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Increasing service through aggressive dealer inventory return policies

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Keywords Returns, Lead times, Inventory, Service improvements

Abstract In this paper, manufacturer dealer return policies are examined for high volume part sales for long-life cycle products. Exclusive suppliers often use simple returns policies for high-value products to persuade their independent dealers to stock and price items aggressively. For low-value products, a return policy problem occurs; dealer requests for low-value returns are routinely rejected. Because a manufacturer may make over 300 return request decisions per day, a fast algorithm is required. Two fast algorithms that evaluate multiple factors are presented and tested for six months against dealer inventory requests at heavy equipment manufacturer, Caterpillar, Inc. The results show that the proposed algorithms may eliminate nearly 1,000 back-orders per month. The results indicate that exclusive suppliers can modify their return policies to improve service to customers by analysing not only product value, but also inventory level and lead-time.

Problems with current dealer inventory return policies

Manufacturers in the heavy equipment, vehicle, military, appliance, and computer industries manage multi-echelon inventory systems with millions of service parts. All companies in a recent survey struggled with the question of how to deploy parts in their distribution network (Cohen et al., 1997). As technology improves and new models are introduced, the number of service parts stocked increases and the shelf life of service parts also tend to increase. As a result, stocking policies for low usage items were developed (Cohen et al., 1986, Muckstadt and Thomas, 1980). Furthermore, inventory flow dynamics include returns. Heavy equipment manufacturers use return policies for high-value products to persuade their independent dealers to stock and price items aggressively (Konsynski and McFarlan, 1990). Low-value products are excluded from contracts in order to avoid a financial loss to the manufacturer when transportation and returns processing costs are greater than the resale value of the low-value return. A return policy problem occurs when dealers do not sell low-value items. For example, suppose there are three dealers: A, B and

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C. Under the common returns policy, a manufacturer would decline Dealer A's request to return 20 low-value products despite backordered requests for those same products from Dealers B and C. Typically, the manufacturer or a third party processes return requests independent of the forward supply chain. Therefore, the question raised is: “How will a multi-factor evaluation of manufacturer service level to dealers and returns processing costs be applied to dealer inventory returns requests for low-value products?” In this paper, returns policies are expanded in order to improve service to dealers by analyzing not only product value, transportation and processing costs, but also forward supply chain characteristics such as inventory level and lead-time. When heavy equipment manufacturers conserve valuable resources by redistributing unsold goods from one dealer to another dealer with demand for those goods, they reduce dealer risk and improve service levels while simultaneously sustaining social responsibility.

The potential decisions related to dealer return requests are illustrated in Figure 1. This paper focuses on decision 1 in Figure 1: should the manufacturer accept or reject the dealer inventory return request? If the manufacturer rejects the dealer inventory return request due to insufficient demand and high transportation cost, then the dealer can seek local recycling opportunities. Once a manufacturer accepts the return, the return is inspected to determine if it needs to be repackaged, undergo minor repair or be scrapped for recycling. Following minor repair and/or repackaging, the manufacturer either sends the
product to another dealer or stores the product for future sale. A heuristic for
decisions 2 and 3 is given in Wongweragiat et al. (2003).

In the heavy equipment industry, service level for long-life cycle products is
based on the accuracy and speed for which service part orders are filled from
manufacturer to dealer (Newbanks and Srinivasan, 1990; Sandvig and Allaire,
1998). If service level is the only consideration, then at decision point 1 in
Figure 1, the manufacturer should accept all returns. On the other hand, if
profit is the only consideration, then the manufacturer should accept only
profitable returns. However, in this paper, the problem is expanded such that
the manufacturer considers multiple factors, including profit and service level.
For manufacturers with long-life cycle products, high service levels may
increase profits over the long-term by fostering customer loyalty.

This study is motivated by collaboration with the World Wide
Headquarters - Global Distribution Center (GDC) for Caterpillar, Inc., the
world's largest manufacturer of construction and mining equipment, diesel and
natural gas engines and industrial gas turbines. Named in the Dow Jones
Sustainability World Index, in September 2002, Caterpillar seeks to integrate
long-term economic, environmental and social aspects into its business
strategies. (Rao et al., 2000) discuss how Caterpillar distributes service parts for
their heavy equipment to their exclusive independent dealers worldwide. Of the
36.4 million line items that are shipped annually from GDC, hundreds of
thousands of unsold and unused items are eventually requested for return by
the dealers. Caterpillar processes each dealer return request independently on a
first-come, first-served basis; Caterpillar does not compare or rank dealer return
requests. Since there are more than 200,000 returns each year or approximately
500 decisions each day for Caterpillar, a fast decision algorithm is required for
real-time evaluation. The items accepted for return are processed through the
Caterpillar GDC. For decision 1 in Figure 1, Caterpillar previously used a fixed
value threshold for returns. As shown in Figure 2, if the product's value
exceeded the threshold, it was accepted; otherwise, it was rejected.

In the next section, previous research is discussed and gaps are identified.
Then the dealer return policy problem is stated. The proposed multi-objective
algorithms compare product value, inventory level and lead-time to returns

![Figure 2. Original returns policy at Caterpillar, Inc.](image-url)
processing cost, safety stock level and returns processing lead-time to make dealer inventory return decisions for low-value products. The proposed algorithms are validated with a case study. The paper concludes with a discussion of the findings.

Literature review
Multi-echelon service part inventory models seek to balance distribution costs and the time to deliver a low-demand service part to a customer (Muckstadt and Thomas, 1980; Cohen et al., 1986). These models may help the manufacturer determine their safety stock levels in a manner that balances cost and service (Cohen et al., 1990). However, a gap in the service part literature is the link between service part safety stock decisions and manufacturer acceptance or rejection of dealer inventory returns.

Research in the retail literature demonstrates the importance of balancing inventory control for customer service, high-demand returns for fast resale and low-demand returns for discount sales, as discussed in Lee (2001), Mantrala and Raman (1999); Marvel and Peck (1995); Lau et al. (2000) and Emmons and Gilbert (1998). Unlike the short-life cycle of retail products, the heavy equipment industry has product life cycles that can exceed 20 years.

Research for returns of products with long product life cycles has focused on high-value products that require remanufacturing, which involves complete product disassembly, repair, reassembly and resale. Research in manufacturing and remanufacturing demonstrates that the cost of processing a high-value return, subsequent net product value and inventory management costs are important considerations for supply chain decisions (Inderfurth et al., 2001; Toktay et al., 2000; Van der Laan et al., 1996, 1999; Johnson and Wang, 1998; Krikke et al., 1998; Uzsoy and Venkatachalam, 1998). For low-value or obsolete products, the decision to reject a return and select among materials recovery options is modeled in Lu et al. (2002).

A question not directly addressed in the literature above is: “How can a manufacturer with high-volume sales and returns improve the returns policy for low-value, long-life cycle products with respect to forward supply chain service part delivery to their customers?”

Fast multi-objective algorithms for dealer returns of low-value, long-life cycle products
The proposed algorithms use real-time data to link forward supply chain characteristics to improve reverse supply chain decisions. The goal of the proposed algorithms is to improve customer service levels by reducing back-orders with dealer inventory returns. Formally, the vectors i, l, and v define the real-time inventory, lead-time, and net value, respectively, for k, each product stock keeping unit (SKU). Vectors Φ and Γ, define the threshold inventory and lead-time, respectively, for each product k. Vector Ψ is the net
value for each activity level $j$ from 1 to $J$, where 1 represents the most frequently ordered products and $J$ represents the least frequently ordered products. Specifically, the real-time terms have the following meanings:

- $i_k$: Inventory level of product $k$.
- $l_k$: Manufacturing, procurement and delivery lead-time of product $k$.
- $v_k$: Net value of product $k$ based on the dealer credit minus the returns processing cost where dealer credit is usually the original dealer purchase price from the manufacturer.

The tactical threshold parameters are defined as follows:

- $\Phi_k$: Safety stock threshold for product $k$ based on the manufacturer’s inventory control system.
- $\Gamma_k$: Lead-time threshold for product $k$ based on returns processing time at the manufacturer or third-party returns processor.
- $\Psi_j$: Minimum net return value for activity level $j$ based on the contracts between dealers and the manufacturer.

The first algorithm initially evaluates net value, $v_k$, and accepts high net value products according to current contractual trends. For the low-value product return requests, the proposed algorithm may still accept a return that is unprofitable if service can be improved. The algorithm evaluates the real-time data for inventory level, $i_k$, and rejects the return if safety stock, $\Phi_k$, is exceeded. The safety stock thresholds, $\Phi$, are based on the inventory control system. Theoretical research to set safety stock levels for service parts is explained in Cohen et al. (1986) and Muckstadt and Thomas (1980). If the real-time inventory level is below the safety stock threshold, the algorithm next evaluates the real-time manufacturing, procurement and delivery lead-time for the product, $l_k$, against the return lead-time threshold, $\Gamma_k$. This algorithm will accept low-value product return requests if they improve the customer service level based on both inventory and lead-time considerations as shown in Figure 3. The first algorithm is formally stated as follows:

**Algorithm 1**

1. Step 0: Initialize $\Psi$, $\Gamma$ and $\Phi$. Let $m = 0$.
2. Step 1: For return request $m$ from 1 to $M$ do:
   - Step 1.1: Let $m = m + 1$. Read user input and assign $k$.
   - Step 1.2: Read and assign $j$, $v_k$, $l_k$ and $i_k$ from ordered list.
   - Step 1.3: If $v_k > \Psi_j$, then accept product, go to step 1.1.
     Else if $v_k \leq \Psi_j$, then go to step 1.4.
To discuss the run time of algorithm 1, it is assumed that product activity level, net value, inventory level and lead-time are ordered by product number. Each product return request requires reading user input, a binary search and assignment in step 1.2, and a constant number of comparisons for steps 1.3 to 1.5. The worst-case running time of algorithm 1 using a binary search is $O(\log n)$, where $n$ is the number of products in the ordered list (Harel, 1992).

Next, algorithm 1 is modified to form algorithm 2 by considering the lead-time and inventory level simultaneously. Algorithm 2 seeks to increase service levels for low-value parts by accepting low-value return requests that improve either lead-time or inventory. Figure 4 illustrates the decision hierarchy for the second algorithm, which is formally stated as follows:

**Algorithm 2**

1. Step 0: Initialize $\Psi$, $\Gamma$ and $\Phi$. Let $m = 0$.
2. Step 1: For return request $m$ from 1 to $M$ do:
   - Step 1.1: Let $m = m + 1$. Read user input and assign $k$. 

\[ \begin{aligned} 
&\text{Step 1.4: If } i_k < \Phi_k, \text{ then go to step 1.5.} \\
&\quad \text{Else if } i_k \geq \Phi_k, \text{ then reject product, go to step 1.1.} \\
&\text{Step 1.5: If } l_k > \Gamma_k \text{ then accept product, go to step 1.1.} \\
&\quad \text{Else if } l_k \leq \Gamma_k \text{ then reject product for return, go to step 1.1.} 
\end{aligned} \]
Case study
The proposed concept to include forward supply chain characteristics in the manufacturer's decision-making process for the acceptance or rejection of low-value dealer returns is applicable to a manufacturer-dealer supply chain. To test the proposed algorithms, a validation study was carried out at Caterpillar. Prior to this study, Caterpillar considered only product value rather than net value when deciding to accept or reject a returned line item from a dealer as shown in Figure 2. Caterpillar tracks the inventory level for each line item, which is defined as one product with multiple pieces being processed during the same transaction. Caterpillar accepts or rejects an entire line item. In
this case study, the line item is represented by index \( k \). The threshold \( \Phi_k \) is set equal to the recommended storage quantity, which is based on the forecasted demand and the safety stock for line item \( k \).

In the experimental design, three factors are varied: decision hierarchy, value threshold, and lead-time threshold. The number of levels and values for each are given in Table I. The two decision hierarchies are graphed in Figures 3 and 4. Run 1 in Table I is the base scenario at Caterpillar and provides a means of comparison for runs 2 through 25. A description for each run in the experimental design is provided in Table I and discussed below.

Caterpillar classifies their product by one of four activity levels. In the case study, value thresholds are fixed for each activity level. Caterpillar contracts with dealers to accept general returns with values above $35 at any activity level, as shown in run 1 in Table I. Because Caterpillar was considering contractual increases to $45 for all activity levels, this value was used in runs 2-4, 8-10, 14-16 and 20-22. Higher product values at the lower frequency activity levels are also tested. Value threshold $50 is tested at the third activity level in runs 8-10 and 20-22, while $60 is tested at the fourth activity level in runs 8-13 and 20-25. To test an extreme in the other direction, a reasonable value of $15 is tested at the first activity level in runs 5-7, 11-13, 17-19 and 23-25.

<table>
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<tr>
<th>Run</th>
<th>Description</th>
<th>( \Psi_1 )</th>
<th>( \Psi_2 )</th>
<th>( \Psi_3 )</th>
<th>( \Psi_4 )</th>
<th>( \Gamma )</th>
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<td>45</td>
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<td>45</td>
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<td>Decrease ( \Psi_1 ); increase ( \Psi_2 ), ( \Psi_3 ), ( \Psi_4 ), ( \Gamma )</td>
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<td>45</td>
<td>45</td>
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<td>120</td>
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<td>120</td>
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</table>
The returns processing lead-time at Caterpillar includes the packing and shipping time from the dealer to Caterpillar's third-party returns processing center. Caterpillar allows dealers 90 days to return items accepted at step 1 in Figure 1. Dealers may use up to 90 days to accumulate items to reduce shipment costs. Runs 3, 6, 9, 12, 15, 18, 21 and 24 contain the previous contractual lead-time value of 90 days. Further runs are conducted to test potential changes in contract specifications. Adding 30 days and subtracting 45 days from the contract time of 90 days are both tested. To compare run 1 with runs 2 through 25, the number of manufacturer to dealer back-orders is tracked in each run. We evaluate the number of back-orders because it indicates an important element of manufacturer service level to dealers and their customers.

Case study results
In the experiments, over 700,000 line items requested for return as well as back-orders for a six-month period are analyzed. This case study consists of 25 experiments run on SAS® 6.08 (The SAS Institute, Inc., 2001) on a Hitachi model 9672 computer at a speed of 1163 MIPS (million instructions per seconds) in a total run time of 308.5 minutes or 5.142 hours, to find the number of line items that would be accepted from unsold dealer returns and to find the increase in service rate on dealer orders that would occur for each case. The results are summarized in Table II and Figure 5. Table II summarizes the back-orders eliminated from dealers' returns that meet the threshold value(s) for acceptance by the manufacturer in the proposed algorithms. Figure 5 illustrates the information in Table II in run pairs. The run pair is a run for algorithm 1 and a run for algorithm 2 that have the same threshold values from the experimental design, such as runs 2 and 14. This case study demonstrates that the proposed algorithms can significantly improve order fulfillment. This improvement reflects both a shorter time to fill back-orders as well as potentially reducing the number of back-orders.

Table II and Figure 5 show sensitivity to lead-time, \( \Gamma \), but insensitivity to values differentiated by activity level, \( \Psi_j \). Figure 5 shows that run 14 and run 17 increase service rates the most. In run 14, if the needed return was not accepted based on the value threshold, the return was accepted based on the inventory level and lead-time. In run 17, there is no improvement in back-orders from lowering the value for activity level 1, \( \Psi_1 \), because the needed returns are accepted based on the inventory level and lead-time. In addition, run 14 is preferred because it is simpler to implement common value thresholds across activity levels. The decision hierarchy in algorithm 2, coupled with keeping all activity levels, \( \Psi_j \), at the same threshold level and setting the lead-time to the lowest value studied, results in the highest service level of the 25 runs.
<table>
<thead>
<tr>
<th>Run</th>
<th>Algorithm 1</th>
<th>Algorithm 2</th>
<th>Service level improvement in filled orders</th>
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Table II.
Improvements in back orders filled for all runs

Figure 5.
Total service level improvement in back orders filled
Conclusions and extensions

Two multi-objective dealer inventory return algorithms are presented for long-life cycle products that not only consider a net value threshold for each activity level, but also the lead-time and the inventory level. Of the two algorithms, the second allows for the return of more line items, because the algorithm accepts the product return if either inventory level or lead-time criteria are met. Algorithm 1, on the other hand, requires that both inventory level and lead-time criteria be met, which results in fewer returns. Initially, heavy equipment manufacturers considered profit (net value) as the only consideration for returns decisions. This study suggests that allowing inventory level or lead-time considerations to supersede net value for dealer inventory return requests will reduce back-orders for low-value parts. These algorithms potentially increase the number of returns accepted, but only for those return requests that will be used to fill orders immediately or in the near future. If a manufacturer prioritizes lowering back-orders and increasing service levels, then the multi-objective approach in algorithm 2 will help them with their target.

Extensions to this work may include evaluating multiple dealer return requests simultaneously. One approach may be to select the return requests with the least return transportation time. However, this approach would penalize dealers that are located further from a centralized distribution center. Another approach may be to rank return requests from dealers based on dealer sales volume or other incentives.

References


