Quality Driven Model for Recovery and Disassembly of Used Products Using Multi Objective Chance Constrained Programming

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This paper develops a two-stage recovery and disassembly optimization procedure for used products in reverse supply chain management. The model sorts the used products into three different quality classes, picks the best recovery options and optimizes the disassembly sequence of the recovered products. Chance Constrained Programming as an efficient technique is used to address the uncertainty of the stochastic parameters of the proposed model. The problem is modeled as an integer linear program and solved using goal programming. The solution and the sensitivity analysis of the numerical example proves the model to be robust and effective.

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I. INTRODUCTION

The manufacturing sector of the economy generates the most environmentally harmful waste products with electronic wastes being its major component. Data shows that in 2014, approximately 41.8 million tons of e-waste was generated worldwide. This amount increased to 49 million in 2016 and according to the Columbia University's Earth Institute Blog that number is expected to grow to 60 million by 2021. In 2014, only 6.5 million tons of total global e-waste generation was treated, or about 15.5 percent, by national electronic take-back systems. In the United States, however, the recycling rate has gone up steadily. According to EPA, the e-waste recycling rate in the U.S. was 19.6 percent in 2010, 24.9 percent in 2011, and in 2012, the amount of waste generated in the U.S. was 3.4 million tons of which about 1 million tons was recycled, resulting in a recycling rate of 29 percent.

There has also been a growing trend in the production of environmentally friendly products in the U.S. mainly as the result of government regulations, marketing, and cost advantages. Consequently, there has been a steady increase in the development and analysis of quantitative models for environmentally conscious and friendly product design, and manufacturing. These models suggest producing products that are efficient for disassembly and are produced with recycling and consciousness disposing with none to zero landfill as their objective. These models mainly emphasize Life-Cycle

Analysis (LCA) concepts which are an effective mean of dealing with environmental issues during each stage of the product life cycle. These concepts emphasize that products must be produced, distributed, used, and disposed of in manner that is not harmful to the environment. The interests in LCA has grown in models for the entire supply chain and how to make them “greener” and more environmentally friendly.

The purpose of this study is to develop an optimization model that would help decision makers efficiently manage the economic and environmental issues incurred from used and recovered products. The model allows the decision maker to divide these products into different categories, determines the most profitable recovery choice for each category and then optimizes the disassembly decision of these products.

Specifically, a Multi-Objective Mixed Integer Linear Program (MOMILP) is developed to manage the two phases of *recovery* and *disassembly* in the reverse supply chain. In the first phase, the used products, based on their quality, are assigned to one of the available four recovery channels. These four recovery channels are: Repair, *Disassemble*, Recycle and Landfill. In the second phase, an optimal allocation procedure is developed for the products that are assigned to the *disassembly* option of the first phase. Additionally, in this study, four options are considered for the disassembled components. They are: Equivalent to New (ETN), Reuse, Recycle and Landfill. To address the uncertainty in the supply of the used products of different quality levels, and to represent the uncertainty of the demand parameters in the problem, normal probability distribution is used. Additionally, to address the stochastic parameters we used Chance Constrained Programming. The proposed multi-objective optimization model is solved using goal programming and the branch & bound method. A numerical example is included.

The first phase of the proposed model in this paper builds upon research done by Henrick Lamsali (2013). In his research, he develops a deterministic linear program that finds the optimal allocation of used products with varying quality to different recovery options. In our research, we expand his model to a stochastic scenario where there is uncertainty in the quality levels of the used products and in the market demands of these products. Chance Constrained Programming is used to reflect the uncertainty in satisfying the constraints and the stochastic parameters. To improve the practicality and efficiency of the model, we included set up costs associated with recovery options, landfill penalty costs, and additional practical constraints that trigger recovery channels when necessary, and constraints that limit the landfill. Most notably, the model developed in this paper includes *a second phase* that determines an optimal disassembly allocation for the returned products allocated to the disassembly option of the first phase.

II. LITERATURE REVIEW

The literature on models for used and returned products recovery configuration selection has grown significantly within the last decade. Gupta et al (2010) divide up the literature in four categories of *environmentally conscious design*, *reverse and closed loop supply chain*, *remanufacturing* and *disassembly*. They emphasize that the design for environmentally conscious products (DFE) is detrimental in determining the quality of the products after recovery. DFE is categorized as design for recyclability, design for remanufacturing, design for reusability, design for disassembly, design for maintainability and serviceability and design for energy savings.

The literature for the three areas of reverse or closed loop supply chain, remanufacturing and disassembly in turn, reviews the best trade-off assessment for recovery options in terms of time, cost, quality, waste pollution, and health. The uncertainly associated with the *quality of the recovered products* and the *optimal disassembly sequence* are the dominant factors in determining the salvage value and recoverability. The model that we develop in this research specifically addresses these areas. In the following section, we will review the literature specifically related to these topics.

Robotis et al. (2012) studied the impact of the uncertainty on quality condition with respect to investments in product reusability and used product collection. Their study focused on the inspection capabilities of firms dealing with both manufacturing and remanufacturing operations. Zeballos et al. (2012) use a mixed integer linear programming to analyze the impact of uncertainty in the quality and quantity of used products on the planning and managing of a closed-loop supply chain. In their study, used products are graded into five levels (best, better, average, worse and worst).

Radhi (2012) proposed a mixed integer non-linear programming to maximize the total profit by selecting facilities to operate and optimal quality to accept into each operating facility. The model also considerd the constraints of satisfying market's demand from each operating facility. It indicated that each used item is inspected and assigned a quality grade between zero and a hundred and acceptance to the facility, acquisition price and remanufacturing costs were all dependent on this quality grade.

Kuik et al. (2016) developed an integrated model to determine an optimal recovery plan through maximizing recovery value by considering some practical manufacturing constraints such as lead time, waste, and quality. Genetic algorithm was used for solving the optimization problem. The problem was then formulated as a stochastic linear programming and solved using Cplex. Chang et al. (2017) presented a comprehensive review of the approaches and challenges in product disassembly planning. They addressed the issues involved with sustainable product development through optimizing disassembly in each stage of the product life cycle. Jorjani et al (2004) developed an optimal allocation procedure for the disassembled components of electronic equipment. They used a piecewise linear program to allocate components of a used product to various disassembly options. Gonzales and Adenso-Diaz (2005) reviewed the product structure and the relationships among its components and determined the disassembly depth and the EOL recovery strategy for each dissembled part. This led to most profit and in their (2006) study; they used a scatter search mega heuristic to determine the optimum disassembly sequence for complex products with sequence dependent disassembly costs.

III. DECISION MODEL

The model proposed in this paper consists of two phases. In the first phase, the assignment of used products to one of the four possible recovery channels is optimized and for the products assigned to the disassembly channel, in the second phase, an optimum disassembly sequence is obtained.

The model developed in this research considers three quality levels for used products based on their physical appearance, performance and functionality conditions (q= 1, 2, 3). The three categories from the highest to the lowest quality are as follows: Category 1 are products with highest quality that can be repaired and resold. Category 2 products are defined to be products that can be disassembled into components for potential reuse and/or resell. Category 3 products are categorized as ones that are of little use in their current condition and need to be recycled and/or sent to landfills. Potentially, increasing the quality categories will lead to a more accurate classification of products but for the purpose of this study only three categories are considered.

Once the used products are categorized in the three quality classes, they are then assigned to a proper recovery channel. The four available recovery options are: (1) repair, (2) disassemble, (3) recycle and (4) landfill. Even though the preferred assignments in the recovery options for each category are apparent, this is not mandatory, i.e. it is possible for a returned product of a higher quality to be recovered using a lower option and vice versa. Since the cost of a higher recovery option for a lower quality used product is much higher and the objective of the model is to minimize the total costs involved; this option will not be chosen. Nevertheless, the general model is not restricted to one designated recovery option and it allows the flexibility of all quality levels to be allocated to all recovery options if it is technically feasible. Additionally, the model includes a fixed setup cost associated with the recovery option and a landfill penalty cost.

In the first phase of the two-phased model the optimum recovery option for used products is determined (Repair, *Disassemble*, Recycle and Landfill). In the second phase, an optimum disassembly sequence is obtained for the second option (the disassembly option) and an allocation procedure is developed for the disassembled components. Four options are considered for reusing the disassembled components (l= 1, 2, 3, 4): (1) ETN, parts with high quality and comparable to the new ones can be refurbished and become equivalent to new parts, (2) Reuse, (3) recycle and (4) landfill. The decision-making framework for this problem is depicted in Figure 1.

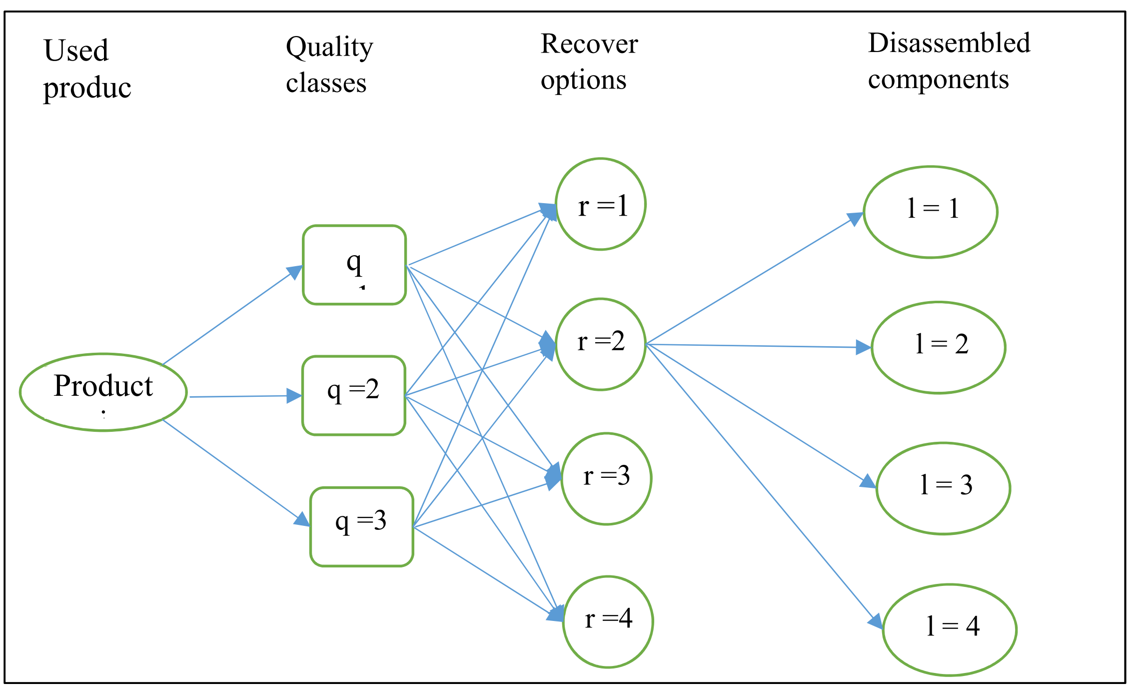

FIGURE 1. THE DECISIN MAKING FRAMEWORK FOR PROPOSED MODEL

3.1. Proposed Models

Two 2-phased models are developed in this research to represent deterministic and stochastic scenarios.

Indices:

i= index of products i= 1, 2… n
j= index of components j= 1, 2…m
q= index of quality classes for products q= 1 (high), 2 (Medium), 3 (low)
h= index of recovery options in first phase; h= 1 (repair), 2(disassemble), 3(recycle), 4(landfill)
l= index of reuse options after disassembling in second phase*;* *l*= 1(ETN), 2(reuse), 3(recycle), 4(landfill)

Parameters and coefficients:

First Phase:

FC_h = set up cost for recovery channel h if selected
TP_i = total amount of returned product i in a given time period
P_{iq} = the amount of returned product i in quality class q
AC_i = acquisition cost per unit of used product i
PR_{ih} = proceeds per unit of product i that is recovered by channel h
SC_i = Inspection and sorting cost per unit of product i
RC_{iqh} = processing cost per unit of product i in quality class q using recovery channel h.
CP_{iqh} = required capacity of item i in quality class q, to be recovered by channel h
ACP_h = available capacity of facility for each recovery channel h
MP_{ih} = market potential for product i that is recovered by channel h
ST_h = minimum units needed for the recovery of channel to trigger the set up
T_i = minimum recovery target for product i (expressed as a percentage of TP_i)
Lf_i = maximum allowable percentage sent to landfill for product i
M = an arbitrarily large number

Second Phase:

DS_i = disassembly cost for unit of product i
D_l = maximum market demand for all components that are planned to use in option l after disassembling
B_{jl} = proceeds per unit of disassembled component j which is reused by option l.
KD_l = capacity of facility for each reuse option l
β_{ij} = number of dismantled components j resulting from disassembling unit of product i
Lf = maximum allowable percentage send to landfill for disassembled components

Decision variables:

X_{iqh} = amount of product i in quality class q recovered using channel h in the first phase
g_h = binary variable (1 when recovery channel h is selected, 0 otherwise)
Fi = excess amount of product i not allocated to any recovered options in phase I
Y_{jl} = number of disassembled component j that is used by option l in the second phase
θ_i = number of product i that are planned to be disassembled in the first phase using recovery channel 2 ($\sum_{q=1}^{3} X_{iq2} = \theta_i$).

Using the above notation, the problem is formulated as a linear program:

Deterministic Model:
Model:

Max $Z_1 = \sum_{i=1}^{n}\sum_{q=1}^{3}\sum_{h=1}^{4}\big(PR_{ih} - (RC_{iqh} + AC_i + SC_i)\big).X_{iqh} - \sum_{h=1}^{4} FC_h \,.\, g_h - \sum_{i=1}^{n} RC_{i4} F_i$

Max $Z_2 = \sum_{j=1}^{m}\sum_{l=1}^{4} B_{jl} \;.\, Y_{jl} - \sum_{i=1}^{n} DS_i \;.\, Z_i$

Subject to:

(First Phase)

$\sum_{i=1}^{n}\sum_{q=1}^{3} X_{iqh} \geq ST_h$; h= 1, 2, 3, 4 (1)

$\sum_{i=1}^{n}\sum_{q=1}^{3} X_{iqh} \leq M.g_h$; h= 1, 2, 3, 4 (2)

$\sum_{q=1}^{3} X_{iqh} \leq MP_{ir}$; i=1, 2…n & h= 1, 2, 3, 4 (3)

$\sum_{h=1}^{4} X_{iqh} \leq P_{iq}$; i=1, 2…n & q= 1, 2, 3 (4)

$\sum_{i=1}^{n}\sum_{q=1}^{3} CP_{iqh} \,.\, X_{iqh} \leq ACP_r$; h= 1, 2, 3, 4 (5)

$\sum_{q=1}^{3}\sum_{h=1}^{4} X_{iqh} \geq TP_i \,.\, T_i$; i=1, 2…n (6)

$\sum_{q=1}^{3} X_{iq4} \leq TP_i \,.\, Lf_i$; i=1, 2…n (7)

$F_i = TP_i - \sum_{q=1}^{3}\sum_{h=1}^{4} X_{iqh}$; i=1, 2…n (8)

(Second Phase)

$\sum_{q=1}^{3} X_{iq2} = \theta_i$; i=1, 2…n (9)

$\theta_i \,.\, \alpha_{ij} \geq \sum_{l=1}^{4} y_{jl}$; i=1, 2…n & j= 1, 2…m (10)

$\sum_{j=1}^{m} y_{jl} \leq D_l$; l= 1, 2, 3, 4 (11)

$\sum_{j=1}^{m} y_{j4} \leq lf.\sum_{i=1}^{n}\sum_{j=1}^{m} \theta_i \,.\, \beta_{ij}$; (12)

$\sum_{j=1}^{m} y_{jl} \leq KD_l$; l= 1, 2, 3, 4 (13)

$X_{iqr}\,, y_{jl}$ *are Integer* & g_i *is binary* ; $\forall\, i, j, q, h, l$ (14)

3.2. Objective Functions

Since there are two separate phases in the decision-making procedure for this problem and the input information for the second phase is provided from the first phase, the two objectives cannot be optimized in one equation. Therefore, multi objective programming is proposed in this model.

The first objective (Z1), maximizes the total profit i.e. revenues from recovered units sold, minus all the variable aggregate costs of acquisition, inspection and processing, minus the fixed cost of setup for recovery channels, minus the landfill cost for excess amount of unrecovered products. This objective is maximized subject to the optimum allocation of returned products to available recovery options. The second objective (Z2), maximizes the profit of allocating the disassembled components to reuse channels subject to meeting demands for different disassembled components and not exceeding available capacity while limiting amount sent to landfill.

3.3. Constraints

Constraints 1 - 8 correspond to the first phase of the decision model and constraints 9 - 13 represent the restrictions associated with the second phase of the model.

- Constraint (1) emphasizes the assignment of a minimum quantity needed to a recovery channel so as to allow the consideration of that option. This constraint ensures that the sum of returned products with all quality assigned to a recovery option h would meet the minimum activation requirement (ST).
- Constraint (2) refers to the binary variables that is defined for considering fixed setup cost for activating each recovery channel. This constraint ensures that binary variable (g_h) take value 1 when recovery channel h is activated and it will take 0 otherwise.
- Constraint (3) ensures that the total amount of recovered products by each option in first phase does not exceed the market potential.
- Constraint (4) is designed to ensure that the number of recovered products of type i from quality class q does not exceed existing amount of returned products available.
- Constraint (5) represents the capacity constraint for each recovery option

One of the distinguishing features of product recovery management is the fulfilment of the recovery target set either by the government or by a specific environmental legislation.

- Constraint (6) represents the recovery target as the proportion of the total amount of returned products based on their technical characteristics. Landfilled products are excluded in this constraint because generally, the landfill option is very unattractive, and no minimum mandatory target is considered to fulfilment.
- Constraint (7) limits landfill as a percentage of the total returned products since landfill is very expensive, both in terms of costs and loss of goodwill for the company, and hence undesirable.
- Constraint (8). This constraint represents the amount not allocated to any recovery option (difference between total amount of returned products and the total amounts assigned to a recovery option). The model will send this amount to landfill.
- Constraints (9 & 10) correspond to the relation between decisions variables used in two phases of model, and ensures that the total amount of recovered disassembled components in all four channels ($\sum_{l=1}^{4} y_{jl}$) does not exceed existing components in-hand ($\theta_i \, . \beta_{ij}$).
- Constraint (11) ensures that the total amount of recovered components by each channel in the second phase does not exceed the total market demand for channel.
- Constraint (12) ensures the amount of disassembled components that is to be landfilled is limited as a percentage of total components similar to the first phase
- Constraint (13) is the capacity constraint and it confirms that the amount of a component used for an option does not exceed the capacity available for that option.

IV. CHANCE CONSTRAINED PROGRAMMING

Chance Constrained programming is used to model the uncertainty that might arise in certain parameters of this problem. Parameters such the uncertainty of the market potential for a product recovered by a given channel (MP_{ih}) and the uncertainly of the quantity of the returned products (P_{iq}) both in the first phase. In the second phase it is assumed that the demand of the disassembled components (D_l) for each option is variable and probabilistic.

In Chance Constrained Programming (CCP), the developed optimization model includes some uncertain parameters in constraints so the objective is optimized with the stochastic constraints satisfied at least α percent of the times, where α a safety margin selected by the decision maker.

Assume that x is a decision vector, ξ is a stochastic vector and gj(x, ξ) are stochastic constraint functions, j= 1, 2… p. Since the stochastic constraints gj(x, ξ) ≤ 0, j= 1, 2… p do not define a deterministic feasible set, they need to be held with a confidence level α. Thus chance constraint is represented as follows (Liu, 2009):

$$\Pr\{ g_j(x, \xi) \le 0,\ j= 1, 2, \dots, p \} \ge \alpha \tag{15}$$

Which is called a joint chance constraint, and when considered separately it is shown as follows:

$$\Pr\{ g_j(x, \xi) \le 0\} \ge \alpha_j, \quad j= 1, 2, \dots, p \tag{16}$$

Theorem 1 Assume that the stochastic vector $\zeta = (a_1, a_2, \dots, a_n, b)$ and the function g(x, ξ) has the form $g(x, \xi) = a_1x_1 + a_2x_2 + \cdots + a_nx_n - b$. If a_i and b are assumed to be independently normally distributed random variables, then $\Pr\{ g(x, \xi) \le 0\} \ge \alpha$ if and only if

$$\sum_{i=1}^{n} E[a_i]x_i + \Phi^{-1}(\alpha)\sqrt{\sum_{i=1}^{n} Var[a_i]x_i^2 + V[b]} \le E[b] \tag{17}$$

Where Φ is the standardized normal distribution function. (Liu (2009)).

In this model, $\widetilde{MP}_{ih}$, $\tilde{D}_l$ and $\tilde{P}_{iq}$ are considered random variables and assumed that they are independently normally distributed. Based on equation (17), we reformulate constraints (3), (4) and (11) to equations (20), (21), (28) respectively to incorporate the uncertainly associated with the problem parameters.

Stochastic Model:

$$\text{Max } Z_1 = \sum_{i=1}^{n}\sum_{q=1}^{3}\sum_{h=1}^{4}\left(PR_{ih} - (RC_{iqh} + AC_i + SC_i)\right).X_{iqh} - \sum_{h=1}^{4} FC_h \cdot g_h - \sum_{i=1}^{n} RC_{i4}F_i$$

$$\text{Max } Z_2 = \sum_{j=1}^{m}\sum_{l=1}^{4} B_{jl}\ .Y_{jl} - \sum_{i=1}^{n} DS_i\ .Z_i$$

Subject to:

(First Phase)

$$\sum_{i=1}^{n}\sum_{q=1}^{3} X_{iqh} \ge ST_h \quad ; \quad h= 1, 2, 3, 4 \tag{18}$$

$$\sum_{i=1}^{n}\sum_{q=1}^{3} X_{iqh} \le M.g_h \quad ; \quad h= 1, 2, 3, 4 \tag{19}$$

$$\sum_{q=1}^{3} X_{iqh} + \phi^{-1}(\alpha_1)\sqrt{Var(\widetilde{MP}_{ih})} \le E[\widetilde{MP}_{ih}] \quad ; \quad 1, 2\dots n \ \&\ h= 1, 2, 3, 4 \tag{20}$$

$$\sum_{h=1}^{4} X_{iqh} + \phi^{-1}(\alpha_2)\sqrt{Var(\tilde{P}_{iq})} \le E[\tilde{P}_{iq}] \quad ; \quad i=1, 2\dots n \ \&\ q= 1, 2, 3 \tag{21}$$

$$\sum_{i=1}^{n}\sum_{q=1}^{3} CP_{iqh}\ .X_{iqh} \le ACP_r \quad ; \quad h= 1, 2, 3, 4 \tag{22}$$

$\sum_{q=1}^{3}\sum_{h=1}^{4} X_{iqh} \geq TP_i \, . T_i$; i=1, 2…n (23)

$\sum_{q=1}^{3} X_{iq4} \leq TP_i \, . Lf_i$; i=1, 2…n (24)

$F_i = TP_i - \sum_{q=1}^{3}\sum_{h=1}^{4} X_{iqh}$; i=1, 2…n (25)

(Second Phase)

$\sum_{q=1}^{3} X_{iq2} = \theta_i$; i=1, 2…n (26)

$\theta_i \, . \alpha_{ij} \geq \sum_{l=1}^{4} y_{jl}$; i=1, 2…n & j= 1, 2…m (27)

$\sum_{j=1}^{m} y_{jl} + \phi^{-1}(\alpha_3)\sqrt{Var(\widetilde{D}_l)} \leq E[\widetilde{D}_l]$; l= 1, 2, 3, 4 (28)

$\sum_{j=1}^{m} y_{j4} \leq lf . \sum_{i=1}^{n}\sum_{j=1}^{m} \theta_i \, . \beta_{ij}$; (29)

$\sum_{j=1}^{m} y_{jl} \leq KD_l$; l= 1, 2, 3, 4 (30)

$X_{iqr} \, , y_{jl}$ *are Integer* & g_i *is binary* ; $\forall\, i, j, q, h, l$ (31)

V. NUMERICAL EXAMPLE

The following hypothetical numerical example is developed to demonstrate the agility of the model.

In this example, we assume three different returned products to be allocated to any of the four available recovery channels. Table 1 displays the total amount of each product returned, its recovery target, acquisition and sorting costs.

TABLE 1. TOTAL PRODUCT TP_i, T_i, AC_i And SC_i FOR PRODUCT i

i	TP_i	Ti	AC_i	SC_i
1	1500	85%	6	2
2	3500	95%	12	2
3	2500	75%	5	2

The proceeds per unit of recovered products, fixed cost of setup for each recovery channel and minimum recovery requirement for setup in each channel are listed in Table 2. Tables 3 and 4 list the unit recovery costs and capacity related parameters respectively.

TABLE 2. PROCEEDS PER RECOVERED UNIT S_{ih}, Fixed Setup Cost, FC_h , MIN SETUP REQUIREMENT ST_h AND AVAILABLE CAPACITY, ACP_h

i \ h	1	2	3	4
1	85	65	28	0
2	38	25	15	0
3	95	70	25	1.2
FC_h	12	8	10	4
ST_h	50	35	40	0
ACP_h	2200	3800	1700	950

The unit selling prices vary for different recovered products. These differences are due to the variability in the quality levels of the recovered outputs; hence, the quality of a recovered product is indicated by its price. A high price denotes the high quality of the recovered product.

As mentioned above, it is assumed that the supply and the demand of returned products in each quality level are normally distributed random variables. Tables 5 and 6 summarizes supply and demand distributions. (As mentioned above the coefficients are hypothetical)

TABLE 3. PROCESSING COSTS PER UNIT, RC_{iqh}

i,q \ h	1	2	3	4
1,1	17	14	8	3
1,2	42	25	10	3
1,3	75	62	13	1
2,1	20	10	5	2
2,2	58	15	7	1
2,3	70	15	7	1
3,1	35	18	10	3
3,2	69	35	12	0.5
3,3	95	40	22	1

TABLE 4. NEEDED CAPACITY, CP_{iqh}

i,q \ h	1	2	3	4
1,1	0.20	0.30	0.15	0.05
1,2	0.35	0.20	0.15	0.05
1,3	0.40	0.25	0.20	0.05
2,1	0.27	0.30	0.10	0.05
2,2	0.35	0.20	0.10	0.05
2,3	0.40	0.25	0.12	0.05
3,1	0.25	0.30	0.2	0.05
3,2	0.30	0.20	0.2	0.05
3,3	0.42	0.25	0.23	0.05

TABLE 5. QUALITY DISTRIBUTION OF USED PRODUCTS, P_{iq}

Type of product (i)	$E[\tilde{P}_{iq}]$			$Var[\tilde{P}_{iq}]$		
	q=1	q=2	q=3	q=1	q=2	q=3
1	400	600	500	500	300	100
2	1000	800	1700	400	600	400
3	1000	800	700	100	200	500

TABLE 6. DISTRIBUTION OF MARKET DEMAND

Type of product (i)	$E[\widetilde{MP}_{ih}]$				$Var[\widetilde{MP}_{ih}]$			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
1	800	900	400	100	500	500	500	0
2	2000	1500	500	100	600	700	400	0
3	1500	1200	500	100	1000	200	600	0
Maximum market demand for disassembled components	$E[\widetilde{D}_l]$				$Var[\widetilde{D}_l]$			
	l=1	l=2	l=3	l=4	l=1	l=2	l=3	l=4
	80,000	65,000	50,000	30,000	50,000	50,000	50,000	0

The maximum allowable landfill is assumed to be 5% for both the returned products and the disassembled parts.

The second part of the model is designed to optimize the allocation of the disassembled parts to four pre-defined channels. Table 6 represents the number of disassembled components for each product and their costs.

TABLE 7. NUMBER OF DISASSEMBLED COMPONENTS IN EACH PRODUCT α_{ij} , DISASSEMBLING COST, DS_i

i \ j	β_{ij}				DS_i
	j=1	j=2	j=3	j=4	
1	8	5	0	1	10
2	2	7	3	0	8
3	4	1	2	4	6

TABLE 8. PROCEEDS PER UNIT OF DISASSEMBLED COMPONENT, B_{jl}; AND CAPACITY KD_l

j \ l	B_{jl}			
	1	2	3	4
1	10	6	3	0
2	9	7	4	0
3	5	8	2	0
4	8	5	2	0
KD_l	60,000	60,000	30,000	1,000

5.1. The result

The stochastic multi objective mixed integer model is solved with Goal Programming solver in MATLAB R2017b. Confidence level for satisfying the chance constraints embedded in stochastic model is assumed to be .9 for the three associated constraints (20, 21 and 28). Table 9 shows results of the first stage of recovery of used products. This includes integer variables denoted for allocating products to channels and binary variables used to activate each channel.

F_i represents the excess amount of product i that is not allocated to any recovered options in phase I. Table 10 represents the optimum values for F_i. This is very impressive result as about 95 percent of the total products (7108/7500) are allocated for recovery in the three quality classes. As Table 10 indicate the total uncovered product are 392, that is about 5% of the total products (TPi).

Table 11 represents the optimized values of the second phase decision variables (Y_{jl}).

TABLE 9. AMOUNT OF PRODUCT i In Quality Class q THAT IS RECOVERED USING OPTION r; X_{iqh}

X_{iqh}				
i,q \ h	1	2	3	4
1,1	371	0	0	0
1,2	375	202	0	0
1,3	25	0	371	0
2,1	974	0	0	0
2,2	311	0	457	0
2,3	0	1466	17	100
3,1	987	0	0	0
3,2	472	309	0	0
3,3	0	671	0	0

TABLE 10. AMOUNT OF UNRECOVERED PRODUCTS

	i=1	i=2	i=3
F_i	156	175	61

TABLE 11. NUMBER OF DISASSEMBLED COMPONENT j THAT IS USED BY OPTION l , Y_{jl}

Y_{jl}				
j \ l	1	2	3	4
1	8,468	0	0	0
2	2,410	9,842	0	0
3	0	6,358	0	0
4	4,122	0	0	0

The above results also show that the proposed model works properly in selecting the best recovery strategy when quality levels and processing costs vary; the higher quality products move up to higher level channels in a predetermined hierarchy of recovery channels. In both phases of the model, there is minimum assignment to the landfill option, indicating that the proposed model incorporates environmental considerations appropriately.

As previously mentioned, the proposed model is a two-objective integer linear program. Due to the dependency between the variables of the two phases, to solve the model, goal programming approach is used. Consequently, instead of two values for the two objective functions, one optimized objective function value is calculated in the first phase and the deviation from the goal is calculated for the second phase objective. Table 12 shows the optimized objective function value and the deviation value.

TABLE 12. OPTIMIZED OBJECTIVE FUNCTION AND DEVIATION FROM THE GOAL

Z	d^+
233,640	121,100

TABLE 13. SENSITIVITY ANALYSIS ON CONFIDENCE LEVEL

α	0.8	0.85	0.9	0.95	0.99
Objective function	236,644	235,446	234,040	231,860	227,720
Goal deviation	121,280	121,260	121,100	120,930	120,570

5.3. Sensitivity Analysis

In order to test the agility of proposed model and to justify the robustness of result, sensitivity analysis is used. The satisfaction probability for chance constraints embedded in our stochastic model is represented by α. Table 13 shows how the objective function and the goal deviation change with varying confidence level α.

As expected, table 13 demonstrates how increasing the confidence level when the other parameters remain constant increases the margin of errors, worsening the objective function value and the deviation from the goal.

Table 14 illustrates the comparison of two different settings for ST_h,, the minimum requirements that each channel needs to be triggered. The first setting, "Example Setting", is the one used for developing the numerical results shown in this paper, and the second setting, "Test Setting", is for a much more stringent value, even higher than the optimized value of the numerical results ($\sum_{q=1}^{3}\sum_{i=1}^{3}X_{iqh}$),.

The results indicate that, for satisfying the new minimum requirements for a channel, the coverage is increased even if the cost of this allocation is relatively high, as it is the case for channels 2 and 3 in this analysis. The new requirements led to worsening of the objective function which is expected as satisfying the new minimum requirements will lead to a change of the product allocation to a higher and more undesirable channel.

V. CONCLUSION

Reverse Supply Chain Management has proven to be an effective strategy to achieve environmental and economical sustainability because not only it strives for waste and pollution reduction but it also calls for optimum utilization of the limited resources. As used products recovery has remained an integral part of RSCM, numerous models have been developed to find the best selection of recovery options. To increase the recovery profit and to avoid additional harm to the environmental, it is essential to select the recovery option that best matches the product/component quality.

TABLE 14. SENSITIVITY ANALYSIS ON MINIMUM REQUIREMENTS FOR TRIGGERING THE CHANNEL

		h=1	h=2	h=3	h=4	Objective Function	Total Covered Products
Example Setting	ST_h	50	35	40	0		
	$\sum_{q=1}^{3}\sum_{i=1}^{3}X_{iqh}$	3,515	2648	845	100	233,640	7,108
Test Setting	ST_h	3,000	3,000	1,000	0		
	$\sum_{q=1}^{3}\sum_{i=1}^{3}X_{iqh}$	3,099	3,000	1,000	100	226,095	7,199

In this paper, a novel quality-driven two-stage decision model based on uncertain parameters is proposed, developed and solved. The first stage optimizes the assignment of used products with varying qualities to four predetermined recovery channels and in the second stage, the emphasis is on products that are selected for disassembling in first phase of recovery. At the disassembly stage, an optimal allocation procedure is developed for the disassembled components. Four options are considered for reusing the disassembled components. A Multi-Objective Mixed Integer Linear Program (MOMILP) is formulated subject to constraints that limit landfills of e-wastes and address relevant economical and environmental issues. Normal probability distribution is used to represent the uncertainty in the supply of varying quality levels and also the demand parameters. Chance Constrained Programing is then used to address the uncertain parameters, and to allow the reformulating of the developed model as a stochastic program. The MOMILP is solved using Goal Programming and branch & bound approach for the numerical example using MATLAB R2017b. The numerical example showed the optimal allocation to available channels and options in both stages. Sensitivity analysis on selected parameters is used to test the robustness of the model. The results indicate that the model is reliable for making effective decisions in the reverse supply chain management.

A future research direction would be to address the uncertainties associated with time-dependent costs and including continuous variables for grading different quality levels. This would be based on the unique condition of each recovered item, instead of using discrete number of quality levels developed in this paper. Implementing robust optimization might also be an effective method of improving the stochastic formulation of the model since it is considered to be a very effective approach in stochastic programming. Additionally, a multi-stage recovery approach instead of the two- stage recovery method used in this study can prove to be more robust and effective in the reverse supply chain decision making process.

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