Reducing costs through improved returns processing
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Abstract
Purpose - To provide fashion catalog distributors with an approach to reduce costs from returns processing by considering an array of characteristics related to demand, lead-time, and inventory level.

Design/methodology/approach - Apparel return rates from catalog sales are frequently 10-30 percent of shipped orders. Despite the magnitude of returns processing, return operations are characterized by high backlogs, inefficiency, and excess material handling. Typical catalog clothing returns processing considers the condition of the returned item, fashion obsolescence, and back-order status to make disposition decisions. In the proposed algorithm, added considerations to select a disposition option for a return include inventory level, demand pattern, cost, and lead-time factors.

Findings - The current and proposed algorithms are tested using disguised data from a fashion catalog sales company. It is shown that the proposed algorithm fills back-orders more quickly, while reducing the returns-processing cost and time by over 20 percent.

Research limitations/implications - By combining the tasks, open packaging, credit customer, and evaluate item characteristics including backorder status at the first workstation, the training for staff at the first workstation is increased.

Practical implications - Fashion catalog distributors should examine their returns-processing system for opportunities to reduce returns-processing time and costs by consolidating and eliminating tasks and by considering inventory level, demand pattern, cost, and lead-time when selecting a disposition option for a return. The proposed algorithm can be integrated into the information technology system at the fashion catalog distributor.

Originality/value - This paper addresses how to reduce inefficiency and excess material handling in returns processing at a fashion catalog distributor.

Keywords Distribution centres, Customer service management, Product liability, Clothing, Product catalogues

Paper type Research paper

Introduction
The returns process incurs a hidden cost that one industry analyst estimates can be as high as 30-35 percent of potential profits (Rosen et al., 2001). Since the costs of handling
product returns are estimated at $35-$42 billion per year in the US, it is important to improve the returns decision process (Norek, 2003; Rogers and Tibben-Lembke, 2001; Meyer, 1999). Distribution experts recently pointed out that “Managing returns wisely means thinking about returned goods not as costly mistakes but as products waiting to be sold profitably – an opportunity to be exploited” (Stock et al., 2002). In a recent survey, distributors indicated only moderate success in recovering assets and reducing inventory investment in their reverse logistics programs (Autry et al., 2001).

In the apparel industry, product return rates as a percentage of catalog sales are reported to range from 10 to 20 percent for casual apparel and as high as 35-40 percent for high fashion (Dowling, 1999; Catalog Age, 2002). Return rates are high for catalog apparel shoppers since they cannot see or feel the apparel or try it on prior to ordering (Wood, 2001). Industry experts relate that the top reasons for apparel returns are size, color, and fabric (Barry, 2000; Catalog Age, 2002; Trebilcock, 2001). For an apparel company that uses catalogs or the internet as primary correspondence with its customer base, a significant level of product returns is inherent to the business. Thus, a catalog distribution center manager asks the question, how can we reduce the inventory and material handling costs associated with returns. In this paper, we show how the returns process can be re-designed to not only reduce inventory and material handling costs, but also improve order fulfillment.

Typically, catalog distribution center functions are divided into separate order fulfillment and returns processing functions. The returns process involves crediting the customer, evaluating the returned product condition, and directing the returned product to one of the five options shown in Figure 1: immediate resale, restock, sale to third party retailer, donation, or disposal. A four-class product condition and demand based code system is shown in Figure 1. Class A products are in saleable condition and will appear in future catalogs. Although class B items are in saleable condition, they are obsolete. Class C and D items are non-saleable condition items directed to charity and disposal, respectively.

In our collaboration with a large catalog distributor of fashion goods, we studied more than 300 workers processing returns. The time from returns arrival to disposition decision completion ranged from two to three days while material handling and processing costs averaged more than $1 per item. The centralized distribution and returns center studied considers product condition, back-order status and obsolescence.
as illustrated in the disposition algorithm in Figure 2. Product condition is either acceptable, refurbishable, or non-refurbishable (Meyer, 1999). Back-order status reflects insufficient inventory to fill demand. Obsolescence is defined as exclusion from future catalogs.

Despite this catalog distributor’s diligence in processing returns faster than 58 percent of the companies surveyed in Rogers and Tibben-Lembke (2001), we show that the return disposition completion time to fill back-orders can be further improved at a
lower cost. Next, we discuss past literature in reverse logistics and returns. Then we define our apparel returns disposition problem and offer a more comprehensive solution. We test our algorithm with disguised data from an industrial collaborator and analyze its performance. We conclude with recommendations for catalog and internet distributors.

**Literature review**
Carter and Ellram (1998), Blumberg (1999) and Guiltinan and Nwokoye (1975) review the drivers, regulations, businesses, and customers, for reverse logistic systems. They explain that constraints include lack of data, coordination, and incentive systems. Andel (1997) and Rogers and Tibben-Lembke (1999) point out the potential to coordinate information in centralized reverse logistics systems. Stock (1998) explains that reverse logistics activities should be coordinated with functions within the firm such as production, marketing, information systems, and forward logistics. Tibben-Lembke (2004) explores the importance of secondary markets. In research focused on the retail sector, supply chain procurement and returns coordination improvements have been identified for more profitable inventory management by the manufacturer and retailer (Eppen and Iyer, 1997; Lee, 2001; Taylor, 2001; Miner, 2001). Similar research is needed for the catalog distributor sales and consumer returns scenario.

Van-Hoek (1999) recommends extending reverse logistics to the system perspective of extended green supply chains. Tibben-Lembke (2002) discusses the impact of the product life cycle on return rates and disposition decisions in extended supply chains. For long-life cycle products such as aircraft engines, a disposal option helps control inventory in an extended supply chain with procurement, production, and remanufacturing of returns (van der Laan et al., 1996a, b). Guide and Wassenhove (2002) mention the need to make disposition decisions as early as possible in the returns process.

Much of the research in apparel procurement, supply chain coordination, and remanufacturing emphasized a cost objective. In our interactions with catalog apparel distributors, we learned that service objectives sometimes supercede cost objectives in order to maintain long-term customer loyalty. Retaining customer business is supported by good returns operations (Tan et al., 2003). An important area of research is how a distributor of catalog sales should handle the returns received from mail-order customers in order to increase service level while managing costs. In our problem, we seek to improve customer service and reduce costs by identifying product and system characteristics in addition to those included in the returns center disposition algorithm shown in Figure 2.

**Improving the returns process**
The current returns disposition decision is based on a sequential consideration of product condition, obsolescence, and back-order status as shown in detail in Figure 2. The problem with this approach is that obsolete items defined based on future catalog inclusion may still be on back-order. Thus, the current algorithm fails to fill back-orders for items that are not appearing in the next catalogs. To improve the link between order fulfillment and returns processing, while managing inventory levels, we propose to re-design the returns decision logic to consider back-orders earlier in the
process and to additionally consider inventory level, net return value, back-order lead-time, and marketing pattern. Inventory level represents the product stored in the catalog distributor's warehouse. Inventory level and marketing pattern are considered to better determine whether to store returns or sell them to third party discount outlets. Net return value is defined by the value of the item minus the processing, refurbishing and holding costs. Back-order lead-time is evaluated to compare the time to refurbish and repack and the time to receive a new item from the manufacturer. Marketing pattern refers to the frequency an item is included in future catalogs. The catalog apparel industry defines three marketing patterns: core, seasonal, and trendy by item appearance in three consecutive, two consecutive and one catalog per year, respectively. For example, Figure 3 shows the demand and return rates for a core marketing item. Core marketing items may have fluctuating demand patterns. For example, white short-sleeved shirt sales increase as summer approaches, and fleece coat sales rise as temperatures drop in the fall. The weather factor in Figure 3 is significant; temperature and sales of the core item rise and fall similarly. Figure 3 shows that the returns of the same item follow a pattern similar to the demand at a lower magnitude and a two to three-week lag.

The logic for the proposed algorithm is shown in Figure 4. By reallocating tasks to fewer workstations, the number of different types of workstations is reduced from seven in the current algorithm in Figure 2 to four workstations in the proposed algorithm in Figure 4. By reviewing back-order status at workstation 1 rather than workstation 4, earlier identification of a back-ordered return item directs the item to repackaging and shipping more quickly to improve service level.

To test our algorithm under random demand and random product return conditions, we developed a discrete-event simulation model (Law and Kelton, 1991). To create a distribution for random demand, monthly data provided by an industrial collaborator was analyzed using the Kolmogorov-Smirnov goodness-of-fit test in Arena 6.00.02®.
Input Analyser by Rockwell Software Inc. (2002). Table I shows the distributions with their parameters for three products with the three different marketing patterns.

We disaggregated the monthly demand data by applying the discrete distributions to weekly and daily demand given in Table II. The weekly demand distribution represents demand correlation with monthly and bi-weekly pay days while the daily
demand distribution reflects the peak customer orders over weekends. Daily demand patterns represent a potential area for further research.

The decision handling and task times for both the current and proposed algorithms are given in Table III. Table III shows that the proposed algorithm eliminates one action, consolidates two actions, consolidates eight evaluations, and adds two evaluations at workstation one. As a result, the total workstations in the proposed algorithm are four compared to seven in the current algorithm.

Our assumptions for refurbishment, back-order lead-times, return rate conditions, item worth per class, and minimum order quantities are given in Table IV. Inventory space is assumed to be unconstrained.

For a core marketing item, a continuous review (Q, r) inventory model is used to determine the discount price, replenishment quantity, Q, and re-order point, r. When the quantity discount of the core item studied in the computational study is $0.25 per item for every 2,500 items, the discounted distributor price is as shown in Table V.

The replenishment quantity, Q, is calculated using the Economic Order Quantity (EOQ) in equation (1):

\[ Q = \sqrt{\frac{2AD}{h}} \]  

(1)

where A is the ordering cost; D, the anticipated demand level shown in Table II and h is the holding cost (Russell and Taylor, 2000). We assume that A is 2.5 percent of the total item cost where the total item cost equals the product of the order quantity and the discounted distributor purchase price. The holding cost is calculated in equation (2):

\[ h = (S + C) \cdot \left( \frac{I}{D} \right) \]  

(2)

where S is the cost to store one unit of product; C, the product opportunity cost, and I is the product inventory level. The opportunity cost is calculated as the product of the

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<table>
<thead>
<tr>
<th>Table I. Collaborator demand distributions tested</th>
<th>Distributor purchase price ($)</th>
<th>Marketing pattern</th>
<th>Monthly apparel demand distribution (parameter)</th>
<th>Goodness of fit (Kolmogorov-Smirnov test statistic)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>Core</td>
<td>EXP (741)</td>
<td>0.159</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>Trendy</td>
<td>EXP (188)</td>
<td>0.302</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>Seasonal</td>
<td>TRIA (0, 25.7, 257)</td>
<td>0.358</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Table II. Weekly and daily demand distributions</th>
<th>Week</th>
<th>Percent of monthly demand</th>
<th>Day</th>
<th>Percent of weekly demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>Monday</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>Tuesday</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>Wednesday</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>Thursday</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Friday</td>
<td>14</td>
<td></td>
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</table>
### Table III. Decisions and actions to process returns

<table>
<thead>
<tr>
<th>Description</th>
<th>Current algorithm</th>
<th>Proposed algorithm</th>
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<tbody>
<tr>
<td></td>
<td>Work station</td>
<td>Time (seconds/item)</td>
</tr>
<tr>
<td>Evaluate time to refurbish versus remaining back-order lead-time</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Evaluate anticipated demand versus current inventory review</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Evaluate condition of item</td>
<td>2</td>
<td>30</td>
</tr>
<tr>
<td>Evaluate obsolescence</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Evaluate class A characteristics</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Evaluate class B characteristics</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Evaluate if condition refurbishable</td>
<td>3</td>
<td>20</td>
</tr>
<tr>
<td>Evaluate class C characteristics</td>
<td>3</td>
<td>20</td>
</tr>
<tr>
<td>Evaluate back order status</td>
<td>4</td>
<td>20</td>
</tr>
<tr>
<td>Evaluate frequency status</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Re-evaluate high frequency storage status</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>320</td>
<td>1.38</td>
</tr>
</tbody>
</table>

Reducing costs

interest rate and the distributor purchase price. Using the data in Tables V-VIII and expressions (1) and (2), the replenishment quantity for the core item studied in our computational study is 3,699 and its discount price is $49.75 (Table V).

Since trendy and seasonal items do not need constant replenishment throughout the year, the order quantity, $Q_j$ for product $j$ is set to either the minimum order quantity or 80 percent of the anticipated demand, whichever is greater. The re-order point, $r_j$, for trendy and seasonal items, is calculated with equation (3):

$$r_j = D_j * L_j$$

where $L_j$ is the back-order lead-time of product $j$ (Hopp and Spearman, 2000).

Based on the random demand, random returns, deterministic processing times, and cost assumptions discussed, a simulation model was developed in Automod™ Student Version 10.0 (Brook Automation, 1999) and run on a Dell Optiplex GX240 desktop computer. Both the current and proposed algorithms were run for 336 days for core, trendy, and seasonal items. To achieve a standard error of 5 percent, we ran 75 replications (Banks et al., 1995). The 95 percent confidence intervals (CI) for total demand and returns are shown in Table VI for both the current and proposed algorithms. Next we summarize the results.
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35,7

Refurbishment (dry cleaning)
Back-order lead time for domestic items
Back-order lead time for import items (with air shipment)
Back-order lead time for import items (with sea shipment)
Returns rate as a percent of sales
Returns in sellable condition
Returns in refurbishable condition
Returns in non-refurbishable condition
Refurbished items in sellable condition
Class A item worth as percent of distributor purchase price
Class B item worth as percent of distributor purchase price
Class C item worth as percent of distributor purchase price
Minimum order quantity for domestic vendors
Minimum order quantity for non-domestic vendors
Refurbishing (dry cleaning) costs

Table IV.
Returns parameters

Table V.
Order quantity range
Discounted distributor purchase price per product ($)

Table VI.
Mean and 95 percent CI of demand and returns for Tables VII and VIII

Results and conclusions
The proposed algorithm improves the number of back-orders filled and reduces the processing costs. Table III shows that the new algorithm reduces the return processing time and cost by 22 percent. By aggregating tasks, the repetitive material handling tasks are eliminated and fewer workstations are required. The workstation reductions translate into reduced costs for labor, workstation equipment, and material handling equipment. Our discrete event simulation model results indicate cost savings too. For
the core item studied, the proposed algorithm directs damaged returns to a third party when inventory is high as indicated in Tables VII and VIII. This reduces dry cleaning cost by 24 percent. Since the CI for the quantity restocked are distinct in Tables VII and VIII, we conclude that the restocking of trendy returns is lower for the proposed algorithm than for the current algorithm. This reduces inventory holding costs. Combining these cost savings, the total returns processing costs are compared for both algorithms in Figure 5 for the three catalog products for one year. The proposed algorithm boasts a greater than 22 percent improvement in returns processing costs.

Tables VII and VIII summarize the number of returned items that fill back-orders and new orders for the current and proposed algorithm, respectively. Tables VII and VIII also demonstrate that the proposed algorithm maintains inventory to fill back-orders while reducing the number of items restocked. The current algorithm evaluates back-order status at work station four in the process flow, while the proposed algorithm evaluates back-order status at station one. As a result, the proposed algorithm improves customer service by increasing the number of back orders filled. The sensitivity of the returns process for each catalog marketing pattern is shown in Figure 6. The proposed algorithm dramatically increases the number of back-orders filled for trendy and seasonal items.
Figure 5.
Total cost comparison to process returns for one year for three catalog products

Figure 6.
Sensitivity for return items filling back-orders for different marketing pattern

Recommendations for catalog distributions
Since catalog return operations may handle a significant number of products, some of which may be on back-order, and the costs of handling product returns exceed billions of dollars per year, it is important to design a process and decision algorithm that effectively improves customer service (Meyer, 1999). We demonstrate that evaluating
back-order status early in the returns process improves customer service. Furthermore, we recommend that catalog distributors consider current inventory level, the returns processing lead-time versus the manufacturer lead-time, the expected timing of resale of the returned item, and the economical value of items in addition to product condition and obsolescence. Catalog distributors should examine their returns process for opportunities to reduce returns processing time and costs by consolidating and eliminating tasks. The proposed algorithm shown in Figure 4 may easily be integrated into the information technology system at a catalog distribution center.

References
Brook Automation (1999), Automod 10.0, Salt Lake City, UT.
Rockwell Software Inc. (2002), Arena 6.00.02, Sewickley, PA.


