Reverse Logistics Network Design – Location of Retail Refurbishing Centers

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The issue of reverse logistics network design is of increasing importance given that there is a growing market for refurbished products. A common problem in this area is to determine the optimal location choice of refurbishing centers, which serve as intermediate facilities between collection centers and secondary markets. In this paper, we develop a cost minimization model to identify the optimal configuration of refurbishing centers. Our model integrates transportation costs, operating costs and fixed cost for establishing refurbishing centers. It also accounts for a random rate of return at each retailer's collection center, and the yield of used products that will be refurbished. In order to solve the model, we design an efficient algorithm using Benders Decomposition and, through an extensive numerical analysis, illustrate the trade-offs between the key parameters of the model.

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I. INTRODUCTION

As companies try to achieve leaner business processes and increasing cost savings, they place a significant focus on managing efficiently their logistics and supply chains. Traditionally, a company pays a greater attention to moving materials and items forward in the supply chain, but one of the prevailing operational and cost-related challenges is to move goods backwards. In general, the concepts of moving goods and materials backward from the point at which they are purchased or consumed, or moving them back to a previous supply chain point to recapture value, is referred to as "reverse logistics."

Numerous definitions of reverse logistics (RL) can be found in various literature sources including textbooks, research and practitioner papers. We agree with the RL definition presented by Rogers & Tibben-Lembke (1998), which describes RL 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." It should be clearly understood that reverse logistics is not a homogeneous subject but a term that encompasses a number of different logistics and managerial decisions. Govindan et al. (2015) expand the definition by stating that RL starts from end users where used products are collected from customers (return products) and then attempts to manage products through different decisions including: (a) recycling (to have more raw materials or raw parts); (b) remanufacturing and repairing to resale them to secondary markets; and (c) disposing of some used parts.

As a return flow due to a product recovery, goods return, or overstock, RL forms a closed-loop supply chain (Jayant et al., 2012). The success of the closed-loop supply chain depends on actions of manufacturers, retailers, and customers. Now, manufacturers are required to produce finished goods which are easy for disassembly, reuse and remanufacturing owing to the law of environmental protection. In addition, hazardous waste and related disposal methods place stringent restrictions on the RL management, and thus the number of customers supporting environmental protection by delivering their used products to collection points is increasing (Lee and Chan, 2009).

Reverse logistics receive growing attention from both the academic world and industries in recent years. There are a several reasons for this attention. Service and manufacturing companies spend on average 9 to 14% of their sales on returns (Pollock, 2010). For the traditional bricks-and-mortar retail operations, returns are three to four times more expensive than forward shipments. In some industries, such as book publishing, catalog retailing, and greeting cards, over 20% of all products sold are eventually returned to the vendor (Burnson, 2016). In addition, most companies realize that the total processing cost of returned products is higher than the total manufacturing cost, and it is found that strategic collections of returned products can lead to repetitive purchases and reduce the risk of fluctuating the material demand and cost (Jayant et al., 2012).

Within the retail industry, RL plays a critical role in consumer returns and efficiency of the retailers' processes. While this may appear to be a simple process of moving goods from customers to returns centers, retailers face numerous operational challenges. One of the critically important challenges in retail is to create an optimal RL network design of collection points, remanufacturing (refurbishing) centers, and secondary markets in order to minimize the total reverse logistics costs (Jayant et al., 2012). Another critical challenge arises from the fact that quantity and quality of retuned products can be quite uncertain, which may dramatically affect the performance of RL network, its capacity, and cost-related results.

To overcome these challenges, many retail companies are in a constant pursuit of modifying and improving their RL network design. GameStop, a global retailer of multichannel video games and pop culture collectibles, consumer electronics and wireless services, is one of such examples. The company operates more than 6,900 stores in 14 countries across Europe, Canada, Australia and the United States (About GameStop, 2016). These stores serve as collection points for a large spectrum of returned items for potential refurbishing and further resale. Originally mostly focusing on video games and consoles, GameStop has recently started expanding their refurbishing and recycling model to other kinds of electronics as well, for example, Android and iOS devices, responding thereby to requests from their customers (Hollister, 2012). The company's refurbishing centers are not third-party remanufacturing companies, but are directly owned by GameStop. The items repaired at a company's refurbishing center are then returned to the GameStop stores for resale in the secondary markets. The success in the used product sales market and the significant amount of returns motivated the GameStop to strengthen its RL network by: (a) reinforcing the returns through the trade-in program by operating store credits and cash back; and (b) investing in creating refurbishing centers in various locations, and increase their capacity and capability to refurbish a variety of retuned products. From this standpoint, GameStop's RL challenges are similar to those we discussed above, i.e., identifying the optimal location of the refurbishing centers and their capacities, and also resolving the issue of uncertainty (quantity and quality) in supply of returned products.

The need to address and solve these issues in the retail RL network design has motivated our research. It is focused on developing a cost minimization model to (a) identify the optimal locations of refurbishing centers by minimizing the transportation costs, operating costs and fixed costs for establishing refurbishing centers; (b) address in this optimization model the issue of uncertainty in supply of returned products from each retailer; (c) utilize a special application of Benders Decomposition to fragment and solve this rather complicated model; and (d) analyze the optimization model's parameters, and evaluate their applicability for the real-world retail RL network.

The structure of this paper is as follows. After the Introduction Section, we discuss literature review in Section II, provide the problem statement and model formulation in Section III, describe the model solution based on the application of Benders Decomposition in Section IV, and numerically analyze the model parameters in Section V. We finish the paper with the conclusions in Section VI.

II. LITERATURE REVIEW

Due to the importance of reverse logistics in the modern business environment, a significant number of literature sources address various aspects of the RL phenomenon. A comprehensive review of the RL research and practitioner literature has been presented by Govindan et al. (2015). This review provides analyses of existing RL surveys, quantitative and qualitative methods and tools used for RL analysis and improvement. Based on the literature review, the authors suggest that one of the main research topics in reverse logistics has been the RL network design. A similar conclusion is made by other studies of RL literature sources (Jayant et al., 2012; Harris and Martin, 2014; Vahabzadeh and Yusuff, 2015).

One of the leading aspects of RL network design is the location of a collection and recycling/refurbishing facilities. Govindan et al. (2015) define the designing decisions like locations and capacities of facilities (configurations and structures) among the most important decisions in RL network design. Not surprisingly, the location decision is a very popular subject in the RL literature sources. Srivastava and Srivastava (2006) present a conceptual model that provides an estimation of returns for different categories of products, in order to make decisions related to location and capacity of facilities. Fleischmann et al. (2000) propose generic characteristics of RL network recovery including the location decision. Based on real-world cases discussed in their paper, the authors suggest that the recovery networks can roughly be divided into three parts. In the first part, corresponding to the collection phase, flows are converging from the disposer market (collection stores and facilities), typically involving a large number of sources of used products, to refurbishing facilities. The second part is the refurbishing facility itself that recovers used products or disposes them. In the last part, corresponding to re-distribution, flows are diverging from the refurbishing facilities to demand points in the re-use second market. This recovery networks are very similar to the case of GameStop's RL we discussed in the previous section. The contribution from Fleischmann et al. (2001) includes creation of a generic facility location model for reverse logistics networks. They also find that supply uncertainty can be expected to have some effect on the network design, and, therefore, deterministic and probabilistic modeling approaches, in most cases, are appropriate for recovery network design.

Richey et al. (2005) conclude in their paper that RL network design deserves special attention in terms of labor due to the lack of standardization and that management should be focused on innovative ways to handle returns. They also suggest that there may be enough exceptions in RL network design to warrant the development of customized technology. We concur with this conclusion, specifically linking it with some retailers, e.g., GameStop (see the previous Introduction section of the paper), that have developed its own refurbishing centers customized to the needs of this particular retailer.

Analysis of the existing literature sources shows that the principal configuration of RL network design varies dramatically. However, it typically involves refurbishing (remanufacturing) at the locations of the products' original manufacturers (Suyabatmaz, 2014; Das and Chowdhury, 2012; Piphani and Saraswat, 2012; Tuzkaya et al., 2011; Lieckens and Vandaele, 2007; Blumberg, 2005; Realff et al., 2004). At the same time, we did not find a research paper which would analyze development of an RL network design in the retail industry in case of a refurbishing facility being a part of this retailer's vertically-integrated supply chain, or otherwise, a part of the retailer's close-loop supply chain. In order to fill this gap, our RL network model, presented in the next section of this paper, incorporates a refurbishing center as an integral part of the retailer's close-loop supply chain.

Many researchers have conducted quantitative analyses of RL design network, including the location of recycling/refurbishing centers, and have proposed various mathematical models (Yuchi et al., 2016; Dubey et al, 2015; Tavakkoli-Moghaddam et al., 2015; Soleimani, 2014; Mounir et al., 2011; Lee and Dong, 2009, Pishvaee et al., 2010; Sahyouni et al, 2007). A wide range of modeling approaches presented in these papers can be clustered into linear and mixed-integer programming models, stochastic modeling, simulation, and fuzzy modeling. Our analysis of multiple RL literature sources shows that these models, in most cases, consider the total transportation cost to be a single objective function. However, in the real world, the RL design involves multiple objectives, such as transportation cost, fixed and variable costs of RL resources like refurbishing centers, as well as their capacity and service level. Some researchers design RL network by utilizing multiple-objective optimization. Pati et al. (2008) formulate a mixed-integer goal programming model to assist in the proper management of a paper recycling logistics system. The objectives considered in this paper were a reduction in the reverse logistics cost, product quality improvement through increased segregation at the source, and environmental benefits through increased waste paper recovery. Li et al. (2012) provide an optimization model to design a multi-objective RL with the cost and service level. They consider the objectives of the cost, the total tardiness of the cycle time, and the coverage of customer zones. We agree with the multi-objective considerations in the RL network design, and, therefore, in our model, presented in the next section of this paper, we also consider an objective function with various cost categories, as well as the yield of used products to be refurbished, and a service level of the refurbishing center.

Various approaches are used by researchers to solve mathematical problems in RL design. As discussed by Govindan et al. (2015) in their RL literature review, some researchers try to solve problems with analytical or exact methods, which is complicated and limited in terms of solving large-scale problems. For large-size problems, heuristic methods and meta-heuristic algorithms like generic algorithm (GA) or Simulated Annealing (SA) are also being used. However, Costa (2005) suggests that Benders Decomposition may be considered as one of the most successful solution approaches to RL network design. The basic idea behind this method (Benders, 1962) is to decompose the problem into two simpler parts: the first part, called "master problem," solves a relaxed version of the problem and obtain values for a subset of the variables. The second part, called "sub-problem" (or "auxiliary problem"), obtains the values for the remaining variables while keeping the first ones fixed, and uses these to generate cuts for the master problem. The master and sub-problems are solved iteratively until no more cuts can be generated. The conjunction of the variables found in the last master and sub-problem iteration is the solution to the original formulation.

We find only a few research papers that utilize the Benders Decomposition approach in RL network design. Üster et al. (2007) design a semi-integrated network in which the direct logistics network exists and only collection and recovery centers must be located. The model optimizes the direct and reverse flows simultaneously. Easwaran and Üster (2009) consider a network design problem in a multiproduct closed-loop supply chain setting. Their solutions approaches include a mixed-integer linear program, Tabu search heuristics, and Benders Decomposition. The Benders approach computationally verifies the high quality of the Tabu search heuristic solutions. In our research, we also apply the Benders decomposition to solve a complex RL model for locating refurbishing centers (see Section IV of this paper).

TABLE 1. NOTATIONS.

Notations	*Explanations*
Q_i	Sales of product in the last period at R_i
θ_i	Random return rate of product at R_i, with a probability density function $f(.)$ and cumulative distribution function $F(.)$
D_k	Demand for the refurbished product at M_k
U_j, L_j	Upper and lower bounds for total throughput of F_j
f_j	Fixed cost of building the facility F_j
v_j	Variable cost of sorting and refurbishing at F_j
c_{ij}	Transportation cost per a unit of collected product from R_i to F_j
c_{jk}	Transportation cost per a unit of collected product from F_j to M_k
α_j	Yield of used product to be refurbished at F_j
β_i	The service level at collection center R_i
Decision Variables	*Explanations*

x_{ijk}	Number of used products flow from R_i through F_j to M_k
y_{jk}	is1 if F_j sends the refurbished products to M_k, 0 otherwise
z_j	is 1 if F_j is setup, 0 otherwise

III. PROBLEM STATEMENT

In this section we propose a general quantitative model for reverse logistic network design. Our model is based on the RL recovery network properties presented in Fleischmann et al. (2000) and discussed in Section II of this paper, and also on the specific case studies, e.g., GameStop, we referred to in the Introduction section. Our model inherits from the mixed integer linear programing (MILP) and classical warehouse location models (WLM). It also captures other unique features such as supply uncertainty and varying level of yield at the refurbishing centers.

We consider a company who markets a single product P through n retailers. The company is considering the implementation of a sustainable supply chain by designing the reverse logistics channel to collect and refurbish the used products. There are three parts in the RL network: (i) collection centers R_i , $i = 1,2,\ldots,n$, which are actually the retail stores (e.g., in the case of GameStop); (ii) refurbishing centers, $F_j, j = 1,2,\ldots,m$, which perform the sorting and refurbishing activities. The sorted used products will be refurbished and then delivered to secondary markets for sell, and the remaining will be disposed; and (iii) secondary market, $M_k, k = 1,2,\ldots,t$ where the demand for the refurbished products are been realized by secondary market. The retail locations and the secondary markets are known priory. The company needs to decide on the location of the refurbishing centers to minimize the total logistics cost of the reverse channel. We assume that the demand D_K for the refurbished products at each secondary market is exogenous. The notions are listed in Table 1.

We assume that each collection center can supply to multiple refurbishing centers, and each secondary market receives refurbished product from one and only one refurbishing center. In order to meet the required demand for a refurbished product at a secondary market M_k, the throughput of each refurbishing center F_j should be $\sum_k D_k y_{jk}$. Our objective is to minimize the total cost associated with the reverse logistics channels. The formulation of the problem is as follows.

$$\min_{x\geq 0} \sum_{i,j,k}(c_{ij}x_{ijk} + c_{jk}\alpha_j x_{ijk}) + \sum_j\left(f_j z_j + v_j \sum_k \frac{D_k}{\alpha_j}\, y_{jk}\right) \tag{1}$$

Subject to,

$$\left(\sum_i x_{ijk}\right)\alpha_j = D_k y_{jk} \qquad \forall j,k \tag{2}$$

$$P\left(\sum_k \sum_j x_{ijk} \leq Q_i\theta_i\right) \geq \beta_i \qquad \forall i \tag{3}$$

$$\sum_j y_{jk} = 1 \qquad \forall k \tag{4}$$

$$L_j z_j \leq \sum_k \frac{D_k}{\alpha_j}\, y_{jk} \leq U_j z_j \qquad \forall j \tag{5}$$

$$z_j - y_{jk} \geq 0 \qquad \forall j,k \tag{6}$$

The objective function includes transportation cost, set-up cost for building refurbishing centers, and the variable cost of refurbishing. The decision variables z_j, y_{jk} are binary. The demand constraint (2) stipulates that all the demand in secondary market must be met. Constraint (3) represents a supply constraint, which requires that the probability of returned products at each collection center R_i, out of the total collected amount of $Q_i\theta_i$, should at least be β_i, where β_i measures the service level of each collection center. Constraint (4) states that the refurbished products from each refurbishing center must go to a single secondary market. The reason behind constraint (4) is as follows: we assume that the demand at secondary markets is exogenous, and the demand constraint (2) stipulates that all the demand should be satisfied. Constraint (5) means that the established lower and upper bounds of capacity in this center bound the throughput in each refurbishing center. Finally, constraint (6) ensures that the correct logical relationship between y_{jk} and z_j.

If we assume that the random return rate θ_i follows the Normal distribution $N(\mu_i, {\sigma_i}^2)$, then the supply constraint (3) can be replaced by constraint (7) with a more rigorous expression:

$$\sum_k \sum_j x_{ijk} \leq (\mu_i + Z_{\beta_i}\sigma_i)Q_i \qquad \forall i \tag{7}$$

IV. APPLICATION OF BENDER'S DECOMPOSITION

The formulation (1) – (6) represents a large-scale complex model, for which analytical methods may not be directly used. To solve this model we apply Benders Decomposition, which is, as discussed in Section II of this paper, an effective method of solving a complex RL network design model (Costa, 2005; Üster et al., 2007). The main advantage of Benders Decomposition is that it provides a way of decomposing the problem into two simpler parts: (a) the master problem that solves a relaxed version of the problem and obtain values for a subset of the variables; and (b) the sub-problem that obtains the values for the remaining variables while keeping the first ones fixed, and uses these to generate cuts for the master problem**.** To be specific, the binary variables are temporarily held fixed so as to satisfy constraints (4) – (6) (the master problem). The remaining formulation (1) – (3), with a single type of variable $\boldsymbol{x}$, is the classical transportation problem, which is also the sub-problem in Benders Decomposition. For those $\boldsymbol{y_{jk} = 1}$, $\boldsymbol{\bar{j}\,(K)}$ is defined uniquely for each k, and $\boldsymbol{z_{\bar{j}(k)}}$ must equal to 1. Then, for the fixed binary variables $(\boldsymbol{y_{jk}}, \boldsymbol{z_k})$, the *transportation problem* becomes:

$$\min_{x\geq 0} \sum_{i,k} (c_{i\bar{j}(k)} + c_{\bar{j}(k)k}\alpha_{\bar{j}(k)})x_{i\bar{j}(k)k} \tag{8}$$

subject to,

$$\left(\sum_{i} x_{i\bar{j}(k)k}\right)\alpha_{\bar{j}(k)} = D_k y_{\bar{j}(k)k} \qquad \forall k$$

$$\sum_{i}\sum_{\bar{j}(k)} x_{i\bar{j}(k)k} \leq (\mu_i + Z_{\beta_i}\sigma)Q_i \qquad \forall i$$

where for those fixed binary variables, when $y_{jk} = 1$, $x_{ijk} \geq 0$ for any *i=1, 2, …n*; when $y_{jk} = 0$, $x_{ijk} = 0$ for any *i=1, 2, …n*.

Let (*t, s*) be the optimal dual solution for the *transportation problem* (8), where *t* is the dual variable corresponding to demand constraint (2) and s is the optimal dual variable corresponding to supply constraint (7). The dual problem of (8) is as follows:

$$\max_{s\geq 0;t} \sum_{jk} t_{jk}\left(-\frac{D_k}{\alpha_j}\, y_{jk}\right) + \sum_i s_i[-(\mu_i + Z_{1-\beta_i}\sigma)Q_i] \tag{9}$$

subject to,

$$-t_{jk} - s_i \leq c_{ij} + c_{jk}\alpha_j \qquad \forall i,j,k$$

Notice that for any fixed s, the optimal choice of t is easily defined since there is no joint constraint on t and t is bounded below by:

$$t_{jk} \geq \max_i\{-s_i - (c_{ij} + c_{jk}\alpha_j)\}$$

Apparently, if $(-\frac{D_k}{\alpha_j}\, y_{jk})$ ≤0 then the optimal t_{jk} is $\max_i\{-s_i - (c_{ij} + c_{jk}\alpha_j)\}$, while if $(-\frac{D_k}{\alpha_j}\, y_{jk})$ =0 then the optimal t_{jk} could be any number greater or equal to $\max_i\{-s_i - (c_{ij} + c_{jk}\alpha_j)\}$. But in the case of $(-\frac{D_k}{\alpha_j}\, y_{jk})$ =0 or $y_{jk} = 0$, the corresponding demand constraints in (2) can actually be dropped, and, thus, there is no need to consider the corresponding dual variable t_{jk} whose optimal value is greater or equal to $\max_i\{-s_i - (c_{ij} + c_{jk}\alpha_j)\}$.

With the derived dual variables, we define *the master problem* as:

$$\min_{y;z} \sum_j (f_j z_j + v_j \sum_k \frac{D_k}{\alpha_j}\, y_{jk}) - \sum_{jk} t_{jk}\left(-\frac{D_k}{\alpha_j}\, y_{jk}\right) - \sum_i s_i(\mu_i + Z_{1-\beta_i}\sigma)Q_i \tag{10}$$

subject to,

$$\sum_j y_{jk} = 1 \qquad \forall k$$

$$L_j z_j \leq \sum_k \frac{D_k}{\alpha_j}\, y_{jk} \leq U_j z_j \qquad \forall j$$

$$z_j - y_{jk} \geq 0 \qquad \forall j,k$$

Next, we apply Benders Decomposition via the following algorithm.

<u>Step 0: Initialization.</u>

Set $UB = \infty$ and the iteration step $H = 0$. Select a convergence error $\epsilon \geq 0$. Arbitrarily choose a binary array (y^{H+1}, z^{H+1}) satisfying constraint (4), (5) and (6). Let $LB = \sum_j (f_j z_j^{H+1} + v_j \sum_k \frac{D_k}{\alpha_j}\, {y_{jk}}^{H+1})$.

<u>Step 1: Solving *the transportation problem.*</u>

Given (y^{H+1}, z^{H+1}), solve the linear *transportation problem* (8). Denote the optimal solution by x^{H+1} and the corresponding total transportation cost in problem (8) by $T\,(x^{H+1})$. Let t^{H+1} be the current optimal dual variable corresponding to demand constraint (2) and s^{H+1} be the current optimal dual variable corresponding to supply constraint (8).

Then the value of $\sum_j (f_j z_j + v_j \sum_k \frac{D_k}{\alpha_j}\, y_{jk}) + T(x^{H+1})$, or the current total cost, serves as an upper bound on the optimal value of the original minimization problem (1)-(7). If this value is less than *UB*, we replace *UB* with this value and store the current solution $(y^{H+1}, z^{H+1}, x^{H+1})$ as the *Incumbent*. Terminate if $UB - LB \leq \epsilon$; otherwise, go to Step 2.

<u>Step 2: Solving *the master problem.*</u>

Given (t^{H+1}, s^{H+1}) from Step 1, update the master problem (10). Set *H=H+1*, solve (10) and denote the optimal solution as (y^{H+1}, z^{H+1}). Let LB equal to the current optimal value of master problem (10). Terminate if $UB - LB \leq \epsilon$; otherwise, go to Step 1.

It should be noticed that the proposed algorithm could converge to optimal solution with finite steps. There are couple of reasons. First, even though there is no guarantee that (8) is feasible for any choice of (y^1, z^1) at the Step 0 (Initialization). However, we can preclude this by simply assuming that $\sum_i Q_i \geq \sum_k D_k$ and that all possible *ij* combination is technically allowed. Therefore, by these assumptions, (8) is feasible and has a finite optimal solution for every binary variable combinations (y^{H+1}, z^{H+1}). Second, as H increases, the minimal value of *the master problem* increases due the accumulation of "benders cuts"; also, the upper bound *UB* decreases each time an improved *Incumbent* is found. Therefore, the degree of optimality is achieved by iterating the steps. Finally, the ϵ-optimal termination criterion assures that at each step, the current *master problem* objective is within (*LB*, *UB*) while both *LB* and *UB* coincide to within ϵ upon termination. Hence, finite convergence is assured for any pre-defined $\epsilon \geq 0$.

V. NUMERICAL EXPERIMENT AND RESULTS

In this section, we use the data from the GameStop reverse logistics network to solve the RL network design model formulated in Section III by applying the Benders Decomposition formulation from Section IV. We also perform numerical experiments, aiming at analyzing the impact of multiple parameters, i.e., the fixed cost of building the refurbishing center (f_j), the random return rate (θ_i), and yield (α_j).

5.1. Setting of Parameters

To model the randomness of the geographical impact, we choose the 5 representative stores of GameStop in 5 cites across the United States, which are Los Angeles, Chicago, Boston, New York City, and Atlanta. These 5 stores serve as collection centers, as well as the secondary markets. The sales in the previous period (Q_i) at each store are assumed to be same, and are proportional to the annual dollar sales of a single GameStop store. According to WikiInvest.com (2016), the annual dollar sales of a single GameStop store are \$1.4 million. With a assumption that average price of a game console is at \$7, their sale is estimated as 20,000 units. The demand (D_k) for refurbished product at each store (or secondary market) is estimated roughly based the number of registered member.

In terms of the potential choice for the refurbishing centers, we use the same 5 sites as the potential location choice. This is a reasonable assumption since GameStop previously relied on a local third-party organization to refurbish their game consoles. Variable cost of operations (including evaluating and refurbishing activities) at each potential refurbishing cites (v_j) is randomly generated form a Uniform Distribution, $U(1,5)$. The required service level at each refurbishing center is fixed at $\beta_j = 95\%$. The per-unit transportation cost parameters are scaled based on the quote of unit transportation cost shipping among the 5 cities that is described at FreightCenter.Com (2013). We also consider the geographical distance between each pair of the 5 cities.

The varying parameters are the fixed cost (f_j), the random return rate (θ_i), and yield (α_j). Given the option that product can be refurbished at a third-party remanufacturer where the one-time fixed cost is almost negligible, one option of fixed cost is 0. The high value of fixed cost is considered at \$1,000,000 (the higher cost is set to match with the scale of transportation cost). We use the coefficient of variation (*CV*) to model randomness of return rate. We assume the return rates at all the collection centers are identical independent variable following the normal distribution, i.e., $\theta_i \sim Normal\ (\mu, \sigma^2)$. The value of μ is fixed at 0.2, and the CV is defined at three levels – 0.1, 0.15 and 0.2. We again assume the same yield at each potential refurbishing center. Consistent with Bakal and Akcali (2006), we vary the value of yield in the range of 50% - 95%. In particular, α_j is at three levels – 50%, 75% and 95%.

Under these parameter settings, the problem involves 30 binary variables, 625 continuous variables, and 90 constraints. The algorithm of Benders Decomposition proposed in Section IV is developed in C++ programing language and incorporates a standard CPLEX 10.0 Optimizer.

Given the setting above (including those fixed parameters and the varying parameters), there are 18 cases with differing values of the coefficient of variation $CV(\theta_i)$, α_j and f_j, as listed in Table 2.

TABLE 2. CASE SETTINGS OF VARYING PARAMETERS.

	$CV(\theta_i)$	α_j	f_j
Case 1	0.1	0.5	0
Case 2	0.1	0.5	1000000
Case 3	0.1	0.75	0
Case 4	0.1	0.75	1000000
Case 5	0.1	0.95	0
Case 6	0.1	0.95	1000000
Case 7	0.15	0.5	0
Case 8	0.15	0.5	1000000
Case 9	0.15	0.75	0
Case 10	0.15	0.75	1000000
Case 11	0.15	0.95	0
Case 12	0.15	0.95	1000000
Case 13	0.2	0.5	0
Case 14	0.2	0.5	1000000
Case 15	0.2	0.75	0
Case 16	0.2	0.75	1000000
Case 17	0.2	0.95	0
Case 18	0.2	0.95	1000000

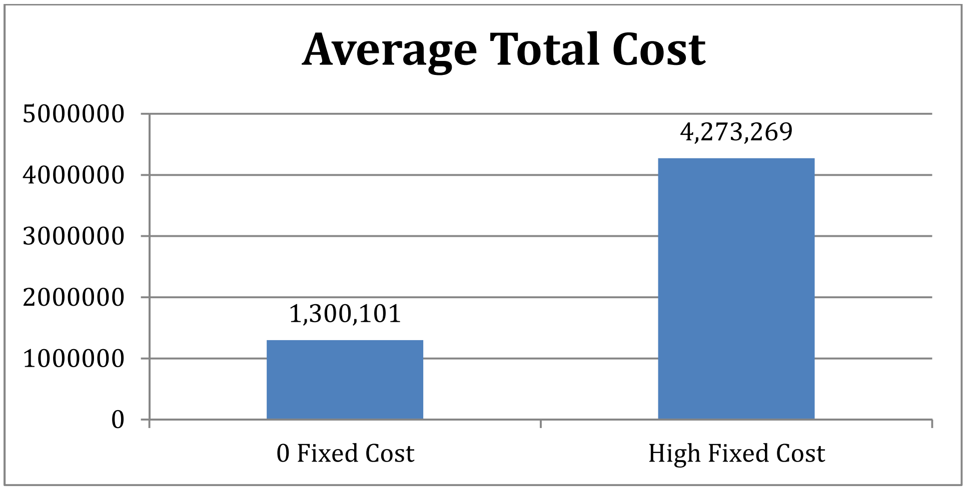

FIGURE 1. COMPARISON OF TOTAL COST OVER 0 AND HIGH FIXED COST f_j.

FIGURE 2. OPTIMAL RL NETWORK AT 0 FIXED COST, MEDIAN $CV(\theta_i)$ AND α_j.

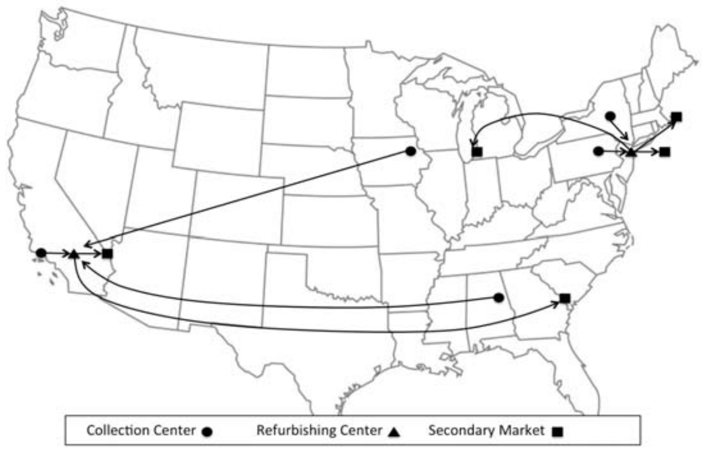

FIGURE 3. OPTIMAL RL NETWORK AT HIGH FIXED COST, MEDIAN $CV(\theta_i)$ AND α_j.

5.2. Impact of Fixed Cost f_j

Half of the cases (9 cases) are with 0 fixed cost and the other 9 cases are with high fixed cost. We compute the average total cost among the cases (for each case, the total cost includes transportation cost and refurbishing cost) under 0 fixed cost, and compute the average total cost among the cases under high fixed cost. The comparison is shown in Figure 1. As shown in this figure, the average total cost under high fixed cost is almost three times higher than the one under 0 fixed cost.

We then compare the optimal reverse network design for the two levels of fixed cost (0 fixed cost and high fixed cost), at the median of the coefficient of variation of return rate and yield. As shown in Figure 2 (corresponding to the parameter setting in Case 9 in Table 2), when at a 0 fixed cost, and $CV(\theta_i)$ and α_j are kept at median level, the optimal network shows that at each of the 5 selected sites, a local refurbishing center would be built up to minimize the transportation cost. On the contrary, when the fixed cost is high, as is shown in Figure 3 (corresponding to the parameter setting in Case 10 in Table 2), the refurbishing center in Los Angeles takes over the returned products from Chicago, Atlanta and Los Angeles, and supplies for Los Angeles and Atlanta. Another refurbishing center serves New York City, Boston, and Chicago's secondary market. Such design of RL network guarantees the minimum total cost and the capacity constraint of the refurbishing center.

5.3. Interacted Effect of Return Rate θ_i and Yield α_j

In this section, we analyze the interacted impact of variability of return rate and yield. Figure 4 and Figure 5 compares the total cost under different setting of the coefficient of variation of return rate and yield, at 0 fixed cost and high fixed cost, respectively.

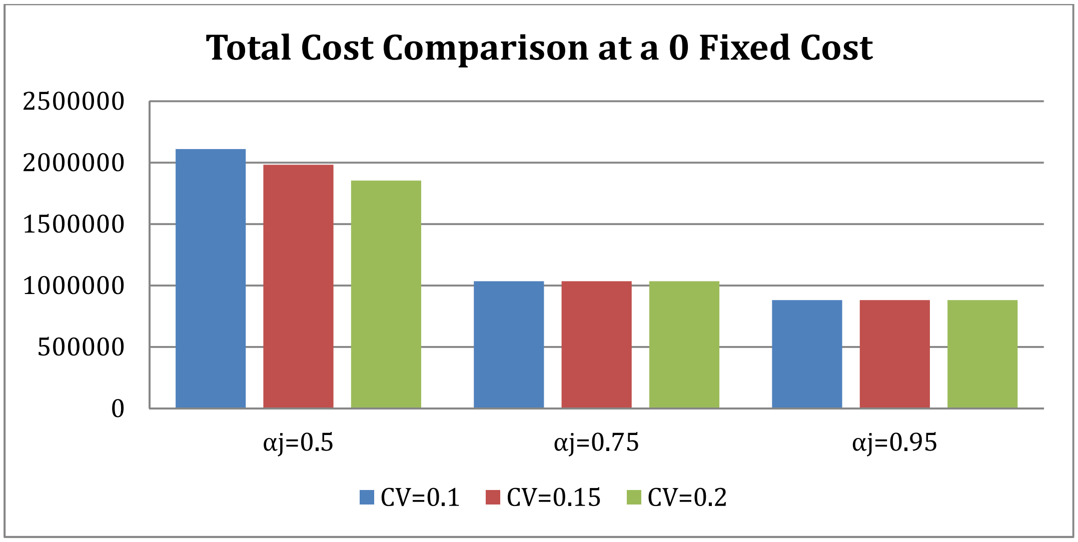

FIGURE 4. COMPARISON OVER VARIOUS $CV(\theta_i)$ AND α_j, AT A 0 FIXED COST.

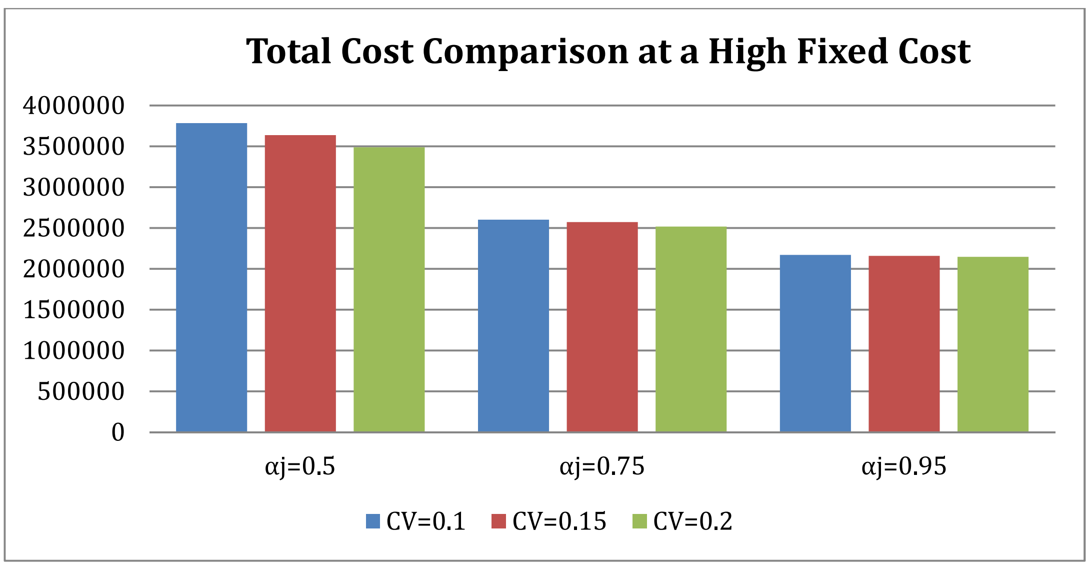

**FIGURE 5. COMPARISON OVER VARIOUS $CV(\theta_i)$ AND α_j,
AT A HIGH FIXED COST.**

The above Figures 4 and 5 demonstrate that, in general, increasing either variability of return rate (i.e., the coefficient of variation of return rate) or the yield will decrease the total cost. The rationale behind this relationship is that the high variability of return rate incentivizes a collection center to receive more returned products that will be transported to the closest refurbishing center, and hence reduces the transportation cost from other collection centers to this refurbishing center. The same rationale applies to the yield. The high yield decreases the transportation cost from a refurbishing center to secondary markets. However, we can still observe a slight difference over the interacted effect of these two parameters. Comparing with the yield, the effect of variability of return rate on the transportation cost is limited. At each level of the coefficient of variation, increasing the yield will reduce the total cost significantly; however this is not the case when we are fixing the level of yield, for example, when yield is 0.75 and 0.95, the reduction of total cost is quite minor.

5.4. More Managerial Findings

Knowing that the total cost will increase significantly when the fixed cost of building a refurbishing center increases from 0 to a high level, it would be interesting to look at the rate of cost growth under effect of random return rate and yield of refurbishing. We define the *rate of cost growth* as $\frac{(total\ cost\ under\ high\ f_j - total\ csot\ under\ 0\ f_j)}{total\ csot\ under\ 0\ f_j}$. This rate of cost growth reflects the price that the company needs to pay if they decide to buildup their own refurbishing center instead of outsourcing to a third-party. Of course, there are many other factors which affect the decision of remanufacturing in-house or to outsource, e.g., technology advances, cost structure, and product characteristics (Wang et al., 2016). Due to the limited scope of our model, where the focus is on location selection and network design, we imply that there is an additional cost of building the company's own refurbishing center versus using a third-party remanufacturer.

Figure 6 shows the rate of cost growth at differing level of the coefficient of variation of return rate and yield.

When the yield is at a low level, at all levels of the coefficient of variation of return rate, the rate of cost growth is relatively when the fixed cost is changing from 0 to a high level. Contrary, when the yield is at a moderate or higher level, the rate of cost growth becomes much higher than that in the previous case. As yield keeps on increasing to the highest level, i.e., 0.95, we observe that the rate of cost growth becomes slightly lower. This implies that the yield of refurbishing greatly affects the switching cost from a third party refurbishing to an in-house refurbishing. In addition, given a complete parameter setting of other, we infer that there exists a yield point that resulting in the highest rate of cost growth. On the contrary, when the yield is fixed, the impact of the coefficient of variation of return rate is limited.

We also observe an obvious two-way interaction between these two parameters. When the coefficient of variation is as low as 0.1, the impact of yield on the rate of cost growth is the greatest; whereas when the coefficient of variation is as high as 02, the impact of yield on the rate of cost growth becomes subtle.

Next we compare the optimal network design at different level of coefficient of the variation of return rate and yield, when the fixed cost is 0 or high respectively. First we observe that as long as the fixed cost is 0, the optimal network is always the same as in Figure 2, which is not moderated by the level of other parameters. In this case, it always minimizes the transportation cost, and hence total cost, if refurbishing locally. Then we analyze the cases when fixed cost is high.

From the two-way interaction analysis of the coefficient of variation and yield, we find that the yield (α_j) has a more significant impact on the total cost and subsequently the optimal network design. Therefore, we map out the optimal RL networks while fixing variance of return rate at a median level, i.e., $CV(\theta_i)$=0.15, which corresponding to case 8, 10, and 12. Since case 10 has already been demonstrated in Figure 3. Figure 7 and 8 demonstrate case 8 and 12, respectively.

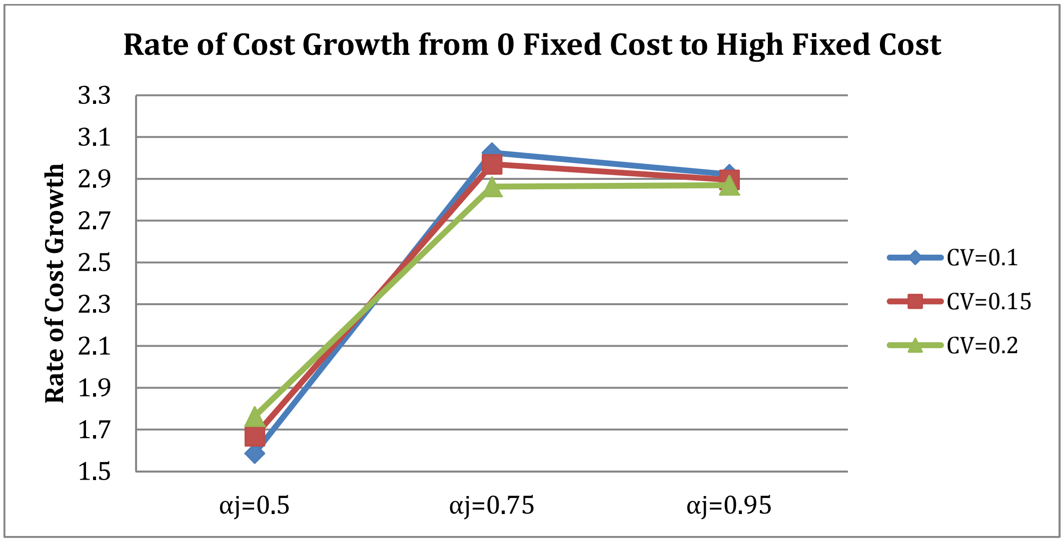

FIGURE 6. COMPARISON OF RATE OF COST GROWTH.

FIGURE 7. OPTIMAL RL NETWORK AT HIGH FIXED COST, $CV(\theta_i) = 0.15$ AND $\alpha_j = 0.5$.

FIGURE 8. OPTIMAL RL NETWORK AT HIGH FIXED COST, $CV(\theta_i) = 0.15$ AND $\alpha_j = 0.95$.

From Figure 7 and Figure 8, we can see the following trend. When yield is at lower level, the company needs 3 refurbishing centers to meet the high demand from these 5 cites; each of the 3 refurbishing centers need at least 2 supply sources of returned products. For example, the refurbishing center in Los Angeles receives returned products locally and even as far as from Atlanta. However, when the yield is at a higher level, the company's decision over refurbishing centers reduces to 2 – one for east coast secondary markets, and the other for the west coast secondary market.

VI. CONCLUSION

In this paper, we propose a mixed-integer linear programming (MILP) model to identify the optimal location of refurbishing (recycling) centers in RL network design. This model is based on generic characteristics of a case study of GameStop, where the retailer stores serve as used product collection centers, as well as the secondary market to sell the refurbished products. The model determines the optimal number and locations of refurbishing centers, aiming to minimize the total cost, which includes expense of transportation, operating cost and fixed cost of refurbishing. Our research and developed optimization model provides several important contributions to the research and practical application of RL network design. First, we develop a new RL network design model for the retail industry, where retail stores serve as collection centers and secondary markets, and refurbishing/ recycling centers belong to the retailer. Second, we incorporate in the model the quantity uncertainty of the rate of returned products to the collection centers (random rate of return), and also consider varying level of yield of used products to be refurbished at the refurbishing centers. Finally, for solving the model, we introduce the effective algorithm using Benders Decomposition that was implemented in C++ and CPLEX. The Benders Decomposition method, based on the idea of partition and delay constraint generation, is a perfect solution approach for a network design problem where it is much easier to solve the decomposed problems than the original one.

To analyse the optimal location of refurbishing centers and identify its sensitivity to various parameter settings, numerical experiments were developed by utilizing the example of GameStop's reverse network. We select 5 cities for potential location choices for refurbishing centers, and then perform sensitivity analysis over the fixed cost of building the refurbishing center (f_j), the random return rate (θ_i) and yield of used products to be refurbished (α_j). The other parameters are fixed at an appropriate value (to match with the case of GameStop). The major findings are as follows.

First, the average total cost under high fixed cost is almost two times higher than the one under 0 fixed cost. In particular, as long as the fixed cost is 0, no matter what the values of other parameters are, the optimal RL network with the minimum transportation cost is such that the refurbishing center needs to be located in the same area where the secondary market is located. However, when the fixed cost is high, the company builds fewer refurbishing centers, trading-off the higher transportation expenses for less up-front cost of building fewer refurbishing centers.

Second, we analyse the interacted effect of variability of return rate and yield. In general, increasing either variability of return rate (i.e., the coefficient of variation of return rate) or the yield of used products to be refurbished will decrease the total cost. The reason for this relationship is that the high variability of return rate incentivizes the collection center to receive more returned products, and, therefore, increases the transportation cost from the collection center to the refurbishing center. Comparing with the parameter of yield, the effect of variability of return rate on the transportation cost is limited.

Third, we explore the impact of parameters on rate of cost growth when fixed cost changing from 0 to a high value. This rate of cost growth reflects the price that the company needs to pay if they decide to build their own refurbishing center instead of outsourcing to a third-party provider. Comparing with the variability of return rate, the yield has a more significant effect on the rate of cost growth. When the yield increases from a low level to a higher level, we observe obvious raise in the rate of cost growth.

After analysing the optimal RL design at various parameter settings, we obverse a following trend. When the yield of used products to be refurbished is at lower level, the company needs more refurbishing centers; and each refurbishing center need at least 2 supply sources of returned products. However, when the yield is at a higher level, the company needs less refurbishing centers. The reason behind is in our model, the demand at the secondary markets is enforced to be met; A higher yield in refurbishing center means higher throughput.

The future research in this area of RL network design may cover several new directions. First, we can extend the analysis of the optimal location of refurbishing centers to a large-scale optimization that incorporates, for example, the entire network of GameStop stores (collection centers). A large-scale problem would better bring out the superiority of Benders Decomposition. Second, we may introduce the quality uncertainty of the returned products into this model, given the fact that sorting and refurbishing activities cost varies significantly depending on varying quality of the returned products. Finally, we may also explore the role of product life-cycle stages (introduction, growth, maturity, and demise) in the RL network design.

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