A Generic Network Design for a Closed-Loop Supply Chain Using Genetic Algorithm

Eoksu Sim, Sungwon Jung, Haejoong Kim, and Jinwoo Park

Department of Industrial Engineering, Seoul National University,
San 56-1, Shillim-Dong, Kwanak-Gu, Seoul, 151-742, Korea
{ses, jsw25, ieguru}@ultra.snu.ac.kr, autofact@snu.ac.kr

Abstract. Recently much research has focused on both the supply chain and reverse logistics network design problem. The rapid progress in computer and network technology and the increasingly fierce competition in recent times have compelled global company to consider these two networks in integrated view for efficient decision-making throughout the supply chain. The integrated problem, however, resembles a combinatorial problem, whose computation time to obtain an optimal solution increases exponentially in proportion to the size of the problem. Therefore, an algorithm able to generate a relatively good solution within a reasonable time is needed. In this study, we propose an LP-based genetic algorithm. The experimental results show that the proposed algorithm is superior to MIP solver in time and to traditional genetic algorithm in quality.

1 Introduction

In a world of finite resources and disposal capacities, recovery of used products and materials is key to supporting a growing population at an increasing level of consumption [1]. Reverse logistics is 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 [2]. This process is sometimes treated as an extension of the traditional concept of supply chain management (SCM). In this case, reverse logistics does not treat only the return process from the customer to the manufacturer, but also includes the SCM processes, resulting in a new concept, which is referred to as the 'closed-loop supply chain (CLSC)'.

There are many issues involved in CLSC. Within the framework of the CLSC, there are two major flows to be considered. These are the traditional forward flow from the manufacturer to the customer and the reverse flow from the customer to the manufacturer. The former is referred to as traditional SCM and the latter as reverse logistics. It is not necessary, however, to treat these flows separately. By considering these two flows as constituting a CLSC, we can consider them in an integrated way. Several of the facilities in the CLSC should be considered as the most important sites, because they constitute a virtual enterprise that gives more efficient results to the whole supply chain.

K. Deb et al. (Eds.): GECCO 2004, LNCS 3103, pp. 1214–1225, 2004.

Recently, some research has been done on supply chain network design problem using GA. Chu [3] proposed a new approach to the digital data service network design problem using GA. As in the logistics problem, communication networks have some similar characteristics, such as location and flow decision. The authors compared the results of Tabu search methods. Gen [4] summarized research works on network design problem using GA, including transportation problem, centralized network design issues etc. The authors showed the effectiveness and efficiency of the GA-based approach by performing a large number of numerical experiments. Jaramillo [5] evaluated the performance of GA as an alternative procedure for generating optimal or near-optimal solutions for location problem. Four kinds of problems were considered. The performance of GA-based heuristics was compared with well-known heuristics from the literature. Zhou [6] proposed a new model for designing supply chain networks that optimized the best balance of transportation costs and customer service. The authors made a tree and constructed the solution using Prüfer numbers. Using experiments, the efficiency of the proposed algorithm was shown. These studies, however, usually considered the forward supply chain, and so did not take into consideration the return process.

In this paper, we consider an extended model for closed-loop supply chains taking into consideration potential facilities, multi-commodity aspects, the planning period, and the reverse flow of the return products, in such a way to minimize the overall costs, which consist of transportation costs, operating costs and production/storing costs. We consider the facilities as important decision factors, generate models consisting of all components integrally, propose an LP-based Genetic Algorithm (GA) solution heuristic to solve this problem and perform computational experiments to show the efficiency of this heuristic.

The rest of the paper is organized as follows: Section 2 describes problem definition and mathematical model. The proposed solution procedures are described in Section 3. Section 4 reports on the computational experiments. Finally, Section 5 provides concluding remarks and suggests future research direction.

2 Problem Definition

2.1 Closed-Loop Supply Chain

Fleischmann [1] proposed a generic recovery network model (RNM). The author concentrated on the number of facilities, their locations and the allocation of the corresponding goods flow and formulated an MILP optimization problem. However, the model was kept as simple as possible, by adapting an uncapacitated, single-period, single-commodity formulation. That is, RNM allowed the modeling of reverse logistics situations. Nowadays, other more realistic conditions involved in modeling the whole supply chain need to be considered, for example the transportation mode or planning period. Time-phased planning is important, since the structural decisions made in designing supply chains are irreversible. Also, the possible transportation mode (car, rail, ship or airplane, etc.) is an important factor, because not all of the possible transportation modes can be used or the transportation costs may vary in any planning period. Note that the transportation mode in each planning period is significant, such as in the case of global manufacturing companies. So, there is a need to include the various transportation modes when modeling the network design problem.

In this paper, we consider a generic closed-loop supply chain network model, which is basically an extended version of RNM. As shown in Fig. 1, we consider three intermediate facilities. More precisely, we include the 'reverse center', where the inspection, disassembly and remanufacturing of products are carried out, 'plants' where final products are manufactured and the 'distribution center (D/C)' used for delivering the products to various customers.

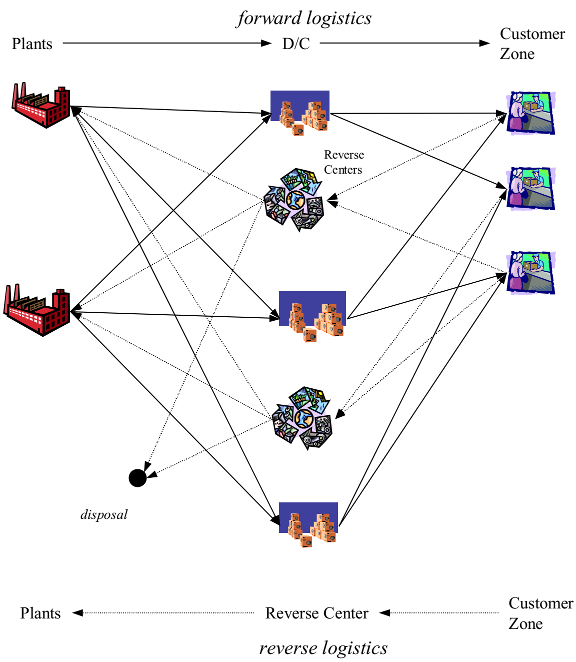

Fig. 1. Structure of the closed-loop supply chain

We assume that the customer demand for each final product is known. The plants produce the final products and deliver these products through the transportation channel to each D/C. The D/Cs also take the products from the plants according to the customer demand quantity and deliver the products to each customer zone. In each time period, we assume that there might exist a return rate for each product. This depends on 1) the final products themselves, due to their limited durability or product life cycle time, 2) the planning period, because of seasonal demand patterns or new product developments and 3) the customer zone, due to the regional propensity to consume the products. We use the return rate for each product in our model. In each reverse center, the returned products would be recycled and decomposed into sub products following the Bill of Materials (BOM) structure. And recycled sub products would be delivered to the plants that want to use them. In each transportation channel, there would exist some constraints; volume or weight constraints and, therefore, not all of transportation modes would be possible. So we assume that there are four types of transportation mode; car, rail, ship and airplane.

In this framework, the objective is to decide the number of facilities, their locations and the allocation of the corresponding goods flow using a specific transportation mode in each planning period. We formulate this problem into an MIP (Mixed Integer Programming) optimization problem, which is similar to a traditional network design problem. We model the potential facility locations as binary variables and the quantities related to the final/sub products as continuous decision variables in each period.

Our objective is to find a solution that minimizes the sum of the transportation and operation costs. Fixed operating costs, e.g., for acquiring land, for infrastructure construction or for leasing existing facilities, will be incurred when these facilities are used. Although economies of scale might be involved in the case of the transportation costs, we presume that this would not have a significant effect on the strategic locations and the decisions affecting the design of the network. Therefore, the variable costs of transportation are assumed to be linear [7]. We consider that the capacity constraint of each facility during any period might be due to a variety of reasons e.g., availability of land or usage contract.

2.2 Mathematical Formulation

A mathematical model to find the best solution of network design for closed-loop supply chain is structured as follows.

$$
\begin{aligned}
Min\ \ Z = & \sum_t \sum_m \sum_l \sum_j \sum_i pc^t_{ijlm} PX^t_{ijlm} + \sum_t \sum_m \sum_l \sum_k \sum_j dc^t_{jklm} DY^t_{jklm} + \sum_t \sum_m \sum_l \sum_n \sum_k cc^t_{knlm} CY^t_{knlm} + \\
& \sum_t \sum_m \sum_{l'} \sum_i \sum_n rc^t_{nil'm} RX^t_{nil'm} + \sum_t \sum_i pf^t_i PZ^t_i + \sum_t \sum_j df^t_j DZ^t_j + \sum_t \sum_n rf^t_n RZ^t_n + \\
& \sum_t \sum_l \sum_i pb^t_{il} \Big(\sum_j \sum_m PX^t_{ijlm} \Big) + \sum_t \sum_l \sum_j dh^t_{jl} \Big(\sum_k \sum_m DY^t_{jklm} \Big) + \sum_t \sum_l \sum_n rb^t_{nl} RQ^t_{nl}
\end{aligned}
$$

The objective function minimizes the sum of the costs required to transfer the products from the source sites to the destination sites, the fixed costs of the operating facilities, and the production and storage costs at various sites. The transportation costs consist of transferring the final products from the plants to the distribution center (D/C), from the D/C to the customer, and of transferring the returned products from the customer to the reverse center(R/C), and the recycled sub products from the R/C to the plant. To decide which facility to use in any planning period, we consider the operating costs of all of the potential facilities and the operation costs of production and storage.

Constraints are as follows.

$$\sum_m \sum_j DY^t_{jklm} = d^t_{kl} \qquad for\ \forall k,l,t \qquad (1)$$

$$\sum_m \sum_n RX^t_{nil'm} \geq a^t_{il'} \qquad for\ \forall i,l',t \qquad (2)$$

$$\sum_l ps^t_{il}(\sum_j \sum_m PX^t_{ijlm}) \leq PU^t_i PZ^t_i \qquad for\ \forall i,\ t \qquad (3)$$

$$\sum_l ds^t_{jl}(\sum_k \sum_m DY^t_{jklm}) \leq DU^t_j DZ^t_j \qquad for\ \forall j,\ t \qquad (4)$$

$$\sum_l rs^t_{nl} RQ^t_{nl} \leq RU^t_n RZ^t_n \qquad for\ \forall n,\ t \qquad (5)$$

$$\sum_l RQ^t_{nl} * q_{ll'} \geq \sum_i \sum_m RX^t_{nil'm} \qquad for\ \forall n,l,t' \qquad (6)$$

$$\sum_m \sum_k DY^t_{jklm} \leq \sum_m \sum_i PX^t_{ijlm} \qquad for\ \forall j,l,t \qquad (7)$$

$$\sum_m \sum_n CY^t_{knlm} = r^t_{kl} * \sum_m \sum_j DY^t_{jklm} \qquad for\ \forall k,l,t \qquad (8)$$

$$\sum_i \mathrm{PZ}^t_i \leq \mathrm{PW} \qquad \mathrm{for}\ \forall \mathrm{t} \qquad (9)$$

$$\sum_j DZ^t_j \leq DW \qquad for\ \forall t \qquad (10)$$

$$\sum_n RZ^t_n \leq RW \qquad for\ \forall t \qquad (11)$$

$$\sum_j \sum_l pv^t_l PX^t_{ijlm} \leq PV^t_{im} \qquad for\ \forall i,\ m,\ t \qquad (12)$$

$$\sum_k \sum_l dv^t_l DY^t_{jklm} \leq DV^t_{jm} \qquad for\ \forall j,\ m,\ t \qquad (13)$$

$$\sum_n \sum_l cv^t_l CY^t_{knlm} \leq CV^t_{km} \qquad for\ \forall k,\ m,\ t \qquad (14)$$

$$\sum_i \sum_l rv^t_l RX^t_{nilm} \leq RV^t_{nm} \qquad for\ \forall n,\ m,\ t \qquad (15)$$

$$PZ^t_i, DZ^t_j, RZ^t_n = 0/1 \qquad for\ \forall i,j,n,t \qquad (16)$$

$$PX^t_{ijlm}, DY^t_{jklm}, CY^t_{knlm}, RQ^t_{nl}, RX^t_{nilm} \geq 0 \qquad for\ \forall i,j,k,l,m,t \qquad (17)$$

Constraints (1) and (2) satisfy the demand requirements of the customer and the plant for the final and sub product, respectively. Constraints (3)~(5) limit the capacity of each facility according to its type. Constraint (6) ensures that the recycled products present at the R/C are transferred to their demand points; constraint (7) reflects the flow conservation such that the inflow quantity to the D/C should exceed the outflow quantity and constraint (8) requires that the predefined return rate of final products be used as the return quantity from the final customer. Constraints (9)~(11) ensure the open limit of each facility during any time period. Constraints (12)~(15) reflect the transportation constraints, in that no transportation channel can transfer more than the prespecified quantity of product during any one planning period. The binary decision variable constraint is (16) and the continuous variable constraint is expressed in (17).

This generic formulation can be extended to reflect any other constraint. If there are some weight constraints to be considered in the transportation channel, then some supplementary constraints, similar to constraints (12)~(15), can be added. Refer to Appendix I for further explanation of the variables in the above formulas.

3 Solution Methodologies

This network design problem is an extension of the traditional uncapacitated facility location problem (UFLP). UFLP was shown to be NP-complete by Krarup [8], which implies that the problem that we are studying also belongs to the NP-complete class of problems. Therefore, we propose an efficient heuristic algorithm for solving this kind of problem using LP-based Genetic Algorithm.

3.1 LP-Based Genetic Algorithm

The more decision variables there are, especially binary variables, the more time it takes to solve an MIP problem. In the case of the closed-loop supply chain network design, there are a lot of decision variables involved, so we need to generate an efficient heuristic. If there are no binary variables, the problem becomes an LP problem. So first, we relax the binary variables in the MIP problem and solve the resulting LP-relaxed problem. Using these results, we make an initial population that forms the input data to the GA. The binary variables are converted to 0/1 values by performing the following steps: (1) set the Lower Value (LV) to the sum of the relaxed values, (2) let the Upper Value (UV) be equal to the facility open limit, (3) divide the each relaxed value by the LV and use this value as the weight and (4) assign a value of 0 or 1 to each binary variable in proportion to the weight so that the total number of 1-value variables is between the LV and the UV. In this way, we can make the initial population be closer to the feasible solution group. Based on these generated initial solutions, we can find the final solution through evolutionary process.
The proposed algorithm is as follows.

Step 1: Generate LP-relaxed formulation
Step 2: Solve the relaxed problem using LPSolver
Step 3: Set t=0
Step 4: Generate initial population using the result of the relaxed problem, P(t)
Step 5: Evaluate each of the strings in P(t)
Step 6: While (not termination condition) do
Step 7: Select two parents P1 and P2 from P(t) using selection criteria
Step 8: Apply genetic operators
Step 9: Repeat step 7 and step 8 until a new population is generated
Step 10: Evaluate this new population
Step 11: Set t=t+1 and go to Step 6
Step 12: Generate the final optimal solution

As shown in Jaramillo [5], we use two termination criteria: either the GA converged (i.e. the improvement in the objective function value fell below the tolerance limit of 10^{-5}) or it was executed for a prespecified number of interventions.

3.2 Genetic Operators

3.2.1 Representation Scheme

To design a GA for a particular problem, we first need to devise a suitable representation scheme that shows the solution characteristics. In solving the location problem using a GA, previous researchers usually defined the chromosomes as being the potential sites [5], [6]. In this paper, we developed a representation scheme that consisted of 2-dimensional binary strings as the chromosome structure. This chromosome structure represents both the potential facility sites and planning time periods. A value of 1 for the i^{th} time period and j^{th} facility site implies that the j^{th} facility is located and used in i^{th} period. The 2-dimensional binary representation of an individual's chromosome is illustrated in Fig. 2.

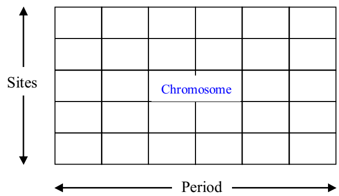

Fig. 2. Expression of a solution

3.2.2 Fitness Function and Parents Selection

The fitness function is a measure of goodness of a solution. In this paper, we use the fitness function as its objective function. For the crossover operation, we select two parent solutions. The various selection operators have one principle in common, in that the probabilistically superior solution is the one to be chosen. In this study, we used the simplest and most frequently used roulette wheel method [9].

3.2.3 Crossover Operator

Crossover combines the features of two parent chromosomes to form two similar offsprings by swapping the corresponding segments of the parents. With the application of the crossover operator, the genetic information pertaining to the selected parent solutions is passed on to the offspring in various combinations. In this study, we choose the one-point crossover operation, the most widely known and simple, in order to form better offspring that inherit superior genetic information from the parent solutions. In addition to the general crossover operation, we consider the feasibility of constraint on the number of open facilities. In any time period, there is a limit to the number of open facilities, so we use the non-linear one-point crossover operator, as shown in Fig. 3.

3.2.4 Mutation Operator

Mutation arbitrarily alters one or more genes of a selected chromosome, by a random change with a probability equal to the mutation rate. It can be used as a policy to prevent solutions from being trapped in local optima. In this study, we randomly select one of the open facilities in a certain period and transfer this state of being open

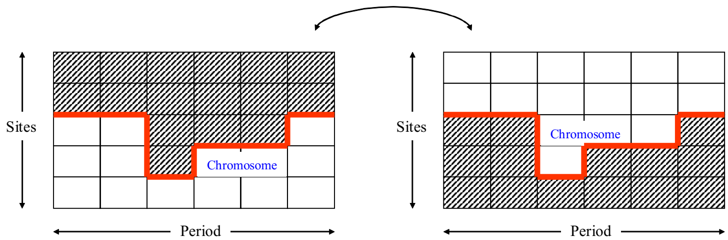

Fig. 3. Non-linear one-point crossover operator

to another facility and select the widely used non-uniform mutation as the mutation operator. This results in the mutation rate being gradually decreased as the algorithm proceeds and thereby raises the convergence speed of the solution with the unfolding evolution.

4 Computational Experiments

In performing the computational experiments, we wanted to show (1) the relative complexity of the solution in relation to the complexity of the problem, (2) the performance superiority of the proposed algorithm and (3) the statistical significance of the difference between the solution qualities.

We use the LP-based GA, so we need to run the algorithm multiple times, because GAs have stochastic characteristics. The problem data sets were generated randomly, but systematically, to reflect the system environment. We generated a set of 100 problems in order to experiment the algorithm.

The number of facility open limits in each period is specified as experimental parameters, and four periods are considered as the planning horizon. For experimental simplicity, we set the number of final products to 2. Each final product can have one or two subproducts. The number of transportation mode in each transportation channel is generated randomly from 1 to 4. The population size and the number of generations are set to one hundred and one thousand, respectively. The heuristic algorithm developed in this study was coded in C++ on the Pentium IV 1.4GHz computer. The comparison of LP-based, traditional GA with the optimization package (CPLEX 7.0) is also provided in Table 1.

The gap between the best feasible solution that was generated by the algorithm and the optimal solution that was generated by the CPLEX engine can be used as the solution quality criteria.

Table 1 led to an important insight. The LP-based GA heuristic is superior to the MIP solver in terms of the time required to find a solution. For a small size problem, the proposed heuristic has poor quality in time and quality. As the size of the problem increases, however, the MIP solver requires a much longer time to solve the problem. The proposed heuristic can produce an optimal or near-optimal solution in a reasonable time. Although the initial population generated by the LP-relaxed solution

Table 1[1]**.** Comparison of LP-based, Traditional GA and optimal solution

P	D	C	R	CPLEX		LP-based GA		Traditional GA		No. of
				Time(s)	Obj.	Time(s)	GAP(%)	Time(s)	GAP(%)	var.
2	3	3	2	0.2	1.66	3.32	0.39	4.33	2.25	2340
2	3	5	3	1.63	1.76	7.98	0.77	7.76	1.96	2788
2	3	10	2	10.2	1.83	2.50	0.76	1.60	2.15	3894
2	3	10	3	9.5	1.92	7.30	0.05	8.95	1.08	4770
2	5	10	2	12.2	1.99	8.01	0.99	7.02	2.94	5386
2	5	10	3	20.3	2.08	13.91	0.60	13.59	1.51	6324
3	5	10	2	15.6	2.22	15.11	0.08	14.01	2.70	5915
3	5	10	3	27.11	2.22	23.99	0.59	25.68	1.82	6822
3	5	15	2	21.41	2.36	5.73	0.62	5.96	2.81	8220
3	5	15	3	1195.09	2.54	49.19	0.81	47.49	1.41	10314
3	10	15	2	1769.56	2.64	67.4	0.42	68.83	2.22	13927
3	10	15	3	1856.25	2.79	73.07	0.34	74.98	1.87	15197
5	10	15	2	1648.27	2.83	74.29	1.32	73.81	3.59	15455
5	10	15	3	2087.26	2.84	77.31	1.85	78.87	1.13	16872
5	10	15	4	2415.25	2.87	73.35	0.20	73.99	1.43	17992
5	10	20	2	2435.54	3.00	88.32	1.58	88.44	3.33	19335
5	10	20	3	2428.45	3.03	76.1	1.21	77.81	3.70	20923
5	10	20	4	2711.07	3.14	73.27	1.91	72.07	4.01	22615
5	15	20	2	2864.50	3.15	94.04	2.92	95.12	4.52	27456
5	15	20	3	2985.42	3.26	96.03	2.54	94.77	3.05	28925
5	15	20	4	2845.89	3.29	100.7	1.50	100.81	2.52	30612
8	15	20	2	2931.06	3.45	112.37	2.19	112.42	3.31	30687
8	15	20	3	3080.23	3.57	123.45	1.64	121.13	3.13	32374
8	15	20	4	3190.97	3.69	128.06	2.04	128.86	3.50	34267
10	15	20	2	2934.26	3.79	131.64	2.09	130.98	3.06	32840
10	15	20	3	3268.29	3.93	144.18	1.61	143.64	3.86	34694
10	15	20	4	3394.19	4.00	140.94	1.83	138.17	3.40	36733
10	15	20	5	3394.19	4.12	151.91	1.93	151.70	4.34	38861
10	15	30	3	4926.30	5.18	162.29	2.08	162.18	4.61	46309

could not guarantee the optimality of the final solution, the solution obtained by the LP-relaxed GA was closer to the optimum than the traditional GA solutions.

[1] GAP = (heuristic solution value – optimal value)/optimal value*100
P: Plant, D:D/C, C: Customer, R: Reverse Center, Obj.: Objective Value($\times 10^{+5}$).

In Fig. 4 and Fig. 5, a comparison is made between the solution time and quality for each method. As shown in Fig. 4, the more complex the problem becomes, the more time is needed to solve the problem. Fig. 5 shows that the LP-based GA is superior to traditional GA in terms of solution quality.

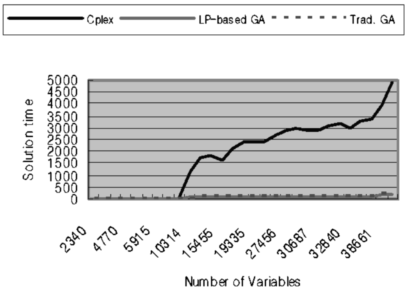

Fig. 4. Comparison of solution time

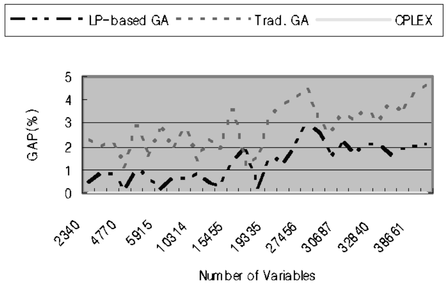

Fig. 5. Comparison of solution GAP

In table 2 and Table 3, the solution quality and time in LP-based/traditional GA and optimal solution package results are compared. In these paired t-test results, the difference in quality between LP-based GA(LGA) and MIP solver is not statistically significant. So, we can support that there is no difference in solution quality performance between them. In terms of solution time, the differences between LP-based GA and traditional GA(TGA) are not significant.

Table 2[2]**.** Paired *t*-test in solution quality

	TGA	LGA	CPLEX
TGA		S	N.S
LGA	S		N.S
CPLEX	N.S	N.S	

Table 3[2]**.** Paired *t*-test in solution time

	TGA	LGA	CPLEX
TGA		N.S	S
LGA	N.S		S
CPLEX	S	S	

In real world problem, there are much more decision variables in closed-loop supply chain network design problem. In that case, the MIP solver cannot obtain optimal solution in a reasonable time. The proposed LP-based GA can find a near-optimal solution in an affordable time.

5 Conclusion

In this paper, we consider an extended supply chain network design model that allows for the reverse logistics. To solve this problem, we propose an LP-based genetic algorithm that uses the LP-based solution and genetic operators. In order to evaluate the superiority of the proposed method, we performed an experiment. Through this

[2] Significance level = 0.05, S: significant, N.S : non-significant.

experiment, we compare the results from MIP solver (CPLEX), traditional GA (TGA) and the LP-based GA (LGA).

The result shows that the time taken to obtain optimal solution using CPLEX increases exponentially as the problem size grows while LGA and TGA reduces the influence of the problem size on the time. In terms of cost, it shows that the solution obtained by LGA is as good as the optimal solution solved by CPLEX while it is superior to the solution obtained by TGA.

In real time application aspects, the size of the problem is much larger than that of the test data. In such environments, it is infeasible to find an optimal solution in a reasonable time. Hence the proposed LP-based genetic algorithm can be usefully used in real situation.

But more studies are required to solve some weakness in LGA. In evolutionary process, genes have high correlation among them, so there can be some perturbation in the process. To reduce this perturbation, further researches should focus on the design of the operators themselves.

References

1. Fleischmann, M.: Quantitative models for reverse logistics. Springer-Verlag, Berlin (2001)
2. Stock, J. : Development and Implementation of Reverse Logistics Programs. Council of Logistics Management. USA (1998)
3. Chu, C.H., Premkumar, G., Chou, H.: Digital data networks design using genetic algorithms. European Journal of Operational Research 127 (2000) 140-158
4. Gen, M., Cheng, R., Oren, S.S.: Network design techniques using adapted genetic algorithms. Advanced in Engineering Software 32 (2001) 731-744
5. Jaramillo, J.H., Bhadury, J., Batta, R.: On the use of genetic algorithms to solve location problems. Computers & Operations Research 29 (2002) 761-779
6. Zhou, G., Min, H., Gen, M.: The balanced allocation of customers to multiple distribution centers in the supply chain network: a genetic algorithm approach. Computers & Industrial Engineering 43 (2002) 251-261
7. Verter, V.: An integrated model for facility location and technology acquisition. Computers & Operations Research 29 (2002) 583-592
8. Krarup, J., Pruzan, P.M.: The simple plant location problem: survey and synthesis. European Journal of Operational Research 12 (1983) 36-81
9. Michalewicz, Z.: Genetic Algorithms + Data Structures = Evolution Programs. 3rd edn. Springer-Verlag, Berlin Heidelberg New York (1996)

Appendix I

Indices

I : set of possible locations for plant, indexed by $i \in I$, J: set of possible locations for D/C, indexed by $j \in J$

K : set of locations for customers(customer zones), indexed by $k \in K$, L : set of products, indexed by $l \in L$

N : set of possible locations for reverse logistic centers, indexed by $n \in N$ T : time period

M : transportation mode

Decision Variables

PX^t_{ijlm}	transportation quantity of product l from plant i to D/C j at time period t using transportation mode m
DY^t_{jklm}	transportation quantity of product l from D/C j to customer k at time period t using transportation mode m
CY^t_{knlm}	transportation quantity of product l from customer k to reverse center n at time period t using transportation mode m
$RX^t_{nil'm}$	transportation quantity of product l from reverse center n to plant i at time period t using transportation mode m
PZ^t_i	Indication as to whether a plant i is open at time period t
DZ^t_j	Indication as to whether a D/C j is open at time period t
RZ^t_n	Indication as to whether a reveres center n is open at time period t
RQ^t_{nl}	processing quantity of product l at reverse center n at time period t

Parameters

pc^t_{ijlm}	transportation cost per unit of product l from plant i to D/C j at time period t using transportation mode m
dc^t_{jklm}	transportation cost per unit of product l from D/C j to customer k to at time period t using transportation mode m
cc^t_{knlm}	transportation cost per unit of product l from customer k to reverse center n at time period t using transportation mode m
$rc^t_{nil'm}$	transportation cost per unit of product l from reverse center n to plant i at time period t using transportation mode m
pf^t_i	fixed, operating cost for plant i at time period t
df^t_j	fixed, operating cost for D/C j at time period t
rf^t_n	fixed, operating cost for reverse center n at time period t
pb^t_{il}	production cost for product l in plant i at time period t
rb^t_{nl}	disassembly cost for product l in reverse center n at time period t
dh^t_{jl}	holding cost for product l in D/C j at time period t
d^t_{kl}	demand quantity for product l in customer (zone) k at time period t
$a^t_{il'}$	demand quantity of recycled product l in plant i at time period t
ps^t_{il}	required production capacity per unit of product l in plant i at time period t
ds^t_{jl}	required inventory holing capacity per unit of product l in D/C j at time period t
rs^t_{nl}	required reverse processing capacity per unit of product l in reverse center n at time period t
PU^t_i	total available production capacity in plant i at time period t
DU^t_j	total available holding capacity in D/C j at time period t
RU^t_n	total available reverse processing capacity in reverse center n at time period t
PW	upper limit on the number of open plant
DW	upper limit on the number of open D/C
RW	upper limit on the number of open reverse center
r^t_{kl}	return rate of product l for customer k at time period t
$q_{ll'}$	BOM quantity of child product l to parent product l
$pv^t_l, dv^t_l, cv^t_l, rv^t_{l'}$	unit volume of product l(l) at time period t
PV^t_{im}	total volume capacity of transportation mode m from plant i at time period t
DV^t_{jm}	total volume capacity of transportation mode m from D/C j at time period t
CV^t_{km}	total volume capacity of transportation mode m from customer k at time period t
RV^t_{nm}	total volume capacity of transportation mode m from reverse center n at time period t