11th International Research/Expert Conference
"Trends in the Development of Machinery and Associated Technology"
TMT 2007, Hammamet, Tunisia, 05-09 September, 2007.

A HEURISTIC APPROACH FOR REVERSE LOGISTICS NETWORKS

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ABSTRACT
Environmental concerns, competition, economic factors, etc. motivates both the academicians and practitioners to study on reverse logistics activities. Reverse logistics contains activities such as product returns, recycling, substitution, reuse, disposal, refurbishment, repair and remanufacturing. Product returns constitutes an important portion in total company costs. A company can take competitive advantage with cost reductions in product returns in terms of transportation, inventory and warehousing costs. Determining convenient quantities and location places for centralized return centers is an important decision in reverse logistics networks. In this paper a heuristic approach is proposed for this decision making area.
Keywords: Reverse Logistics Networks, Genetic Algorithms, Heuristics

1. INTRODUCTION
Due to the threatening level of environmental problems, environmental initiatives, which are enforced by governments, customers or companies themselves, have become an obligation. As a part of environmentally conscious initiatives, reverse logistics has taken considerable attention both from academicians and practitioners. Rogers and Tibben-Lembke [1] defined reverse logistics (RL) as "the process of planning, implementing and controlling the cost effective flow of row materials, in-process inventory, finished goods and related information from the point of origin for the purpose of recapturing value or proper disposal". Traditionally, the term of "logistics" is perceived only with the forward side of the concept. On the other hand, many reasons, such as manufacturing returns, commercial returns (B2B and B2C), product recalls, warranty returns, service returns, end-of-use returns, end-of-life returns cause reverse direction product corridors and this additional reverse side of the logistics provides a closed-loop [2]. Usually, RL can be perceived as exactly the reverse of the forward logistics (FL), however, in lots of decision making areas, RL is not similar to the FL. RL may have different channels, collection points, decision making units, product characteristics, etc. Differences between forward and reverse logistics are in Table 1 [3]:

Table 1. Differences between forward and reverse logistics [3]

Forward Logistics	Reverse Logistics
Forecasting relatively straightforward	Forecasting more difficult
One to many transportation	Many to one transportation
Product quality uniform	Product quality not uniform
Product packaging uniform	Product packaging often damaged
Destination/routing clear	Destination/routing unclear
Standardized channel	Exception driven
Disposition options clear	Disposition not clear
Pricing relatively uniform	Pricing dependent on many factors
Importance of speed recognized	Speed often not considered a priority
Forward distribution costs closely monitored by accounting systems	Reverse costs less directly visible
Inventory management consistent	Inventory management not consistent
Product lifecycle manageable	Product lifecycle issues more complex
Negotiation between parties straightforward	Negotiation complicated by additional considerations
Marketing methods well-known	Marketing complicated by several factors
Real-time information readily available to truck product	Visibility of process less transparent

A company can take competitive advantage with cost reductions in product returns in terms of transportation, inventory and warehousing costs. Determining convenient quantities and location places for centralized return centers is an important decision in reverse logistics networks. Figure 1 represents general structure of a reverse logistics network. In this paper a heuristic approach is proposed for this decision making area. In the next section, the genetic algorithms is briefly explained. In the third section, a reverse logistics network design application is given.

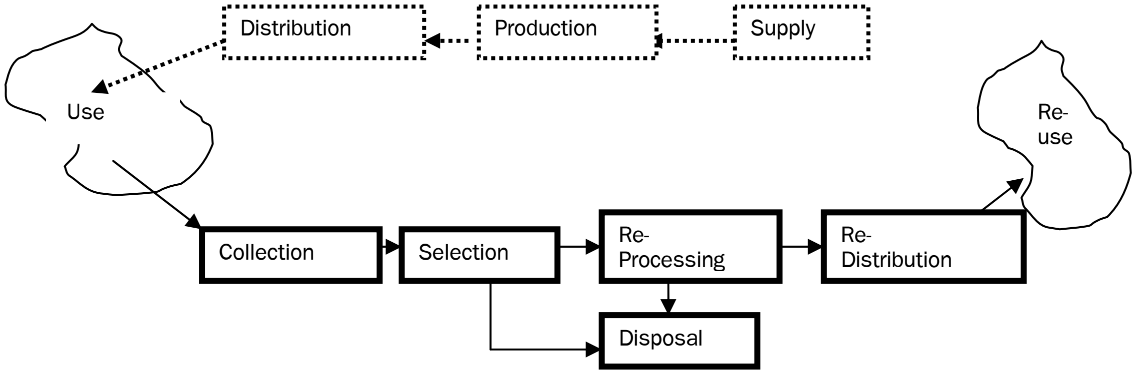

Figure 1. General structure of a reverse logistics network [4]

2. GENETIC ALGORTIHMS (GAs)

The GAs were firstly proposed by (Holland) in 1960s inspired from the Darwin's theory of evolution. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection [5].

GAs are stochastic search techniques based on the mechanism of natural selection and natural genetics. GAs, differing from conventional search techniques, start with an initial set of random solutions called population. Each individual in the population is called a chromosome, representing a solution to the problem at hand. A chromosome is a string of symbols; it is usually, but not necessarily, a binary bit string. The chromosome evolves through successive iterations, called generations. During each generation, the chromosomes are evaluated, using some measures of fitness. To create the next generation, new chromosomes, called offspring, are formed by either, (a) merging two chromosomes from current generation using a crossover operator or (b) modifying a chromosome using a mutation operator. A new generation is formed by (a) selecting, according to fitness values, some of parents and offspring and (b) rejecting others so as to keep the population size constant. Fitter chromosomes have higher probabilities of being selected. After several generations, the algorithms converge to the best chromosome, which hopefully represents the optimum or sub optimal solution to the problem [6].

Given a clearly defined problem to be solved and a bit string representation for candidate solutions, a simple GA works as follows [7]:

1. Start with a randomly generated population of n l-bit chromosomes (candidate solutions to a problem).
2. Calculate the fitness $f(x)$ of each chromosome x in the population.
3. Repeat the following steps until n offspring have been created:

3.1. Select a pair of parent chromosomes from the current population, the probability of selection being an increasing function of fitness. Selection is done "with replacement", meaning that the same chromosome can be selected more than once to become a parent.

3.2. With the probability p_c (the "crossover probability" or "crossover rate"), cross over the pair at a randomly chosen point (chosen with uniform probability) to form two offspring. If no crossover takes place, form two offspring that are exact copies of their respective parents. (Note that here the crossover rate is defined to be the probability that two parents will crossover in a single point.

There are also “multipoint crossover” versions of the GA in which the crossover rate for a pair of parents is the number of points at which a crossover takes place.)

3.3. Mutate the two offspring at each locus with the probability p_m (the mutation probability or mutation rate), and place the resulting chromosomes in the new population.

If n is odd, the new population member can be discarded at random.

4. Replace the current population with the new population.
5. Go to step 2.

3. AN APPLICATION

In this paper we investigated the Min et al. [8]’s article and their mixed integer linear programming model is utilized for a different application. The same chromosome representation is used with the [8] and can be seen from the Figure 1. The first part of each four-bit group represents the opening/closing decision for each collection point, i.e., 1 represents the opening decision, 0 represents the closing decision. The remaining three genes of the group represent the open days of the collection point. The last part of the chromosome is related with the opening/closing decisions of the centralized return centers. Table 2 contains the input parameters utilized in the solution.

<table>
<tr><td colspan="4">cp1</td><td colspan="4">cp2</td><td colspan="4">cp3</td><td>...</td><td colspan="4">cp8</td><td colspan="4">cp9</td><td colspan="4">cp10</td><td>crc1</td><td>crc2</td><td>crc3</td><td>crc4</td><td>crc5</td></tr>
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Figure 1. The chromosome representation of the model

Table 2. Input Parameters [8]

Parameter	Index	Value
Annual cost of renting an initial collection point	a	$200
Daily inventory carrying cost per unit	b	$0,1
Working days per year	w	250
Unit handling cost at the collection point	h	$0,1
Cost of establishing a centralized return center	q_k	$3000
Capacity of centralized return center	m_k	1000 units
Service coverage	l	25 miles
Unit standard transportation cost	E	1
Discount rate with respect to shipping volume		
	α_1	0,8
	α_2	0,6
	p_1	200 units
	p_2	400 units
Penalty rate with respect to the shipping distance		
	β_1	1,1
	β_2	1,2
	q_1	25 miles
	q_2	60 miles
Minimum number of established collection points	z	1
Minimum number of established centralized return centers	g	1

In the Figure 2, the locations of the customers (cust), central return centers (crc) and the collection points (cp) can be seen.

Table 3 shows the coordinates of the central return centers and collection points and Table 4 shows the coordinates of the customers.

Table 3. The coordinates of the central return centers and collection points

Potential sites for initial collection points	Site coordinate		Potential sites for central return centers	Site coordinate	
	x	y		x	y
cp1	42,39	63,09	**crc1**	57,66	8
cp2	58,6	13,25	**crc2**	21,83	36,2
cp3	30,85	24,95	**crc3**	31,73	29,31
cp4	12,57	29,81	**crc4**	58,54	29,56
cp5	31,06	39,86	**crc5**	27,53	50,71
cp6	61,61	11,6			
cp7	54,72	33,19			
cp8	33,65	5,29			
cp9	30,24	59,17			
cp10	42,06	55,81			

Table 4. The coordinates of the customers

No	Coordinate x	Coordinate y	Daily demand
1	10,95	10,22	21
2	2,81	54,55	33
3	61,8	55,87	17
…	…	…	…
25	38,66	47,33	45
26	2,28	52,23	6
27	59,53	47,48	32
28	62,25	42,78	11
29	39,03	50,84	9
30	32,55	36,31	4

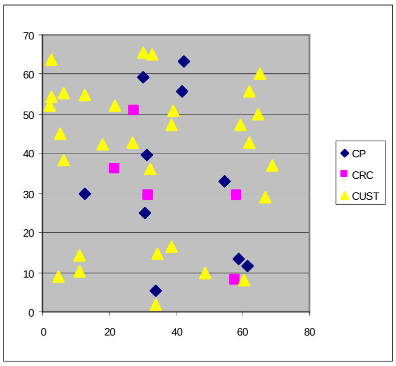

Figure 2. Initial locations of the collection points, central return centers and

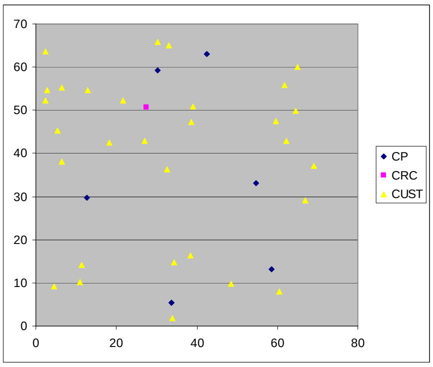

Figure 3. Final locations of the collection points, central return centers and

In the Figure 3, the final locations of the collection points, central return centers and customers can be seen. The final chromosome representation is as “101011000000101100000000010101100101100000000 1” and the value of the objective function is “308232”. In the best solution, we have ever reached two customers can not be satisfied and a objective value is punished with additional 200000, thus, the real cost value is 108232 unit. The customers which can not be satisfied are customer two and customer twenty-four. The 2th customer’s distance to the central return center is 26,596 miles and the 24th customer’s distance to central return center is 28,134 miles, and they can not be satisfied, because of their distances.

4. CONCLUSIONS

Due to the threatening level of environmental problems, environmental initiatives, which are enforced by governments, customers or companies themselves, have become an obligation. As a part of environmentally conscious initiatives, reverse logistics has taken considerable attention both from academicians and practitioners. In this paper, a reverse logistics network design problem is investigated and an illustrative example is presented. Future works may consider the usage of the other heuristics such as Lagrangean, Scatter Search, Tabu Search, etc. for this problem area. Also, a comparison of the heuristics for reverse logistics networks may be prepared.

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