Proceedings of the 2005 International Conference on Simulation and Modeling
V. Kachitvichyanukul, U. Purintrapiban, P. Utayopas, eds.

DESIGNING A REVERSE SUPPLY CHAIN NETWORK FOR PRODUCT REFURBISHMENT

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ABSTRACT

Shortened product life cycle resulting in an increasing number of obsolete products has caused growing environmental concerns. In recent years, product recovery, which is one way of overcoming the waste problem, is becoming popular. To effectively implement product recovery or refurbishment activities, a reverse supply chain network design that can facilitate reverse flow of used products in an efficient way is required. In this paper, an approach to design a reverse supply chain network for product refurbishment, incorporating multi-objective functions, multi-period planning horizons, and dealing with uncertainties is presented. This approach consists of mathematical and simulation models; mathematical model in the form of mixed integer programming is used to model the multi-objective, multi-period problem of network design, whereas simulation models are used to capture uncertainties. Due to its complexities, spanning-tree based genetic algorithms are employed to find non-dominated solutions, and preferred non-dominated solutions are simulated under several scenarios of uncertainties to determine the best-preferred reverse supply chain network design.

1 INTRODUCTION

The product life cycle, especially for electronic products, has reduced significantly in recent years mainly due to rapid advances in technology. This situation results in increasing number of obsolete products that caused environmental concerns due to the rapidly depleting waste disposal capacity.

Product recovery activity thus gained increasing importance because it is considered a way of reducing waste. It aims to minimize the amount of total waste sent to landfills by recovering materials and parts from used or obsolete products by means of recycling and remanufacturing, including reuse of parts and products (Gungor and Gupta, 1999).

There are three main motivations underlying the implementation of product recovery activities. First, the environmental regulations enforced by governments in several countries charging manufacturers with responsibility for the entire product life cycle, including their safe disposal. Take-back obligations have been enacted or are underway for a number of product categories, including electronic equipment in the European Union and Japan, motor vehicles in the European Union and Taiwan, and packaging materials in Germany. Secondly, there is the opportunity to recover economic value in used products, and thirdly, the customers' expectation of "green" products. It was reported that customers are showing preference for environmentally conscious firms and products and are willing to pay for a better environment (Vandermerwe and Oliff, 1990).

There are two common ways of electronic product recovery, namely, remanufacturing and demanufacturing. Remanufacturing focuses on rebuilding product cores whereas demanufacturing focuses on disassembling products and recovering materials to reduce waste and extract economic value, wherever practicable.

However, the rapid change in technology and the rapid depreciation in the value of refurbished products limit their time-to-market. Therefore, a reverse supply chain network that can facilitate the reverse flow of used products from consumers to manufacturers in an efficient manner is required. Reverse supply chain may be described as the process of moving goods from their typical final destination to the manufacturers, for the purpose of capturing value or proper disposal.

A number of reverse supply chain models for product recovery have been developed in the past decades. Fleischmann et al. (1997) provided a review of the quantitative models of reverse logistics. Regarding the reverse supply chain network models for product recovery, most of the existing models dealt with single objective function (minimizing costs or maximizing net revenue), single period and did not take into account of uncertainties (Shih, 2001; Jayaraman et al., 2003). Several models incorporated multi-objective function, multi-period or uncertainties (Luo et al., 2001; Realff et al., 1999), but they did not consider the aforementioned characteristics altogether.

In this research, we developed an approach to design a reverse supply chain network for product refurbishment for product with modular design and multi-product configurations. Besides maximizing net revenue, minimizing environmental impacts in terms of minimizing energy consumption and CO_2 emission are also considered. The reason underlying the inclusion is that investments in "green" can be resource saving, waste eliminating and productivity improving (Porter and van der Linde, 1995). Furthermore, the main driver of product recovery activity is environmental concerns, and so it is natural to include minimizing environmental impacts as objective functions.

To ensure that the network will be valid for several period of time and can handle uncertain conditions, multi-period planning horizons and uncertainties are also taken into account in the approach.

This paper is organized as follows. The methodology is described in Section 2, followed by a numerical example in Section 3, and conclusions in Section 4.

2 METHODOLOGY

Mathematical model in the form of mixed integer programming (MIP) is developed to model the multi-objective and multi-period reverse supply chain network problem, whereas simulation models of preferred non-dominated solutions are built to capture uncertainties, see Figure 1.

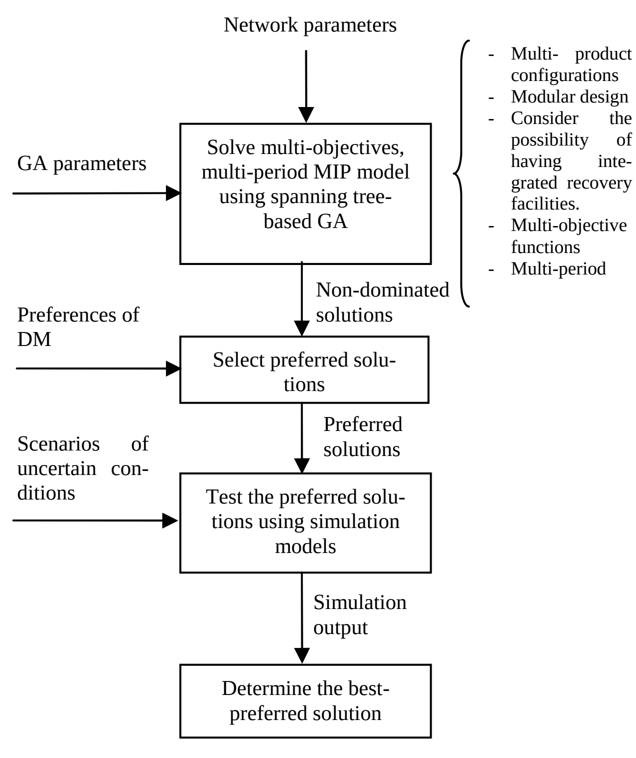

Figure 1: The Methodology

2.1 Mathematical Model

The reverse supply chain network is modelled in the form of a multi-objective MIP. The assumptions are as follows:

1) *Product characteristics*: Multi-product configurations with modular (product) design and part commonalities.
2) *Reverse flow process*: Refurbishment process are assumed to be performed at three different facilities namely collection centre for collecting used products, disassembly centre for disassembly, testing, grading and minor repair of used modules, and refurbishment centre for reassembly. The assumed refurbishment process is the following: Used products are collected and disassembled into modules. Certain types of used modules along with newly manufactured modules are use to build new type of product configurations (refurbished products). It is assumed that new modules are used to replace outdated modules, and this assumption is justified since upgrading is a usual practice in product refurbishment. Worn-out used modules are replaced by recovered used modules (it is assumed that portion of recoverable used modules is always equal or larger than the number required in satisfying demand). Any surplus is sold as spare parts.
3) *Multi-objective Functions*: As mentioned, objectives functions considered in the model are maximizing net revenue, minimizing energy consumption and minimizing CO_2 emission. Revenues considered in the model come from selling refurbished products, recovered used modules, and recyclable used modules. As for the costs, they include transportation costs between facilities, processing costs at disassembly and reassembly centers, disposal costs of unrecyclable used modules, and fixed costs at all facilities. Fixed costs for new facilities comprised of opening and operating costs; opening costs apply at the opening period whereas operating costs apply at the subsequent periods. For energy consumption, the ones considered are energy consumed during transportation between facilities and during processing at disassembly and refurbishment centers. As for the third objective function, CO_2 emissions considered are vehicles' exhaust emission during goods transportation between facilities.
4) *Multi-period*: The model assumes multi-period planning horizon. Supply, demand, prices, costs and capacities of forward chain facilities may be varied across periods. However, both energy consumption and CO_2 emission are assumed to be constant across periods. Used products collected in each period are assumed to be either refurbished, recycled or disposed during that period.

This assumption is justified because logically it is more profitable to recycle or dispose the goods at the end of the period rather than to carry them until next period's demand is received.

5) *Refurbishment Facilities*: Refurbishment activities can be done in forward chain facilities or new refurbishment facilities. Due to its high starting fixed cost, once a new facility is opened, it has to be opened for the rest of the periods (*new facilities constraints*). Collection, disassembly, testing and grading, and minor repair can be done in one location (integrated collection and disassembly center), and disassembly, testing and grading, minor repair and reassembly processes can also be done in one location (integrated disassembly and refurbishment center). However, it is assumed that only existing and new facilities in the next stage (distribution center or potential new disassembly center for integrated collection and disassembly center, and the same condition for integrated disassembly and refurbishment center) are feasible for integrated refurbishment centers. Furthermore, if distribution/new disassembly centers are chosen as collection centers, disassembly center must also be assigned to the respective location and the same condition applies to the integration of disassembly and refurbishment centers (*integrated facilities constraints*).
6) *Recyclability and Recoverability*: Fraction of recyclability and recoverability may be different for each module and period, but assumed to be the same throughout each period. It is assumed that for each type of used module in each period, percentage of recoverability is less than or equal to percentage of recyclability.

The mathematical model can be described as follows:

Maximize net revenue
Minimize energy consumptions
Minimize CO_2 emissions

Subject to:

Balances of inflows and outflows in each facility
Capacity limitations in each facility
Integrated facilities constraints
New facilities constraints

The above model can be used to model network for product refurbishment. It can also model the possibility of having integrated facilities and the flexibility to open new facilities at any period in the multi-period planning horizon. However, these features (especially the last two constraints) make the model difficult to solve using conventional method; therefore genetic algorithms are used to find the non-dominated solutions.

2.2 Solving The Model and Selecting Preferred Non-Dominated Solutions

Evolutionary techniques for multi-objective optimization are gaining attention due to their effectiveness and robustness in searching for a set of global trade-off solutions (Tan et al., 2001). The most well known class of evolutionary techniques is GA, which deals with a coding of the problem instead of decision variables, thus requires no domain knowledge, only the payoff information or fitness function (Goldberg, 1989).

The use of spanning tree based GA for solving some network problems was introduced by Gen & Cheng (1997, 2000). They used Prufer number to represent a candidate solution to the problem and developed feasibility criteria of Prufer number to be decoded into a spanning tree, and they also developed its encoding and decoding procedures. Zhou and Gen (1996) noted that the use of Prufer number is more suitable for encoding a spanning tree. It is shown that it takes only $m + n - 2$ digit numbers to uniquely represent a network with m origins and n destinations, where each digit is an integer between 1 and $m + n$ inclusive.

Syarif et al. (2002) encoded the network problem as a chromosome with a combination of binary and Prufer substrings; binary substrings represent opened/closed facilities whereas Prufer substrings represent the distribution pattern between facilities. Since, infeasible chromosomes can be produced from generation or genetic operations due to infeasible Prufer substrings or unsatisfied constraints; they improved the method by developing feasibility check and repair procedure for infeasible binary and Prufer substrings.

Here, we adopted their coding principle, but made modification to accommodate multi-product flow and multi-period planning horizon. Each period is represented by seven substrings; the first three substrings are binary digits representing feasible locations of collection, disassembly and refurbishment centers, each with a length equals to the number of feasible locations in each stage. The subsequent four substrings are Prufer numbers representing multi-product flows in each period between first market-collection centre, collection centre-disassembly centre, disassembly centre-recovery centre and recovery-centre-second market.

We also modified the feasibility and checking procedures to accommodate the abovementioned characteristics. We also added two feasibility checking and repair procedures related to last two constraints of the model. Furthermore, the decoding procedure of Gen and Cheng (2000) is also modified to incorporate those characteristics and constraints.

One-point crossover, inverse and displacement mutation operations are employed as genetic operators, whereas Pareto ranking-based fitness assignment method (Fonseca and Fleming, 1998) is adopted to determine the individual's fitness value. In this fitness assignment method, restricted fitness sharing is performed to avoid premature convergence. The selection strategy, on the other hand, is a combination of (μ+χ) with roulette wheel selection. Lastly, the non-dominated solutions obtained in a given generation are preserved separately from the population pool. The overall procedure can be summarized as follows:

Step 1: Set GA parameters' values.
Set the population size (*pop-size*), maximum number of generation (*max-gen*), crossover rate (P_c) and mutation rate (P_m).

Step 2: Generate initial population $P(t)$.
Generate each individual, check its feasibility, and repair it if infeasible. Repeat this procedure *pop-size* times.

Step 3: Evaluate all individuals.
Decode each individual, and calculate its objective function values.

Step 4: Record all non-dominated solutions.
Find all non-dominated solutions that exist in initial population and record it in separate set $E(t)$.

Step 5: Perform crossover operation.
Do one-point crossover operation on $P(t)$ with P_c, check the feasibility of the resulted offspring and repair them if infeasible.

Step 6: Perform mutation operation.
Do displacement and inverse mutation operations (randomly chosen) on $P(t)$ with P_m, check the feasibility of the resulted offspring and repair them if infeasible.

Step 7: Evaluate all offspring $O(t)$.
Decode all offspring and calculate their objective function values.

Step 8: Update the non-dominated solution set $E(t)$.
Update $E(t)$ with $O(t)$.

Step 9: Assign fitness values to $P(t)$ and $O(t)$.

Step 10: Select new population $P(t+1)$ from $P(t)$ and $O(t)$.
Select the best *pop-size* chromosomes available from $P(t)$ and $O(t)$, if there are not *pop-size* different chromosomes available, the vacant pool is filled by using roulette wheel selection.

Step 11: Terminating condition.
Increase the generation number, if it is less than or equal to *max-gen*, go to step 5, otherwise stop.

Step 12: Output the non-dominated solutions set.

Only selected non-dominated solutions are tested in uncertain conditions using simulation models. The selection is done by determining the weights of all criteria, which carried out by the decision makers (DMs) using paired-comparisons, and then rank and score the solutions based on those criteria, and finally select solutions with the highest total score. The total score of each solution is the weighted sum of criteria's scores. The number of selected solutions is decided by the DMs according to the time and budget available for the project.

2.3 Simulation Model and Selecting Best-Preferred Solution

To deal with uncertainties, selected (preferred) solutions are simulated under several scenarios of uncertain conditions. Firstly, the simulation models of selected solutions (the network designs and their allocations) are developed. Secondly, scenarios of uncertainties are formed by setting some parameters e.g. supply and demand varied stochastically in each period. Finally, the simulation models are run under those scenarios. For each scenario, the averaged value of each criterion of the selected solutions are ranked and scored. The score of each solution in each scenario is the weighted sum of all criteria's scores. The overall score of each solution is the sum of all scenarios' scores. The solution with the highest overall score is the best-preferred design.

3 A NUMERICAL EXAMPLE

The above methodology is applied to a case study concerning computer refurbishment. The potential network consists of 1 primary market location, 5 feasible locations of collection centers, 3 feasible locations of disassembly center, 3 feasible locations of recovery centers, and 3 secondary market locations. As mentioned, integrated recovery facilities can only be assigned to existing or new locations. Therefore, there will be 7 feasible locations for collection centers and 5 feasible locations for disassembly centers, see Figure 2.

Four types of used PC CPUs (with 17 types of modules) are refurbished into two types of refurbished PC CPUs, and the length of each period is one year with a planning horizon of 5 years.

In this example, it is assumed that DMs think: maximizing net revenue (Objective 1) is weakly more important than minimizing energy consumption (Objective 2), maximizing net revenue is weakly more important than minimizing CO_2 emission (Objective 3), and minimizing energy consumption is as important as minimizing CO_2 emission.

Therefore, the criteria weights of the three objective functions respectively are 0.6, 0.2, and 0.2. Furthermore, it is assumed that a score is given as an inverse of rank and only 3 solutions are tested using simulation models.

The st-GA is developed using C language. Here, the st-GA is run with *pop-size* = 500, *max-gen* = 5000, P_c = 0.4, and P_m = 0.2. The program is run 10 times, and 24 non-dominated solutions are found.

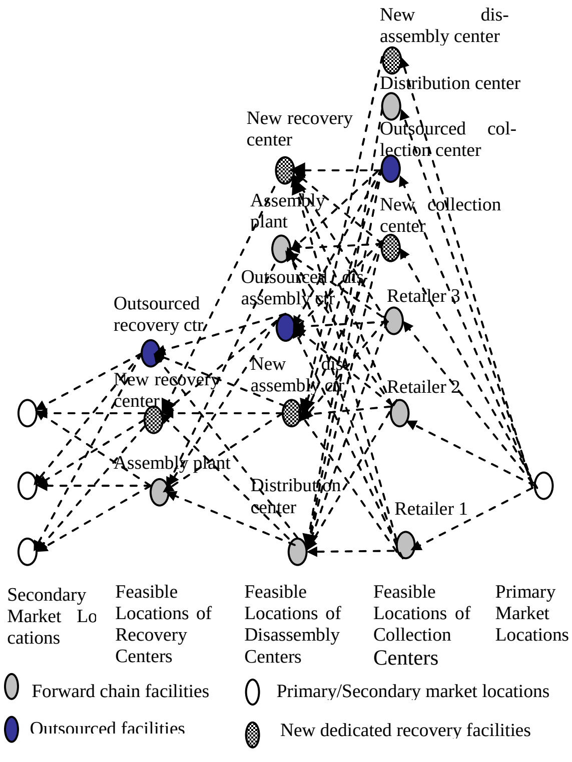

Figure 2: A Case Study

Based on the above paired-comparisons, three solutions with the highest total scores are selected (see Table 1). In descending orders, they are Solutions 8, 3, and 2 (Figures 3 & 4). The first two solutions have the same network design but different allocations of goods between facilities.

Simulation models of these solutions are developed using ARENA 7.01. The simulation models are run (10 replications each) under 8 scenarios of uncertainties. Each scenario is a combination of variability in supply of used PC CPUs (low and high), demand of refurbished PC CPUs (low and high), and recoverability of used modules (low and high).

Overall scores of preferred solutions are calculated based on the simulation output, and the results show that Solution 2 is the best-preferred solution (see Table 2). Thus, even though Solutions 8 and 3 have the highest total score in previous stage, Solution 2 has the highest overall score in the simulation stage, indicating that among the three of them, it has the best performance under uncertainties.

Table 1:
Total Scores of Non-Dominated Solutions

ND Solutions	Total score
Solution 8	18.80
Solution 3	18.80
Solution 2	18.40
Solution 9	18.20
Solution 20	17.50
Solution 14	16.30
Solution 4	15.90
Solution 13	15.80
Solution 15	15.70
Solution 12	13.80
Solution 6	13.20
Solution 11	12.80
Solution 5	12.60
Solution 18	11.10
Solution 22	10.50
Solution 19	9.50
Solution 17	9.40
Solution 16	8.90
Solution 10	8.60
Solution 7	8.40
Solution 21	8.00
Solution 23	6.20
Solution 1	6.00
Solution 24	5.60

Table 2:
Overall Scores of Preferred Solutions

Preferred Solutions	Scenario	Total Score
Solution 8	1	2.2
	2	1.4
	3	2.2
	4	2.2
	5	1.6
	6	1.8
	7	2.2
	8	2.8
	Overall Score	16.4
Solution 3	1	2
	2	2.2
	3	1.4
	4	1.4
	5	1.8
	6	2
	7	1.8
	8	1.6
	Overall Score	14.2
Solution 2	1	1.8
	2	2.4
	3	2.4
	4	2.4
	5	2.6
	6	2.2
	7	2
	8	1.6
	Overall Score	17.4

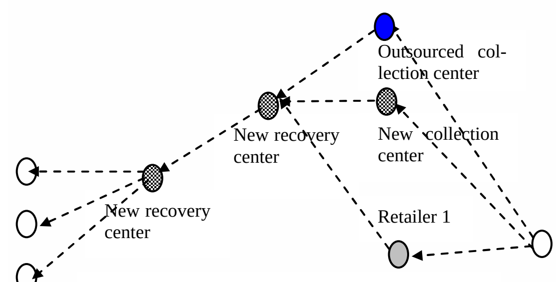

Figure 3: A Depiction of Solutions 8 & 3

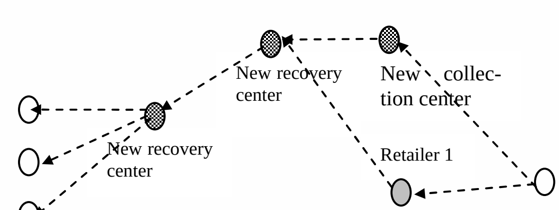

Figure 4: A Depiction of Solution 2

4 CONCLUSIONS

An approach to designing reverse supply chain for product refurbishment, with modular design and multi-product configurations is presented. The method considers the possibility of having integrated recovery facilities and the flexibility of opening new facility at any period in the planning horizon. It also incorporates multi-objective functions, multi-period planning horizons, and uncertainties, so that the resulted network is more applicable in the real world.

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