shoe (stock number) preference. The probability of a particular SKU being chosen is the product of the size probability and stock number probability. This yields 1,140 probabilities ranging from 0.030116 to 0.000001. When these probabilities are sorted into descending order the cumulative values reveal that this data very closely fits the Pareto Principle, as may be seen in Table 1. The top 20 percent of the items account for 81.39 percent of the demands on active inventory. The cumulative curve is shown plotted in Figure 2 where it may be seen that the curve levels off considerably beyond 20 percent of the SKUs. This means that the incremental demand filled by an additional SKU becomes increasingly small as more SKUs are added.

While discontinued inventory represents a significant portion of the sales and inventory, we do not attempt to model it for several reasons. First of all, there are insufficient data available to model what might currently be in inventory. Secondly, this varies considerably by store. Thirdly, the purpose of the study is to evaluate future inventory strategy which means we are primarily concerned with active inventory. Changing from the traditional to the Pareto inventory approach would almost certainly affect the discontinued inventory in the long term.

The active inventory situation is modeled using a decision tree, shown in Figure 3. The first question (question A in Figure 3) is whether the customer wants a stocked item or a non-stocked item. If a non-stocked item is desired, a special order is immediately offered.
Table 1: Distribution of SKU Probabilities

<table>
<thead>
<tr>
<th>% of SKUs</th>
<th>Cumulative % of demand</th>
<th>Incremental demand %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.00</td>
<td>65.78</td>
</tr>
<tr>
<td>10</td>
<td>65.78</td>
<td>15.61</td>
</tr>
<tr>
<td>20</td>
<td>81.39</td>
<td>7.27</td>
</tr>
<tr>
<td>30</td>
<td>88.65</td>
<td>4.58</td>
</tr>
<tr>
<td>40</td>
<td>93.23</td>
<td>2.87</td>
</tr>
<tr>
<td>50</td>
<td>96.10</td>
<td>1.74</td>
</tr>
<tr>
<td>60</td>
<td>97.84</td>
<td>1.03</td>
</tr>
<tr>
<td>70</td>
<td>98.87</td>
<td>0.65</td>
</tr>
<tr>
<td>80</td>
<td>99.82</td>
<td>0.46</td>
</tr>
<tr>
<td>90</td>
<td>99.86</td>
<td>0.14</td>
</tr>
<tr>
<td>100</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2: Plot of Cumulative Demand Distribution
If a stocked item is desired, the next question (B) is whether it is currently in-stock. If so, the demand is immediately fulfilled. If not, a special order is offered. Given the demand distribution, the probability of answering question A affirmatively ($P_a$) is controlled by the choice of which SKUs to stock in the retail store. The probability of answering question B affirmatively ($P_b$) is controlled by the stock-up-to policy. Thus, both of these probabilities are controllable by management. For question C however, the probability of a customer accepting a special order ($P_c$) is determined by the customer, but is controllable by management to the extent to which a special order is made appealing.

Values shown in Figure 3 are those for which approximations were initially available for the current situation. Missing values, such as $pA$, were not known since relevant data had not been collected. However, enough is known about the relationships between the values, that it is possible to estimate the missing values. The decision tree defines many of the relationships. When moving from left to right in

![Decision Tree](image)

**Figure 3: Decision Model**

**Retail Inventory Strategies**

- **Total Sold**: 6/day
- **Average Inventory**: 1,200
- **Inventory Turns**: 1.8
Retail Inventory Strategies

the tree, one multiplies by the probability on a particular branch to find the expected outcome. For example, beginning with the average demand of 7.8 pairs per day, the expected average number of pairs per day demanded from stocked items is: $7.8 P_a = 4.5 + x1 + x2$. In addition, other key relationships are known such as:

- The total number of special orders accepted per day is approximately 1.5 (i.e., $x1 + x3 \approx 1.5$).
- Approximately 58 percent of those desiring to buy from active inventory receive immediate fulfillment. (i.e., $P_A P_B \approx 4.5 / 7.8 = 0.58$)

In addition to the missing values needing to fit these and other relationships, a simulation model was used to validate the current situation.

The Simulation Model

This simulation models a representative retail store's active inventory. As indicated in Figure 4, only the portion of the network within the box is studied. Each simulation was run for one year to observe the long term effects of an inventory strategy. Queuing behavior, store management practices, and discontinued inventory are not addressed. Customers arrive randomly with their interarrival times following the exponential distribution with an average arrival rate that varies according to the day of the week and month of the year, based upon empirical data. For example, sales are highest on the weekend (almost 25 percent of sales occur on Saturday), and late Fall and early

Figure 4: Portion of Network Simulated
Winter are the busiest times of year (October through January). Based on earlier discussion, the average demand per day is 7.8 pairs. As in Figure 3, a random probability is used to determine whether the desired item is a stocked item or not. If so, the customer's shoe size and stock number preference are randomly generated using the discrete probability distributions developed and discussed earlier. Again there are 1,140 different SKUs involved, which agrees very closely with the 1,180 SKUs that the average store carries.

If the desired SKU is in stock a purchase is recorded and inventory reduced. If the item is not in stock then a special order is offered to the customer. Given a specified probability for willingness to accept a special order (currently .45 but likely to improve as a result of quicker, more flexible shipments), customer acceptance is randomly determined whether the customer accepts the special order, or if the sale is lost. Similarly, if the desired item is a non-stocked SKU, a special order is offered with the same random behavior regarding its acceptance.

Once a week inventories are reviewed and a replenishment order is placed, based on a specified stock-up-to level for each item. Orders are placed at the close of business each Sunday (because sales are highest during the weekend) and arrive one week later, being available for purchase Monday morning. The current practice is to stock the vast majority of items only one deep (i.e., one pair per SKU), and stock only the most popular items two deep. In the simulation only about the top one percent of the SKUs used a stock-up-to of two. During the peak October through January period, stock-up-to's were increased by one for about the top two percent of the SKUs.

Results for each simulation include the annual totals for the five outcomes shown on the right side of Figure 3. In addition, the average annual inventory is provided which allows the inventory turns to be calculated. Another result of interest is the number of stocked SKUs which were "not hit," meaning not demanded during the entire year. For the simulations run with all 1,140 items stocked, the average number not hit was about 670 (about 59 percent).

By applying the simulation model to the current inventory strategy the missing values in Figure 3 were estimated to be those shown in Figure 5. Figure 5 presents both the average number of pairs per day and the average number of pairs per year. In the simulation, the stock up to policy led to out-of-stock situations approximately 15 percent of the time (i.e., P_{out}=.85) for demands from stocked active inventory. This means that the previously unknown split between out-of-stock special orders and non-stocked special orders is approximately one to three. Overall results agree quite strongly with reality, especially since many of the estimated averages were not known with certainty. For example, Figure 5's results based on the simulation indicate an overall special order average of 1.42 per day which is lower than the estimated 1.5 per day. Whereas the average sales from in-store inventory are 4.62 per day which is higher than the estimated 4.5 per day. Notice, however, that their total demand from store inventory does come very close to the estimated 6 pairs per day. The average inventory in the simulation was 1,115 pairs versus the estimated average 1,200. Such differences are actually quite small in light of the uncertainty of the estimate values. Overall, the amount of agreement between the simulation results and estimates of the current situation is surprisingly high.

We now have the probabilities associated with the answers to questions A and B in Figure 3. Thus, by stocking about 12 percent of the active SKUs available at the DC, about 70 percent of the demand is being captured by the retail inventory. This also agrees strongly with the Pareto principle and the probability distribution presented in Table 1. This indicates that the current inventory strategy is to
some extent a Pareto strategy already, with respect to all 10,000 SKUs held at the DC.

**The Complete Inventory Strategy**

One easily made improvement in examining Figure 5 is to reduce the probability of a stocked item being out-of-stock (p₀), since 15 percent of the time is rather high. This is accomplished by increasing the stock-up-to levels. However, this is not equally true of all items. During the simulation runs the more popular items were frequently out of stock. These best selling items move quickly, so there is relatively little risk associated with increasing their stock-up-to levels. After repeated simulation runs and fine tuning the stock-up-to levels, we found that p₀ could be increased to .96 by using stock-up-to's as high as six. Only the top three items (0.26%) used a stock-up-to of six, the next 11 items (0.96%) were stocked four deep, the next 15 (1.32%)
were stocked three deep, the next 50 (4.39%) were stocked two deep, and the remainder (93%) were still only one deep. During the peak period, the practice of increasing stock-up-to's by one for the top two percent of SKUs was continued. This resulted in increased inventory and increased sales, while maintaining inventory turns, as shown in Figure 5. Increasing stock-up-to-levels further allows \( p_b \) and sales to be increased further, but inventory turns begin to diminish as inventory growth begins to outpace sales growth.

In deciding which of the active SKUs to stock at the retail store, there does not seem to be any reason to increase beyond the current number. Of the 1,140 SKUs in the simulation, on average 670 (58.8%) were not hit in a one year period. This agrees with behavior observed in the retail store. Therefore, the scenario shown in Figure 6 will be considered our complete strategy, with its only difference from the current reality being the increased stock-up-to's for top sellers. This scenario is summarized in the right hand column of Table 2. If special orders were made more attractive so that the proportion of customers accepting increased to 60 or 75 percent, results are also summarized in the right hand column of this table.

**The Pareto Story**

Moving on to the Pareto scenario, the same decision tree model may be used. The probability of a stocked item being desired \( (p_d) \) will diminish based on the portion of the 1,140 items stocked. The probability of a stocked item being in stock \( (p_b) \) will again be dependent on the stock-up-to policy. Finally, the probability of a customer accepting a special order \( (p_c) \) will depend on the customer and how attractive a special order is made. Simulations were run for an array of values for \( p_c \)

### Table 2: Summary of Pareto and Complete Inventory Options

<table>
<thead>
<tr>
<th>Special order accept rate ( (p_c) )</th>
<th>Percent of 1,140 SKUs stocked</th>
<th>20% ( (p_d=.570) )</th>
<th>30% ( (p_d=.621) )</th>
<th>40% ( (p_d=.653) )</th>
<th>50% ( (p_d=.673) )</th>
<th>100% ( (p_d=.700) )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>In store sales</td>
<td>1,536</td>
<td>1,673</td>
<td>1,735</td>
<td>1,813</td>
<td>1,887</td>
</tr>
<tr>
<td></td>
<td>Ave. inventory</td>
<td>330</td>
<td>431</td>
<td>540</td>
<td>656</td>
<td>1,224</td>
</tr>
<tr>
<td></td>
<td>Items not hit</td>
<td>3.5%</td>
<td>12.5%</td>
<td>21.9%</td>
<td>28.9%</td>
<td>58.8%</td>
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<tr>
<td>45%</td>
<td>Sp. orders</td>
<td>572</td>
<td>511</td>
<td>472</td>
<td>448</td>
<td>414</td>
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<tr>
<td></td>
<td>Tot sales</td>
<td>2,108</td>
<td>2,184</td>
<td>2,231</td>
<td>2,261</td>
<td>2,301</td>
</tr>
<tr>
<td></td>
<td>Inv. turn</td>
<td>6.4</td>
<td>5.1</td>
<td>4.1</td>
<td>3.4</td>
<td>1.9</td>
</tr>
<tr>
<td>60%</td>
<td>Sp. orders</td>
<td>763</td>
<td>681</td>
<td>629</td>
<td>597</td>
<td>542</td>
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<tr>
<td></td>
<td>Tot sales</td>
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<td>2,388</td>
<td>2,410</td>
<td>2,429</td>
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<tr>
<td></td>
<td>Inv. turn</td>
<td>7.0</td>
<td>5.5</td>
<td>4.4</td>
<td>3.7</td>
<td>2.0</td>
</tr>
<tr>
<td>75%</td>
<td>Sp. orders</td>
<td>954</td>
<td>851</td>
<td>787</td>
<td>746</td>
<td>677</td>
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<td>Tot sales</td>
<td>2,490</td>
<td>2,524</td>
<td>2,546</td>
<td>2,559</td>
<td>2,564</td>
</tr>
<tr>
<td></td>
<td>Inv. turn</td>
<td>7.5</td>
<td>5.9</td>
<td>4.7</td>
<td>3.9</td>
<td>2.1</td>
</tr>
</tbody>
</table>
and $P_{c}$ as shown in Table 2. Notice that $P_{c}$ equals the product of 0.7 (the demand captured by the 1,140 SKUs) and the percent of this that is captured by the portion of stocked items. For example, with only 20 percent (228) of the 1,140 SKUs stocked, as in Table 1, we can expect 81.39 percent of these demands to be fulfilled by retail inventory (except for out-of-stock situations), so we have $P_{A} = 0.7 \times 0.8139 = 0.570$. Using the same stock-up-to policy and doing nothing to make special orders more attractive (i.e., $P_{c}$ still equals 0.45), the simulation results indicate that total sales would be 2,108 and inventory turns would increase to 6.4. In general, the simulation results for in-store sales (those with immediate fulfillment), average inventory, and percent of items not hit, are unaffected by the special order acceptance rate. Thus, these three numbers, shown in the upper portion of Table 2, apply to all of the special order acceptance rates. In moving from left to right in Table 2, increasing the portion of items stocked, one can see that while in-store sales improve, the amount
of improvement diminishes, which is not surprising given the nature of the probability distribution. The opposite is true of inventory turns.

The No-Inventory Strategy

The same decision model also applies to the no-inventory or display only inventory strategy, but with \( P_A \) being 0.0. Hence, the model simply reduces to offering special orders. However, unlike the other scenarios, the customer would know beforehand that a special order is the only option. Even the Pareto scenario with only 20 percent fulfills the majority of demands immediately. To avoid angering customers, it would probably be unwise to attempt to present the store as a traditional shoe store. Customers would need to be aware that this is a display-only store. Thus, anyone who found that unacceptable would be unlikely to express a desire to purchase. Hence, \( P \) would be likely to equal essentially 100 percent. This leaves the question of what happens to demand. We can certainly not assume that it remains unchanged. The profitability could be analyzed for an array of demand rates.

Such a store would be similar to catalogue shopping except that the customer could see, touch, and experience the product. The display shoes could be from the full array of sizes so that he might also try one on. It would be unlikely to be the pattern desired, but the shoes are very consistent in size between patterns. So, how the shoe feels and what size is appropriate could be determined. In a traditional shopping setting, such as a mall, it seems unlikely that such a strategy would be successful. However, in settings where having the shoes shipped is less problematic or even desirable, it may have possibilities. One such example is an airport where business travelers often have "time to kill." This possibility is helped by the fact the average buyer of upscale men's shoes is much more likely than the average person to be a business traveler.

Discussion

Several aspects of the models used and other issues warrant additional discussion.

No "Switching" Behavior

The models did not incorporate customer switching. In reality a customer may initially demand a particular shoe that is not in stock. The customer may then switch to another similar shoe to avoid a special order. For example, there may be a similar pattern that is available in the appropriate size and color. Alternatively, if the shoe is available in a number of widths, it is possible that another width may suit the customer. A problem with attempting to model switching behavior is identifying the likely customer preferences for which SKUs are substitutable for one another, both for size and for pattern. Information was not available for customer switching, and would be extremely difficult to obtain accurately due to variations in personal preferences.

The greatest likelihood for switching occurs for patterns that are very similar (where one is stocked and the other is not) and for sizes that are very similar within the same pattern and color. For example the data reveals that very few size 12.5 shoes in any width are sold. It is very unlikely that this reflects the natural foot size distribution. Very likely the reason is that this size is often not stocked, so men whose feet are this size often switch to a size 12 or 13. One question this raises is whether the Pareto inventory approach with express special orders would increase or decrease switching behavior. Currently the man with size 12.5 feet may feel he has little alternative but to buy size 13 because he views his choices as being limited to what the stores stock. The convenience of the express special order may lead to a slightly different sales distribution by size, with more of the unusual sizes being sold. Customers who wear less common sizes would no longer have to make do with a less than ideal size and width. In this regard the Pareto inventory strategy would decrease switching.
but should increase customer satisfaction and loyalty.

The opposite may be true for pattern switching. If two patterns are similar enough that many view them as substitutable, and one is a stocked pattern while the other is not, switching would become quite common. This would increase the demand for the stocked patterns and may necessitate an increase in the stock-up-to level. Such a situation would also imply that there really is no need for both patterns. If the Pareto inventory strategy were to be implemented, watching for such behaviors and adjusting to them should prove useful.

Probabilities Are Treated As Known
As previously discussed, empirical sales data were used to determine the probability distributions regarding the likelihood of a particular item being chosen. Such an estimate is needed for stocked items to determine the stock-up-to level. In reality forecasts must be made using a best guess of probabilities. As in the model used here, two distributions are needed; the size distribution (including both size and width), and the stock number distribution. The probability of a particular SKU being chosen is the product of these two. Fortunately some of the historical data should provide accurate information. The size distribution should be very accurate from historical data. Men's dress shoes are not generally trendy items, so the stock number distribution may use many of last year's sales proportions for existing patterns and those with slight changes for old patterns. For example, the popularity of wing tips and penny loafers is unlikely to change dramatically in one year. While the popularity of a new pattern is always uncertain, the greatest uncertainty will typically be associated with casual and contemporary styles.

In any inventory scenario, it is important to collect data "on the fly" so that probabilities can be updated. A pattern that is selling much better than expected should have its stock-up-to level increased. Conversely a pattern that is selling less well than expected should have its stock-up-to level decreased. Thus, in the Pareto inventory approach, which items are stocked and to what level, should be viewed as flexible, and customer preferences should be continually monitored (from in-store sales, special orders, and lost sales too if possible). It should also be noted that the core stock could certainly vary by store.

Choice Of Stocked SKUs
Given the above discussion regarding estimating the probability of each SKU being selected, these probabilities should be used even in the "complete" inventory scenario to select which SKUs are stocked. As previously discussed, the retail stores currently stock about 1,180 SKUs which represent about 12 percent of the active SKUs at the DC. It was found that these SKUs are capturing about 70 percent of the demand for active SKUs. The current practice is to determine which stock numbers to carry (about the top 100), and then to select a number of sizes for each stock number (on average 11.8 sizes). This process makes use of the probability distribution for stock numbers and the distribution for sizes, but in a two-step process that does not make use of the SKU probabilities. If one instead were to simply use the SKU probabilities and pick the largest 1,180, a slightly different set of SKUs would result. For example, using the current method a particular stock number, say the 95th most popular, might be stocked in eight sizes.

2 It is suggested that this be accomplished by reduced reorders and not by shipping inventory back to the DC.
Using the SKU probabilities, this stock number might instead be chosen in only three sizes. Whereas a very popular stock number, in the top ten, might currently be stocked in 15 sizes. Using the SKU probabilities, this stock number might be stocked in an even larger variety of sizes.

Selecting each SKU based on its own probability would deviate from using a more standard size selection per stock number. However, the sum of the individual SKU probabilities yields the total demand being captured by those SKUs. Thus, for whatever number of SKUs management desires to stock, the total percent of demand captured will be maximized by selecting the SKUs with the largest probabilities. Using such a process it may be possible to increase the 70 percent of demand currently being captured without increasing the number of stocked SKUs.

No Interaction Between Special Order Aversion And SKU

How likely a particular customer, on a particular day is to accept a special order will be random. It is possible that there could be an interaction between this likelihood and the probability of selecting the desired item. For example, a customer who wears an unusual size (for example an SKU with a small probability of being selected) may be much more willing to accept a special order than the customer who wears a common size. The same may be true of the pattern. A more unusual pattern may be harder to find, thus, the customer may be more willing to accept a special order. It seems logical that the more unusual the item the more willing the customer may be to accept a special order. A relationship of this sort could easily be incorporated into the simulation model.

If such an interaction does exist then the probability of accepting a special order (P) would be based on the probability of selecting the particular SKU. Thus, results for the Pareto inventory approach would be even better than those reported because the non-stocked items would be those with smaller probabilities of being chosen. Hence, these special orders would be more likely to be accepted.

No Lack Of Availability At Distribution Center

It should be noted that if a Pareto non-inventory strategy is implemented for a number of retail stores, availability at the distribution center would become an issue. Another study would be useful for evaluating the levels at which items should be stocked in the DC. However, for any particular item, the DC level certainly should be lower than the current total over all retail stores.

Total Cost Analysis

To evaluate which inventory strategy is most beneficial, financial considerations are of primary importance. The various possible scenarios summarized in Table 2 might be transformed to a total cost model in the following way:

\[(R - C) \cdot (\text{In store sales + Special orders}) - H \cdot (\text{Avg. inventory}) - C \cdot (\text{Avg. inventory}) - S_1 \cdot (\text{In store sales}) - S_2 \cdot (\text{Special orders}) = \text{Preliminary Operating Income}\]

where,

\[R = \text{Revenue per pair (average)}\]
\[H = \text{Holding cost per pair per year}\]
\[C = \text{Cost per pair to manufacture or purchase (average)}\]
\[S_1 = \text{Regular shipping cost per pair from DC to store}\]
\[S_2 = \text{Express shipping cost per pair from DC to customer}\]

Only costs which would differ between inventory scenarios need be included to observe the net financial impact of changing from one scenario to another, so this income calculation is not net operating income. For example, overhead costs of running the retail store are not
included because these costs would be unaffected by the inventory strategy. Manufacturing (or purchase) cost is included because the total number of pairs manufactured would be reduced by the Pareto scenarios. For example, as shown in Table 2, moving from 100 percent to 40 percent of the SKUs in the retail store reduces the average inventory from 1,224 to 540. This reduces total inventory over all retail stores considerably, but is not expected to significantly increase DC inventory. The reason the DC inventory is not expected to increase considerably is that the SKUs which have been "backed up" to the DC are the less commonly chosen SKUs. If there were 100 retail stores, each of which previously had one pair of a particular SKU, the DC does not need to increase its stock-up-to level for this SKU by 100 pairs in order to supply demand. Therefore the total number of pairs manufactured is reduced, and this reduction is primarily showing up in reduced retail inventory. Since manufacturing cost is not equal over all scenarios, the above income calculation must include it, and account for the fact that manufacturing cost is incurred not only for what was sold, but also for what is in inventory that did not sell.

Depending on how the above costs are quantified, any of the Table 2 scenarios might be considered "best." However, Table 2 shows that operating in the Pareto mode at 30 or 40 percent provides the majority of the sales of operating at 100 percent. The fact that almost 60 percent of the items are "not hit" in the complete mode (stocking all 1,140 SKUs) implies that stocking only the top 40 percent should suffice. In fact, moving from 100 percent to 40 percent at the 45 percent acceptance rate for special orders, sales decrease only 3 percent (from 2,301 to 2,231) while inventory decreases 56 percent (from 1,224 to 540) and inventory turnover increases 216 percent (from 1.9 to 4.1). The special order acceptance rate is currently 45 percent, which should be easily increased if special orders are made more attractive by express shipment and/or some of the other previously discussed possibilities. In which case, reducing the number of stocked SKUs would be even less detrimental to sales, as shown by the 60 percent and 75 percent rows.

Using the cost values below, the net revenue for the Table 2 scenarios may be calculated. It is estimated that the average per pair costs are:

\[
\begin{align*}
R &= $200 \\
H &= \text{\$15 to \$23 (based on 20 to 30\% of C)} \\
C &= \$75 \\
S1 &= \$1 \\
S2 &= \text{\$5 to \$25 (depending upon method of shipment)}
\end{align*}
\]

The annual holding cost of 20 to 30 percent of an item's value is based upon standards in the inventory and logistics field. In addition to the cost of capital, this cost takes into account the risk of obsolescence of the item, which is a very relevant factor in this type of inventory situation. As mentioned earlier, about one-third of the average retail store's inventory is comprised of discontinued and obsolete shoes. The special order shipping cost will depend on how quickly the item needs to arrive. The low

\[\text{footnote text}\]

\[\text{footnote text}\]
Figure 7a–$23 Holding Costs

Figure 7b–$15 Holding Costs

Figure 7: Preliminary Operating Income:
45% Special Order Acceptance Rate
Figure 8a–$23 Holding Costs

Figure 8b–$15 Holding Costs

Figure 8: Preliminary Operating Income:
60% Special Order Acceptance Rate
Figure 9: Preliminary Operating Income: 75% Special Order Acceptance Rate
end of the range involved using ground transport at a cost of about $5 and taking about four days, which is the current method and cost. The upper end involves overnight airfreight for next morning delivery at a cost of about $25. In between are other alternatives such as second day delivery.

The preliminary operating income results are summarized in Figures 7, 8, and 9. Each figure corresponds to a different special order acceptance rate. Within each figure, two different holding costs and three different shipping costs are used. Thus, the current situation may be found at the right of Figure 7, for $S=5$, using either holding cost. In all scenarios, income appears to be maximized by a stocking level between 20 and 30 percent. Looking between the three graphs, it may be observed that the best stocking level decreases as the special order acceptance rate increases. At the 45 percent acceptance rate, the best stocking level appears to be about 30 percent. Whereas at the 75 percent acceptance rate the ideal stocking level seems to be closer to 20 percent.

Results from the marketing research discussed earlier (Morgan et al., forthcoming) will determine what special order costs are necessary in order to improve special order acceptance rate. For example, if special order acceptance could be improved to 60 percent at an average cost of $15, the two curves for $S=15$ in Figure 8 are relevant. This indicates that stocking in the 40 to 45 percent range would be best, which would be approximately 500 SKUs. This also indicates a net revenue increase of approximately 11 percent and inventory turnover would increase approximately 225%.

5 At these low stocking levels it is possible that the savings in manufacturing cost is over estimated, because of the earlier discussed probable need to increase DC

**Conclusion**

This investigation of the tradeoffs between inventory availability for immediate customer fulfillment and inventory costs has shown that notable improvements could be achieved by adopting the Pareto inventory approach. These improvements include significantly reduced inventory, associated savings in manufacturing costs, improved inventory turnover, and improved profitability. The success of such a strategy hinges upon choosing the right items to stock such that the majority of customers receive immediate fulfillment and making special orders sufficiently attractive for non-stocked items, in order to keep lost sales to a minimum.

The values used in these models are approximations since exact data were unavailable. In addition, there are a number of unresolved implementation issues such as the previously discussed issue of determining stocking levels at the DC. Despite these caveats, there is clear indication that the above improvements are possible. Such a strategy could be applied to a number of other retail inventories where the risk of an individual item not moving is large.

**References**


