Modeling Total Cost of Ownership Utilizing Interval-Based Reliable Simulation Technique in Reverse Logistics Management

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Abstract

Reverse logistics involving closed-loop supply chains in various industry sectors has received growing attention throughout this decade. Reverse logistics considers several channels of reverse material flows from customers to suppliers. The value of product returns now exceeds $100 billion annually in the United States. However, only a small fraction of the returned product value is recaptured by manufacturers. In this paper, the total cost of ownership problem is studied based on a general supply chain framework. An interval-based simulation model is developed to improve robustness when high uncertainties are involved.
Keywords: Reverse logistics, total cost of ownership, interval analysis, probability bound analysis

1. Introduction

Industries usually focus on the traditional forward supply chain management, which is the delivery of products from manufacturer to the marketplace. Only limited attention has been given to the reverse logistics, which studies the flow of returning products from consumer to producer. The total value of products returned by consumers in the U.S. is estimated at $100 billion annually [1]. Companies are losing billions of potential dollars for not being prepared for the reverse flows of products.

The Council of Logistics Management (CLM) published the first known definition of reverse logistics in the early 1990s as [2]: “the role of logistics in recycling, waste disposal, and management of hazardous materials; a broader perspective includes all relating to logistics activities carried out in source reduction, recycling, substitution, reuse of materials and disposal”. Rogers and Tibben-Lembke [3] define reverse logistics as “the process of planning, implementing, and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods, and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal”. Dekker et al. [4] define reverse logistics as “the process of planning, implementing and controlling flows of raw materials, in process inventory, and finished goods, from a manufacturing, distribution or use point, to a point of recovery or point of proper disposal”.

In general, reverse logistics is a process by which companies can become more environmentally and economically efficient through minimization of material usage in products and reduction of waste. The overall objective behind the process is to capture the residual value of used products and dispose them in a good manner so that it does not affect the environment with sustainability concerns.

In this paper, we consider the problem of how to manage the reverse supply chain to maximize net asset value recovered from the flow of returned products. Given the complexity of the problem, we use simulation models to analyze total cost of ownership. To accommodate the uncertainties of data collection and input analysis, an interval-based simulation scheme is developed to improve the robustness of simulation results. In the remainder of the paper, Section 2 gives a brief overview of reverse logistics and interval analysis. Section 3 describes a general framework of closed-loop supply chain in our simulation model. Section 4 introduces the new interval-based simulation mechanism.

2. Background

2.1. Reverse Logistics Strategies

Reverse logistics strategies for end-of-life products are usually developed to allow users to determine the optimal amount to spend on buy-back and the optimal unit cost of reverse logistics [5]. However, besides core competencies, some companies are unwilling to pursue reverse logistics strategies, which are traditionally used for third-party providers. Some decision making models have been developed to link operational characteristics in the reverse logistics process to the selection of third-party logistics providers [6].

A good management strategy is to find the best choices of material recovery channels based on the conditions and values of the used products to maximize the recoverable residual values. Four major recovery choices are:

- Reuse: by which products are reused directly without prior operations. It may need cleaning and minor maintenance (e.g. reusable packages such as bottles, pallets or containers)
- Repair: It is the process of fixing or restoring failed products. However, there is a possibility of a loss of quality (e.g. industrial machines and electronic equipment)
- Recycling: which is material recovery (e.g. scrap, glass and paper and plastic recycling)
- Remanufacturing: is the process of disassembly and recovery of worn, defective, or discarded products. Disassembled products and all components are cleaned and inspected. Those components which can be reused are brought up to specification, and those cannot be reused are replaced. A remanufactured product should match the same customer expectation as new products. (e.g. mechanical assemblies such as aircraft engines and copy machines).

Compared to forward supply chain management, reverse logistics needs to consider a wider variety of product conditions due to different use situations, such as operating conditions, maintenance histories, levels of usage, etc. Moreover, there are uncertainties which arise from limited availability of data and deteriorated quality of data. Hence, we developed a robust simulation mechanism to study reverse logistics and to incorporate the various sources of uncertainties.

2.2. Uncertainty Quantification

The total uncertainty of system is combination of two components, uncertainty and variability [7]. Uncertainty is due to analyst's lack of knowledge whereas variability is the randomness of population [8]. Both uncertainty and variability can be represented by probability density functions and both can be combined in Monte Carlo (MC) simulation. However, the disadvantages of this approach include derived distributions are difficult to interpret, information is lost, and errors are introduced from mixing variables with parameters. The importance of separating uncertainty and variability has been recognized in areas such as risk assessment [9].

To accommodate the uncertainty of simulation parameters, second-order MC simulation method can be applied where the inner-loop is traditional simulation procedure and the outer-loop generates distribution parameters randomly. Thus uncertainty and variability can be modeled separately. The outcome of second-order Monte Carlo is a collection of cumulative distribution functions that simultaneously display the uncertainty and variability in the results [10]. However, its obvious disadvantage is the increased computational time.

In this paper, we propose an interval-based new simulation mechanism to improve the robustness of simulation under uncertainties. Probability bound analysis (PBA) [11] is applied to incorporate uncertainties of simulation models. This creates an efficient way to build reliable simulation models when limited input data is available yet high-risk decision-making is expected from the simulation results in a highly uncertain situation. PBA introduces uncertainties into parameters of probabilistic distributions by replacing real parameters with interval parameters.

2.3. Interval Analysis

Interval mathematics [12] is a generalization in which interval numbers replace real numbers, interval arithmetic replaces real arithmetic, and interval analysis replaces real analysis. The set of intervals corresponding to real numbers is

$$\mathbb{IR} = \{[a,b] \mid a \in \mathbb{R}, b \in \mathbb{R}\} \tag{1}$$

Let $[a] = [\underline{a}, \overline{a}]$, $[b] = [\underline{b}, \overline{b}]$ be real intervals and $\circ$ be one of the four basic arithmetic operations for real numbers, $\circ \in \{+,-,\cdot,/\}$. The corresponding operations for interval [a] and [b] are defined by

$$[a] \circ [b] = \{x \circ y \mid x \in [a], y \in [b]\} \tag{2}$$

For generalized intervals, the Kaucher arithmetic operations are defined as

$$[a]+[b] = [\underline{a}+\underline{b}, \overline{a}+\overline{b}], \qquad [a]-[b] = [\underline{a}-\overline{b}, \overline{a}-\underline{b}],$$

$$[a]\cdot[b] = \begin{cases}
[\underline{a}\cdot\underline{b}, \overline{a}\cdot\overline{b}] & if \quad (\underline{a}\geq 0, \overline{a}\geq 0, \underline{b}\geq 0, \overline{b}\geq 0) \\
[\underline{a}\cdot\underline{b}, \underline{a}\cdot\overline{b}] & if \quad (\underline{a}\geq 0, \overline{a}\geq 0, \underline{b}\geq 0, \overline{b}< 0) \\
[\overline{a}\cdot\underline{b}, \underline{a}\cdot\overline{b}] & if \quad (\underline{a}\geq 0, \overline{a}\geq 0, \underline{b}< 0, \overline{b}\geq 0) \\
[\overline{a}\cdot\underline{b}, \underline{a}\cdot\overline{b}] & if \quad (\underline{a}\geq 0, \overline{a}\geq 0, \underline{b}< 0, \overline{b}< 0) \\
[\underline{a}\cdot\underline{b}, \overline{a}\cdot\underline{b}] & if \quad (\underline{a}\geq 0, \overline{a}< 0, \underline{b}\geq 0, \overline{b}\geq 0) \\
[\min(\overline{a}\cdot\overline{b}, \underline{a}\cdot\underline{b}), \max(\overline{a}\cdot\underline{b}, \underline{a}\cdot\overline{b})] & if \quad (\underline{a}\geq 0, \overline{a}< 0, \underline{b}\geq 0, \overline{b}< 0) \\
[0.0,0.0] & if \quad (\underline{a}\geq 0, \overline{a}< 0, \underline{b}< 0, \overline{b}\geq 0) \\
[\overline{a}\cdot\overline{b}, \underline{a}\cdot\overline{b}] & if \quad (\underline{a}\geq 0, \overline{a}< 0, \underline{b}< 0, \overline{b}< 0) \\
[\underline{a}\cdot\overline{b}, \overline{a}\cdot\overline{b}] & if \quad (\underline{a}< 0, \overline{a}\geq 0, \underline{b}\geq 0, \overline{b}\geq 0) \\
[0.0,0.0] & if \quad (\underline{a}< 0, \overline{a}\geq 0, \underline{b}\geq 0, \overline{b}< 0) \\
[\min(\underline{a}\cdot\overline{b}, \overline{a}\cdot\underline{b}), \max(\underline{a}\cdot\underline{b}, \overline{a}\cdot\overline{b})] & if \quad (\underline{a}< 0, \overline{a}\geq 0, \underline{b}< 0, \overline{b}\geq 0) \\
[\overline{a}\cdot\underline{b}, \overline{a}\cdot\underline{b}] & if \quad (\underline{a}< 0, \overline{a}< 0, \underline{b}\geq 0, \overline{b}\geq 0) \\
[\overline{a}\cdot\overline{b}, \overline{a}\cdot\underline{b}] & if \quad (\underline{a}< 0, \overline{a}< 0, \underline{b}\geq 0, \overline{b}< 0) \\
[\underline{a}\cdot\overline{b}, \underline{a}\cdot\underline{b}] & if \quad (\underline{a}< 0, \overline{a}< 0, \underline{b}< 0, \overline{b}\geq 0)
\end{cases}$$

$$[a]/[b] = \begin{cases}
[\underline{a}\cdot\overline{b}, \overline{a}\cdot\underline{b}] & if(\underline{a}\geq 0, \overline{a}\geq 0, \underline{b}> 0, \overline{b}> 0) \\
[\overline{a}\cdot\overline{b}, \underline{a}\cdot\underline{b}] & if(\underline{a}\geq 0, \overline{a}\geq 0, \underline{b}< 0, \overline{b}< 0) \\
[\underline{a}\cdot\overline{b}, \overline{a}\cdot\overline{b}] & if(\underline{a}\geq 0, \overline{a}< 0, \underline{b}> 0, \overline{b}> 0) \\
[\overline{a}\cdot\underline{b}, \underline{a}\cdot\underline{b}] & if(\underline{a}\geq 0, \overline{a}< 0, \underline{b}< 0, \overline{b}< 0) \\
[\underline{a}\cdot\underline{b}, \overline{a}\cdot\underline{b}] & if(\underline{a}< 0, \overline{a}\geq 0, \underline{b}> 0, \overline{b}> 0) \\
[\overline{a}\cdot\overline{b}, \underline{a}\cdot\overline{b}] & if(\underline{a}< 0, \overline{a}\geq 0, \underline{b}< 0, \overline{b}< 0) \\
[\underline{a}\cdot\underline{b}, \overline{a}\cdot\overline{b}] & if(\underline{a}< 0, \overline{a}< 0, \underline{b}> 0, \overline{b}> 0) \\
[\overline{a}\cdot\underline{b}, \underline{a}\cdot\overline{b}] & if(\underline{a}< 0, \overline{a}< 0, \underline{b}< 0, \overline{b}< 0)
\end{cases}$$

Not only intervals solve the problem of representation for real numbers on a digital scale, but they are the most suitable way to represent uncertainties and errors in technical constructions, measuring, computations, and ranges of fluctuation and variation. Interval analysis has been extensively used in reliable computing in computer science. In engineering fields, methods of interval analysis have been used in robust geometry construction and evaluation [13], set-based modeling [14], imprecise structural analysis [15], design optimization [16], finite-element formulation and analysis [17], soft constraint solving [18], and tolerance analysis and synthesis [19, 20].

3. Closed-Loop Supply Chain Framework

Supply chain network design is commonly recognized as a strategic issue of business success. The location of production facilities, warehouses, and transportation strategies are major keys of supply chain performance. Reverse logistics should be taken in consideration during the design of the support network such as location and capacity of warehouses, plants, choice of outsourcing parties, distribution channel and supporting technology. Returns information captured should be integrated with forward supply chain information to achieve optimum planning and reduction of costs.

In this paper, we model the closed-loop supply chain with a general framework of the forward and reverse material flows. This framework includes the major scenarios that can take place in recovering used product, as shown in Figure 1. Although it is a closed loop logistics, some materials or products will still be disposed due to technical reasons (e.g. damaged products). Collection refers to all activities rendering used products available and physically moving them to some point for further treatment. Sort and inspect denote all operations that determine whether a given product is reusable and which method to apply. Thus, sort and inspect result in splitting the flow of used products according to distinct type of recovery such as repair, reuse, remanufacturing and recycle.

There are two different reverse logistics practices in industry. In Europe, reverse logistics practices are carried out in house. This approach leads to faster recovery rate, direct interaction with customers and control over revenue from the recovered products. However disadvantages of the approach exist. Returned products disrupt the material planning of original manufacturing process, which increases complexity in inventory control, production planning and scheduling. Original equipment manufacturer (OEM) may lack realization of the value of the returned product. In contrast, in U.S., reverse logistics activities are outsourced. This is because many businesses see the entire concept of reverse logistics is unmanageable. As a result, they choose to outsource the problem instead of managing it [21]. A third party collector can be more resourceful and technically advanced in collection and recovery of returned products. Since there is no interference with original manufacturer's production line, planning and control can be simplified. However, technical details of products will be revealed. OEM will not be able to realize full potential of the revenues generated by product recovery.

Understanding the total cost of production and usage of a product is essential to make good decisions in reverse logistics management. In general, the purchase price of a product is only a small fraction of the costs that we will experience over the life of the product. Total cost of ownership (TCO) is the sum of all costs related to a product, from purchase to usage, disposal, and beyond. The TCO for many products are significantly greater than the purchase price [22]. Here, we briefly summarize cost elements in the product life cycle in our study.

Costs involved in the reverse supply chain are similar to those of the forward supply chain in addition to other costs. Costs in the forward supply chain include ordering cost (cost of placing an order), transportation cost, handling inside facilities, inventory holding cost, item and operational cost. While costs in the reverse chain include transportation costs between facilities, handling costs inside facilities and inventory handling cost. There are some other costs which are not found in the forward chain, such as collecting, sorting, inspection, processing costs at disassembly, recovering (repairing, reusing, remanufacturing, recycling, disposing), repackaging and reassembly. Besides, any delay in the returned product flow is considered to be cost since the value of the product decreases.

Almost all the costs in the reverse supply chain is greater than those in the forward supply chain except for the holding inventory cost since it depends on the value of the product and also there are not comparable costs such as disassembly, recovery, repackaging costs. In U.S. retail business, transportation in forward and reverse supply chain is independent. Trucks pick up the return product from retailer(s) and deliver it to distribution centers or centralized return centers (CRC). Fleishmann et al. [23] noted that there was no model known for forward and reverse shipments due to physical difficulties and complexity found to create schedules that fit both parties.

The availability of returned products and their accumulation over time, together with variations in the quantity and condition of the returned products, can also lead to inventory control problems. The costs of recovery and disposal, on the other hand, can be significantly affected by design decisions. Design for disassembly, design for serviceability and design for recycling are thus fundamental to effective remanufacturing and recycling programs. Making decision based on inaccurate information requires risk analysis. We propose an interval-based simulation mechanism to analyze total cost of ownership to improve robustness of simulation models.

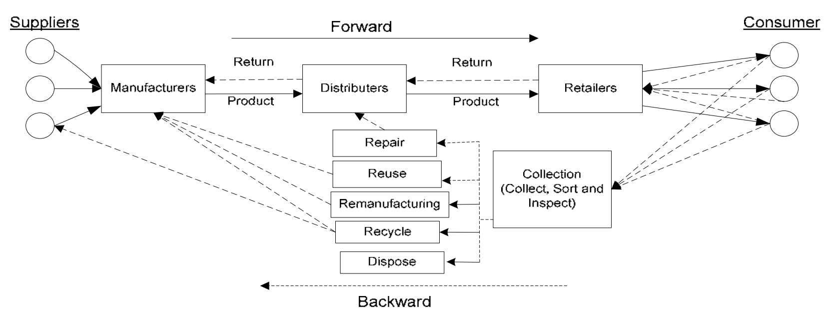

Figure 1: General Supply Chain Framework

4. Interval-based Robust Simulation

The general idea of the new reliable simulation model is to compute and simulate based on intervals rather than traditional floating-point numbers. In traditional simulation models, parameters of probability distributions are estimated based on input analysis. Considering the situations when uncertainty factors are significant, such as data sample size is fairly small, noise or error is not ignorable in data collection, we introduce interval parameters of probabilistic distribution functions.

In random variate generation, instead of a random number, a random interval is generated and used in the simulation process. The concept of random interval generation is illustrated in Figure 2. Instead of having a crispy cumulative distribution function (CDF), a random interval variable's CDF has a lower and an upper bound. Thus, inversely, corresponding to a particular CDF value, a random variate has lower and upper bounds.

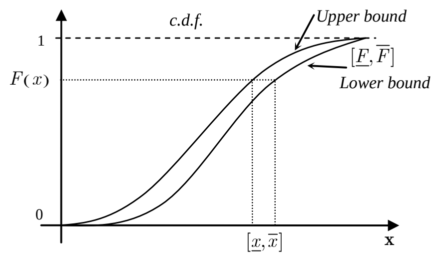

Figure 2: Interval cumulative distribution function for inverse transformation for random interval generation

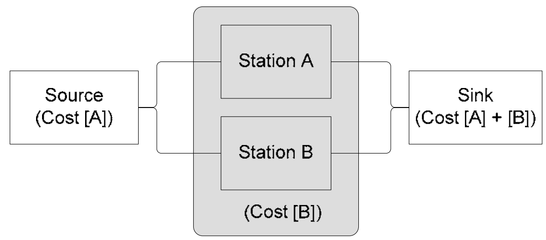

Figure 3: Reliable Simulation Mechanism Based on Intervals

The mechanism of the simulation is illustrated in **Figure 3**. The generated random intervals are used for cost accumulation. The calculation is based on interval arithmetic. A simulation model for total cost of ownership is being developed in a java based object oriented simulation package, called JSim. We implemented the interval based mechanism in JSim. In a simulation model, the initial state of an entity is determined by a Source, which creates entities (products) with initial costs as intervals. The products are then passed through a Branch where they are routed to value added stations. After a product's life cycle ends, it is routed to a Sink where the total cost is calculated.

The outputs of the interval-based simulation model are all interval numbers that incorporate uncertainties. Here is an example to demonstrate the difference between the new model and the traditional ones based on real numbers. In Figure 3, entities are processed by either Station A or Station B. The cost associated with Station A is described by an exponentially distributed random interval variable with the mean value of [25, 37], whereas the cost associated with Station B is described by an exponentially distributed random real variable with the mean of [31, 31]. Notice that a degenerated interval [31, 31] represents a real number 31. The accumulated costs of entities through Station A are intervals such as [7.89, 9.03] in contrast to the ones through Station B as real numbers.

To study how the relationship between the traditional method and our interval-based method is affected by sample sizes, we examined the empirical CDF of the simulation results in the example in Figure 3. . The empirical CDF's with the sample sizes of 160 and 300 are shown in Figure 4 and Figure 5 respectively. The graphs indicate that the run with the larger sample size has a broader width between the lower and upper limits so that it bounds the real number case better.

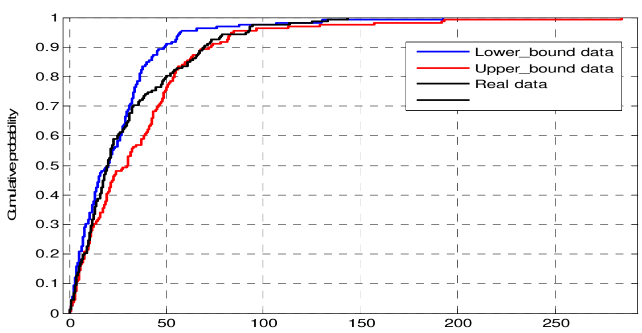

Figure 4: CDF for sample size of 160

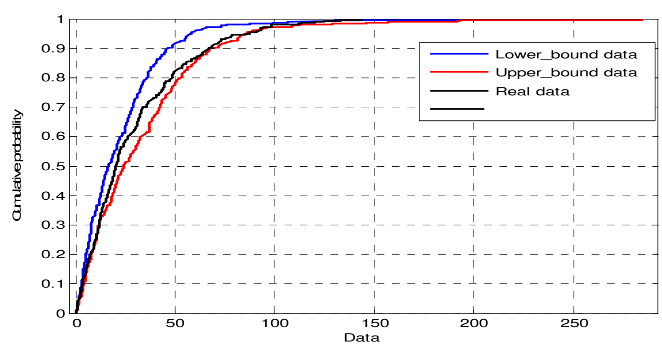

Figure 5: CDF for sample size of 300

5. Concluding Remarks

In this paper we propose an interval based reliable simulation mechanism to estimate total cost of ownership in closed loop supply chain. This model explicitly differentiates uncertainty from variability and incorporates uncertainty factors in data collection, input modeling as well as floating point computation. In the future, we will extend the model based on the generic closed loop supply chain framework and implement different scenarios in order to examine optimal returned product flows and make better decisions.

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