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A Genetic Algorithm Approach for Logistics Network Integrating Forward and Reverse Flows

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역물류를 고려한 통합 물류망 구축을 위한 유전 알고리듬 해법

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As today's business environment has become more and more competitive, forward as well as backward flows of products among members belonging to a supply chain have been increased. The backward flows of products, which are common in most industries, result from increasing amount of products that are returned, recalled, or need to be repaired. Effective management for the backward flows of products has become an important issue for businesses because of opportunities for simultaneously enhancing profitability and customer satisfaction from returned products. Since third party logistics service providers (3PLs) are playing an important role in reverse logistics operations, they should perform two simultaneous logistics operations for a number of different clients who want to improve their logistics operations for both forward and reverse flows. In this case, distribution networks have been independently designed with respect to either forward or backward flows so far. This paper proposes a mixed integer programming model for the design of network integrating both forward and reverse logistics. Since the network design problem belongs to a class of NP-hard problems, we present an efficient heuristic algorithm based on genetic algorithm (GA), of which the performance is compared to the lower bound by Lagrangian relaxation. Finally, the validity of proposed algorithm is tested using numerical examples.

Keywords: third party logistics, reverse logistics, integrated distribution network, genetic algorithm, Lagrangian relaxation

1. Introduction

The competitive business environment in today has resulted in increasing cooperation among individual companies as members of a supply chain. In other words, the success of a company will depend on its ability to achieve effective integration of worldwide organizational relationships within a supply chain. Moreover, consumers now require high levels of

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customer service with a short life cycle. In such an environment, a growing number of companies are under pressure to be concerned with filling their customers' orders, keeping the deliveries of products up to speed, reducing inventory, and implementing reverse logistics. Consequently, the individual companies of a supply chain are frequently faced with the challenges of restructuring their distribution network with respect to global need and volatile market changes.

As a result, third party logistics service providers (3PLs) are playing an increasing role in supporting the design, management, and operation of supply chains. The market for 3PLs in USA was estimated at more than $45 billion in 1999 and is growing by nearly 18 percent annually and the primary growth in 3PLs markets has been in warehousing and distribution. In addition, 74% of Fortune 500 companies in U.S used 3PLs' services during 2000. These services involved transportation management, freight payment, warehouse management, shipment tracking, and reverse logistics. Virtually, all of the companies reported positive cost reduction due to the avoidance of insurance and employee costs as well as material handling equipment and technology purchases (Modern Material Handling, 2000).

Today, using 3PLs such as UPS, FedEx, GENCO, etc. is becoming the wave of the future and a major element in logistics. The main advantage of outsourcing services to 3PLs is that these 3PLs allow companies to get into a new business, a new market. In addition, 3PLs have also become important players in reverse logistics since the implementation of return operations requires a specialized infrastructure needing special information systems for tracking/capturing data, dedicated equipment for the processing of returns, and specialist trained non-standard manufacturing processes. In an integrated logistics network in 3PLs, some products are brought to the original customers through a forward supply chain whose structure may consist of suppliers, manufacturers, distribution centers, retailers, and original customers. After being sold to customers through a supply chain, the product might go back to a manufacturer from retailers/e retailers or original customers. Finally, the products enter into a reverse logistic flow. In the first stage, the reverse process is collection, reclaiming returned products and transporting them to a particular location such as manufacturers or a repair center. To collect these products, there is a need in a transportation network where most companies are using distribution centers, central return centers, or hybrid warehouse-return facilities.

Therefore, this paper deals with the design of a distribution network, considering integrated forward and reverse flows. The network for 3PLs can consist of client's facilities, distribution centers(or warehouses), collection centers, and clients' market places. The collection center especially in this paper is assumed to perform the collection of returned product, minor repair operations, and shipment of the products to original clients. More specifically, the strategic decisions to be considered for 3PLs are related to:

1) Where to locate distribution and collection centers?
2) How many distribution and collection centers are established?
3) How to allocate appropriate space for each product in distribution and collection centers?
4) How to allocate customers into appropriate distribution and collection centers?

This paper proposes a mixed integer programming model for the design of network integrating both forward and reverse logistics. Since the network design problem belongs to a class of NP hard problems, we present an efficient heuristic algorithm based on genetic algorithm(GA), of which the performance is compared to the lower bound by Lagrangian relaxation. Finally, the validity of proposed algorithm is tested using numerical examples.

2. Literature Review

The network design issues in 3PLs can be divided into two categories with respect to the material flows, and most studies of existing network models have involved in dealing with only a single flow such as forward flow or reverse flow. In forward logistics with respect to multi-commodity aspects, Elson (1972) might be the first researcher to solve the multi-commodity capacitated version of the facility location problem, considering a single echelon of transshipment stocking points.

Geoffrion and Graves (1974) developed a model to optimize commodity flows. Their model not only dealt with facility location and commodity flows but also with customer assignment. Later, Geoffrion, Graves and Lee(1978) refined Geoffrion and Graves' model for practical applications in which they developed an optimization procedure by the use of the decomposition theory of Benders(1962). Akins (1985) analyzed the capacitated facility location problem where the size of a plant to be established was bounded and presented a branch and bound algorithm as a solution method. Lee(1991) developed a general model for a capacitated facility location problem that deals with a multi product, multi-type facility model. He proposed an optimal solution algorithm based on Bender's decomposition. Lee (1993) extended a standard capacitated facility location problem to generalization of multi-product, multi type capacitated facility location problem with a choice of facility and presented an effective algorithm based on cross decomposition. The algorithm unifies Bender's decomposition and Lagrangian relaxation into a single framework. Finally, Pirkul and Jayaraman (1998) developed an efficient heuristic procedure for solving the multi-commodity, multi-plant capacitated facility location problem.

In reverse flows, there has been relatively little attention on a reverse logistics network. However, for the last decades, increasing concerns over environmental degradation and increased opportunities for cost savings or high customer satisfaction from returned products prompted some researchers to develop reverse logistics models: reuse logistics, remanufacturing logistics, and recycling logistics models. For reuse logistics models, Kroon and Vrijens (1995) reported a case study concerning the design of a logistics system for reusable transportation packages. The authors proposed a MILP (mixed integer linear programming), closely related to a classical uncapaciated warehouse location model. Spengler *et al*. (1997) dealt with the recycling of industrial by products in the German steel industry. They proposed a MILP model based on the modified multi level warehouse location problem. The model was solved using a modified Benders decomposition.

For recycling logistics models, Barros *et al*. (1998) reported a case study addressing the design of a logistics network for the recycling of sand and presented a MILP model based on a multi level capacitated warehouse location problem. Louwers *et al*. (1999) considered the design of a recycling network for carpet waste. They proposed a continuous location model that used a linear approximation to the more accurate nonlinear model. For remanufacturing logistics models, Kirkke *et al*. (1999) described a case study, dealing with a reverse logistics network for the returns, processing, and recovery of discarded copiers. They presented a MILP model based on a multi-level uncapacitated warehouse location model. Jayaraman *et al*. (1999) analyzed the logistics network of an electronic equipment remanufacturing company in the USA. They proposed a single period MILP model based on a multi-product capacitated warehouse location model.

3. Modeling a Logistics Network for 3PLs

The modeling approach for 3PLs in this paper belongs to a location allocation model. The main differences of this model compared to existing location models might lie in handling in forward and reverse flows simultaneously since 3PLs operate supply chains for a large number of different

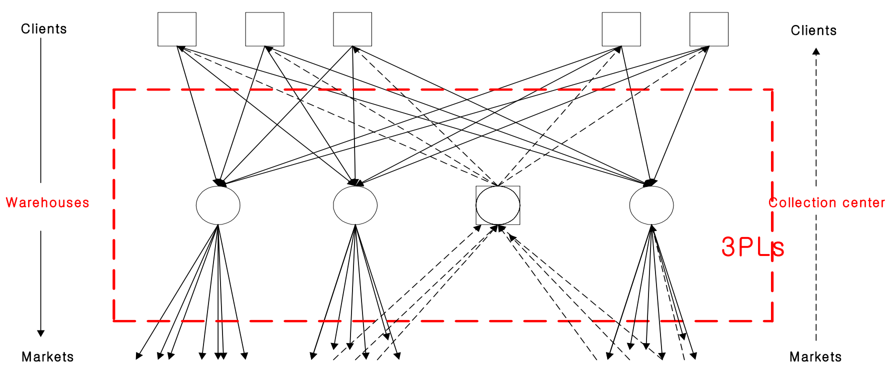

Figure 1. An integrated network structure.

customers requiring various types of logistics services. The network structure of this model is illustrated in <Figure 1>. In this network, instead of dealing with separate distribution center or collection centers, we also considered a new type of a hybrid distribution-collection facility. Advantage of installing a hybrid facility might be cost saving due to sharing material handling equipment, infrastructure, and so on. The problem in this paper assumes that the locations of clients' plants and the clients' customers, together with products to be shipped, are known.

3.1 Indices and Sets

P: set of clients' forward/collection product types
I : set of clients' plant locations
J : set of possible sites for distribution centers
L : set of collection centers
$S = J \cap L$: set of the possible sites for hybrid distribution-collection center
K: set of fixed customer locations

3.2 Model Parameters

M_j : maximum capacity of distribution center j, $j \in J$
M_l : maximum capacity of collection center l, $l \in L$
d_{pk} : amount of product p required by customer k, $p \in P,\ k \in K$
r_{pk} : amount of product p returned from customer k, $p \in P,\ k \in K$
α_p : weight factor of product p based on characteristics of the product type, $p \in P$
w_j : fixed cost of opening distribution center j, $j \in J$
v_j : unit variable cost for distribution center j, $j \in J$
r_l : fixed cost of opening collection center l, $l \in L$
u_l : unit variable cost for collection center l, $l \in L$
h_s : cost savings from opening hybrid distribution -collection center s, $s \in S$
c^f_{pijk} : unit variable cost for transporting and handling product p from plant i via distribution center j to customer k, $p \in P,\ i \in I,\ j \in J,\ k \in K$
c^r_{pkli} : unit variable cost for taking back returned product p from customer k via collection center l to plant i, $p \in P,\ k \in K,\ l \in L,\ i \in I$

3.3 Decision Variables

X^f_{pijk} : amount of forward flows of product p transported from client' plant i through distribution center j to customer k, $p \in P,\ i \in I,\ j \in J,\ k \in K$
X^r_{pkli} : amount of reverse flows of product p transported from customer k through collection center l to plant i , $p \in P,\ k \in K,\ l \in L,\ i \in I$

$$Z_j = \begin{cases} 1 & \text{, if distribution center } j \text{ is open} \\ 0 & \text{, otherwise} \end{cases}, \quad j \in J$$

$$G_l = \begin{cases} 1 & \text{, if collection center } l \text{ is open} \\ 0 & \text{, otherwise} \end{cases}, \quad l \in L$$

3.4 Mathematical Formulation

P : Minimize

$$\begin{aligned} & \sum_{j \in J}[w_j Z_j + v_j \sum_{p \in P} \sum_{i \in I} \sum_{k \in K} \alpha_p X^f_{pijk}] \\ & + \sum_{l \in L}[r_l G_l + u_l \sum_{p \in P} \sum_{i \in I} \sum_{k \in K} \alpha_p X^r_{pkli}] - \sum_{s \in S} h_s Z_s G_s \\ & + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} c^f_{pijk} X^f_{pijk} \\ & + \sum_{p \in P} \sum_{k \in K} \sum_{l \in L} \sum_{i \in I} c^r_{pkli} X^r_{pkli} \end{aligned} \quad (1)$$

Subject to

$$\sum_{i \in I} \sum_{j \in J} X^f_{pijk} \geq d_{pk}, \quad p \in P,\ k \in K \quad (2)$$

$$\sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \alpha_p X^f_{pijk} \leq M_j Z_j, \quad j \in J \quad (3)$$

$$\sum_{l \in L} \sum_{i \in I} X^r_{pkli} \geq r_{pk}, \quad k \in K,\ p \in P \quad (4)$$

$$\sum_{p \in P} \sum_{k \in K} \sum_{i \in I} \alpha_p X^r_{pkli} \leq M_l G_l, \quad l \in L \quad (5)$$

$$X^f_{pijk} \geq 0, \quad p \in P,\ i \in I,\ j \in J,\ k \in K \quad (6)$$

$$X^r_{pkli} \geq 0, \quad p \in P,\ k \in K,\ l \in L,\ i \in I \quad (7)$$

$$Z_j \in \{0, 1\}, \quad j \in J \quad (8)$$

$$G_l \in \{0, 1\}, \quad l \in L \quad (9)$$

This model has the objective (1) of minimizing the total cost of a distribution network that consists of the fixed and variable costs of distribution and collection centers, transportation costs while maximizing cost savings from utilizing hybrid distribution collection centers. Constraint (2) guarantees that the total volume of products demanded by a client's customer should be satisfied. Constraint (3) assures that the total volume of products shipped to customers cannot exceed the capacity of the warehouse serving them. Constraint (4) ensures that the returned products are taken back to the plant of a client. Constraint (5) assures that the total number of returned products cannot exceed the capacity of a collection center. Constraints (6) and (7) preserve the non negativity restrictions on the decision variables while constraints (8) and (9) ensure the binary integrality of decision variables.

This mixed integer model has nonlinear components in the objective function (1), representing cost savings from opening hybrid facilities. After introducing dummy variable Q_s indicating whether incurring cost saving or not, we convert it into a linear model. The objective function can be rearranged using binary variable Q_s as follows:

Minimize

$$\begin{aligned}&\sum_{j\in J}[w_jZ_j+v_j\sum_{p\in P}\sum_{i\in I}\sum_{k\in K}\alpha_pX^f_{pijk}]\\&+\sum_{l\in L}[r_lG_l+u_l\sum_{p\in P}\sum_{i\in I}\sum_{k\in K}\alpha_pX^r_{pkli}]-\sum_{s\in S}h_sQ_s\\&+\sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}c^f_{pijk}X^f_{pijk}\\&+\sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\sum_{i\in I}c^r_{pkli}X^r_{pkli}\end{aligned}\tag{10}$$

Next, we add more constraints into the set of original constraints as follows:

$$Z_s+G_s-2Q_s\geq 0,\quad s\in S\tag{11}$$

$$Z_s+G_s-Q_s\leq 1,\quad s\in S\tag{12}$$

Constraint (11) assures that if either a warehouse located in s $(=Z_s)$ or a collection center located in s $(=G_s)$ is close, Q_s should be 0. Constraint (12) ensures that if both Z_s and G_s are open, Q_s should be 1. Since optimal solution of minimization problem assures that Q_s is 1 if both Z_s and G_s are 1, constraint (12) is not needed.

4. Solution Methodologies

4.1 Genetic Algorithm

GA is referred to as a stochastic solution search procedure that is designed to solve combinatorial problems using the concept of evolutionary computation imitating the natural selection and biological reproduction of animal species (Gen and Cheng, 2000). In the past, GA has been successfully applied to classical combinatorial problems such as capacitated plant location, fixed charge location, network design, and warehouse allocation (Gen and Cheng, 2000; Jaramillo *et al.*, 2002; Palmer 1995; Zhou *et al.*, 2003) Prior to the application of GA, we need to design the genetic representation (or chromosome) of the candidate solutions. Herein, a chromosome represents each solution in the initial solution set of solutions (population). The size of the population depends on the size and the nature of the problem at hand. The chromosome evolves through a crossover operator and a mutation operator to produce children, improving on the current set of solutions. The chromosomes in the population are then evaluated through a fitness function and the less fit chromosomes are replaced with better children. The processes of crossover, evaluation and selection are repeated for a predetermined number of iterations called generations, usually up to the point where the system ceases to improve or the population has converged to a few well performing chromosomes.

4.1.1 Encoding and genetic operators

The initial step is to design a suitable chromosome. This is a key issue for a successful implementation because it applies probabilistic transition rule on each chromosome to create a new population of chromosomes. To achieve this, each chromosome developed in this study is based on a single dimensional array consisting of only binary decision variables to

Distribution center					Collection center				
1	2	3	4	5	1	2	3	4	5
1	0	0	1	0	0	0	1	0	0

Figure 2. A genetic representation scheme.

represent candidate distribution centers and collection centers. For example, the representation of a chromosome is illustrated in <Figure 2>.

It has five distribution centers and five collection centers. Each center has one gene, representing opening (=1) or closing (=0) decisions with binary strings.

Based on the chromosome scheme, there are basic genetic operators for implementing a genetic algorithm such as cloning, parents selection, crossover, mutation, and fitness operators. The cloning operator involves keeping the best solutions. In the proposed GA, the procedure works in such a way that it copies 20 percent of the current best chromosomes to a new population.

The parent selection operator is an important process that directs a GA search toward promising regions in a search space. Two parents are selected from the solutions of a particular generation by selection methods that assign reproduction opportunities to each individual parent in the population. For this experimentation, we used a binary tournament selection method that began by forming two teams of chromosomes. Each team consists of two chromosomes randomly drawn from the current population. The two best chromosomes that are taken from one of the two teams are chosen for crossover operations. As such, two offspring are generated and enter into a new population.

The crossover operator generates new children by combining information contained in the chromosomes of the parents so that new chromosomes will have the best parts of the parents' chromosomes. Herein, we applied the two point crossover where the locations of the crossover points are randomly selected in opening/closing decisions of centers and then swap the blocks of the two parents' strings to produce two children.

After recombination, some children undergo mutation. Mutation operates by inverting each bit in the solution with some small probability, usually from zero percent to ten percent. The rationale is to provide a small amount of randomness, and to prevent solutions from being trapped at a local optimum. The type of mutation varies depending on the encoding as well as the crossover. In the proposed GA, the mutation operator first randomly selects a bit value of opening/closing decision variables on a chromosome. Then, it flips a bit value from 0 to 1, or from 1 to 0. Hence, a good level of diversity in each generation is achieved.

Decoding the chromosome generates a candidate solution and its fitness value based on the fitness function. The fitness function is formed by adding a penalty function to the original objective function. The opening costs of distribution and collection centers are calculated directly from a chromosome, but the transportation costs are calculated from a subalgorithm that is a simplex method for a transshipment problem. The sub algorithm is coded in C++ and combined in the overall GA solution procedure. This sub algorithm can make the whole computation time increased since each chromosome needs the additional procedure for the decisions of allocating customers to facilities. However, this approach can definitely provide the better quality of solutions than that of putting all decision variables in a single chromosome. Finally, the penalty function is needed when some candidate solutions in a population turn out to be infeasible, exceeding the capacity limit of some distribution and collection centers. Whenever each center exceeds the capacity limit, the penalty value is assessed and is subsequently added to the original objective function. A penalty value is considerably larger than any possible objective value corresponding to the current population of individuals. Thus, probability of selecting infeasible chromosomes can be reduced to the next population. The penalty function is mathematically expressed as follows:

$$\text{Penalty function} = \sum_{j \in J} pv \times f(X^f_{pijk}, M_j, Z_j) + \sum_{l \in L} pv \times f(X^r_{pkli}, M_l, G_l)$$

where

pv = penalty value

$$f(X^f_{pijk}, M_j, Z_j) = \begin{cases} 1 & , \text{if } \sum_{p \in P} \sum_{i \in I} \sum_{k \in K} \alpha_p X^f_{pijk} > M_j Z_j \\ 0 & , \text{otherwise} \end{cases} \quad , j \in J$$

$$f(X^r_{pkli}, M_l, G_l) = \begin{cases} 1 & , \text{if } \sum_{p \in P} \sum_{k \in K} \sum_{i \in I} \alpha_p X^r_{pkli} > M_l G_l \\ 0 & , \text{otherwise} \end{cases} \quad , l \in L$$

4.1.2 An overall GA solution procedure

Once the representation scheme is selected, the overall algorithm of the proposed GA can be described as follows. First, read the required data and generate an initial population based on population size, in which each chromosome is a one dimensional array representing decision values. In each chromosome, the opening/closing decision of any facility is randomly made using binary value; second, set the generation zero and evaluate the fitness function of each chromosome in a population. The fitness function is the sum of the objective function of the original problem and the penalty function; third, create a new population by repeating generation operations (cloning, parent selection, crossover, and mutation) until the new population is complete. The combined tournament and elitism method is used for selecting the parent. Two point crossover and random mutation are used for positioning a chromosome; forth, replace new offspring in a new population; finally, stop the iteration if the end condition is satisfied; otherwise go to the next generation.

4.2. Lower Bound by Lagrangian Relaxation

The mathematical model belongs a class of multi commodity distribution network design models which are known to be NP-hard problems making difficult to solve(Pirkul and Jayaraman, 1998). Hence, the solution methodology involves the development of heuristic procedures for the large size problems. In this paper, Lagrangian relaxation method is applied to get the lower bound for the problem so that the performance of the proposed GA may be compared.

Lagrangian methodology relaxes a set of constraints from an original problem (e.g., relaxing integrality constraints) and then adds them to the objective function of the problem using Lagrangian multipliers. This transformation aims to make the relaxed problem easier to solve than the original problem. The solution of the relaxed problem with the suitable multipliers thus provides a lower bound to the original problem (in case of minimization)

Lagrangian relaxation P' is obtained after the constraints (2) and (4) in the original problem P are relaxed by using multipliers ϕ_{pk} and λ_{pk}. In addition, in order to produce tighter lower bounds and increase the chance of getting a feasible solution, the surrogate constraints (13) and (14) are added for LR1 and LR2 respectively:

$$\sum_{j\in J} M_j Z_j \geq \sum_{p\in P}\sum_{k\in K} d_{pk} \tag{13}$$

$$\sum_{l\in L} M_l G_l \geq \sum_{p\in P}\sum_{k\in K} r_{pk} \tag{14}$$

Thus, the mathematical representation of P' is as follows:

$$\begin{aligned} P'{:}\ & \mathrm{LR}(\phi_{pk}, \lambda_{pk}) \\ \text{Min}\ & \sum_{j\in J}[w_j Z_j + v_j \sum_{p\in P}\sum_{i\in I}\sum_{k\in K}\alpha_p X^f_{pijk}] \\ & + \sum_{l\in L}[r_l G_l + u_l \sum_{p\in P}\sum_{i\in I}\sum_{k\in K}\alpha_p X^r_{pkli}] \\ & - \sum_{s\in S} h_s Q_s + \sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c^f_{pijk} X^f_{pijk} \\ & + \sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\sum_{i\in I} c^r_{pkli} X^r_{pkli} \\ & + \sum_{p\in P}\sum_{k\in K}\phi_{pk}(d_{pk} - \sum_{i\in I}\sum_{j\in J} X^f_{pijk}) \\ & + \sum_{p\in P}\sum_{k\in K}\lambda_{pk}(r_{pk} - \sum_{l\in L}\sum_{i\in I} X^r_{pkli}) \end{aligned} \tag{15}$$

Subject to (3), (5), (6), (7). (13), and (14).

Then, problem P' can be easily separated into three sub problems, such as the relaxed forward problem (LR1), the relaxed backward problem (LR2), and the cost saving problem (LR3). In doing so, the sum of objective functions of the three subproblems provides a lower bound on the objective value of the original problem. The subproblems are mathematically expressed as follows:

LR1(ϕ_{pk}) : Minimize

$$\sum_{p\in P}\sum_{k\in K}\phi_{pk} d_{pk} - [\sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}(\phi_{pk} - v_j\alpha_p - c^f_{pijk})X^f_{pijk} - \sum_{j\in J} w_j Z_j] \tag{16}$$

Subject to (3), (6), (8), and (13).

LR2(λ_{pk}) : Minimize

$$\sum_{p\in P}\sum_{k\in K}\lambda_{pk} r_{pk} - [\sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\sum_{i\in I}(\lambda_{pk} - u_l\alpha_p - c^r_{pkli})X^r_{pkli} - \sum_{l\in L} r_l G_l] \tag{17}$$

Subject to (5), (7), (9), and (14).

LR3: Minimize

$$-\sum_{s\in S} h_s Q_s \tag{18}$$

Subject to (11).

Now, since LR1(ϕ_{pk}) and LR2(λ_{pk}) are all knapsack problems, we can easily solve the subproblems for given ϕ_{pk} and λ_{pk}(Bitran *et al.*, 1981). And then LR3 is obtained to calculate cost savings based on the solutions of LR1(ϕ_{pk}) and LR2(λ_{pk}).

5. Numerical Example Problem

The proposed algorithm was applied to a base line model for a 3PL, facing to develop a distribution network for providing forward and reverse logistics services. There were three clients who made a contract with the 3PL, and each of them had ten customers to be served for forward and backward flows. Also, we assumed that plant locations of the clients, locations of their customers, and demands of the customers were known. Demands and returns in each client are assumed to be 10% of forward flow and are summarized in <Table 1>. The plant locations of the clients and the potential locations of distribution centers as well as collection centers are also shown in <Table 1> and <Table 2>. Opening a hybrid distribution collection center is meant when a warehouse and a collection center are open in the same location. This hybrid facility thus achieves cost savings ($=h_s$) by sharing infrastructure, material handling equipment, transportation costs, etc. Additionally, <Table 3> summarizes the parameter settings for this model.

Based on the above data, we solved the base-line model using the genetic algorithm on a Pentium IV personal computer equipped with 512MB of memory. The parameter values are: population size = 200; maximum number of generations = 150; cloning =20%; crossover rate = 80%; mutation = 5%. <Table 4>～<Table 6> show a summary of the base-line model. The solution showed that opening two distribution centers (D3, D9) and three collection centers (R3, R7, R9) was recommended, in which two hybrid facilities were set up so that possible effects of cost savings were gained.

Then, to check the robustness of the base-line solution,

Table 1. Customer data for forward and reverse flows in the base-line model

Index	Client 1				Client 2				Client 3			
	x	y	d_{pk}	r_{pk}	x	y	d_{pk}	r_{pk}	x	y	d_{pk}	r_{pk}
1	126.32	109.07	100	10	122.24	107.40	200	20	24.23	179.80	300	30
2	100.13	57.31	100	10	114.20	189.92	200	20	23.04	80.60	300	30
3	23.51	109.17	100	10	49.04	68.38	200	20	72.18	16.11	300	30
4	91.72	3.33	100	10	25.69	51.08	200	20	79.76	78.11	300	30
5	68.76	173.12	100	10	118.27	107.00	200	20	189.38	126.50	300	30
6	154.10	44.67	100	10	137.47	99.24	200	20	153.59	44.23	300	30
7	96.91	137.61	100	10	152.93	32.58	200	20	6.26	17.85	300	30
8	199.04	135.93	100	10	6.88	185.71	200	20	136.71	108.50	300	30
9	166.96	57.56	100	10	173.68	137.95	200	20	31.51	186.55	300	30
10	186.57	128.87	100	10	150.23	5.47	200	20	108.82	110.44	300	30

Table 2. Facility data in the base-line model

Index	Distribution Center			Collection Center			Plant of Client		
	x	y	Capacity	x	y	Capacity	x	y	Capacity
1	74.30	114.15	6000	74.30	114.15	600	20.12	80.02	6000
2	91.18	166.71	6000	91.18	166.71	600	197.6	16.06	6000
3	98.90	120.47	6000	98.90	120.47	600	150.73	142.9	6000
4	90.85	4.13	6000	90.85	4.13	600			
5	58.90	167.85	6000	58.90	167.85	600			
6	53.48	76.64	6000	53.48	76.64	600			
7	59.53	148.71	6000	59.53	148.71	600			
8	58.27	120.35	6000	58.27	120.35	600			
9	106.15	46.86	6000	106.15	46.86	600			
10	167.64	96.78	6000	167.64	96.78	600			

Table 3. Parameter settings in the base-line model

	Index	Value
Fixed cost of opening distribution center *j*	w_j	\$10,000
Fixed cost of opening collection center *l*	r_l	\$5,000
Weight factor of product *p* based on characteristics of the product type	α_p	1
Maximum capacity of distribution center *j*	M_j	3,000 units
Unit transportation cost from client's plant *i* to distribution center *j*	c_{ij}^f	\$0.05
Unit transportation cost from distribution center *j* to customer *k*	c_{jk}^f	\$0.1
Unit variable cost for transporting and handling product *p* from plant *i* via distribution center *j* to customer *k*	c_{pijk}^f	$c_{ij}^f e_{ij} + c_{jk}^f e_{jk}$
Unit variable cost for distribution center *j*	v_j	\$100
Unit variable cost for collection center *l*	u_l	\$50
Cost savings from opening hybrid distribution-collection center *s*	h_s	\$4,000
Maximum capacity of collection center *l*	M_l	300 units
Unit transportation cost from collection center *l* to client's plant *i*	c_{li}^r	\$0.05
Unit transportation cost from customer *k* to collection center *l*	c_{kl}^r	\$0.5
Unit variable cost for taking back returned product *p* from customer *k* via collection center *l* to plant *i*	c_{pkli}^r	$c_{kl}^r e_{kl} + c_{li}^r e_{li}$

e_{ab} indicates the Euclidean distance between locations *a* and *b*.

Table 4. The summary of the solutions in the base-line model

Index	1	2	3	4	5	6	7	8	9	10
Distribution center	0	0	1	0	0	0	0	0	1	0
Collection center	0	0	1	0	0	0	1	0	1	0
Hybrid	0	0	1	0	0	0	0	0	1	0

1 : opening, 0 :closing

Table 5. Decisions of allocating customers in base-line model

Open facilities	(Client, Customer)
Distribution Center	
3	(1,1) (1,3) (1,5) (1,7) (1,8) (1,10) (2,1) (2,2) (2,5) (2,8) (2,9) (3,1) (3,2) (3,4) (3,5) (3,8) (3,9) (3,10)
9	(1,2) (1,4) (1,6) (1,9) (2,3) (2,4) (2,6) (2,7) (2,10) (3,3) (3,6) (3,7)
Collection Center	
3	(1,1) (1,7) (1,8) (1,10) (2,1) (2,2) (2,5) (2,6) (2,9) (3,5) (3,8) (3,10)
7	(1,3) (1,5) (2,8) (3,1) (3,2) (3,9)
9	(1,2) (1,4) (1,6) (1,9) (2,3) (2,4) (2,7) (2,10) (3,3) (3,4) (3,6) (3,7)

Table 6. The cost summary of the base-line model

Cost components	
Cost of operating distribution centers	\$620,000
Cost of forward transportation	\$64,977
Cost of operating collection centers	\$45,000
Cost of reverse transportation	\$19,342
Savings	\$8,000
Total cost	\$741,319

a computational experiment was conducted to assess the computational effectiveness of the proposed GA. This involved solving five test problems of varying the number of products, distribution centers, collection centers, and customer zones. The potential locations of the centers and customers were generated from a uniform distribution with minimum and maximum distance of 0 and 200, respectively on the *x* and *y* coordinates. Customer demands were also generated as uniformly distributed random numbers from 100 to 300. Cost data and other parameters were appropriately set according to the problem size.

Lower bounds obtained by Lagrangian relaxation were calculated using GAMS software. In addition, the optimal solutions of small problems for the problem No. 1 and 2 were provided, which were 131,974.1 and 380,492.3 respectively. <Table 7> shows the results of the test problems. We found that the proposed genetic algorithm provided the similar solutions in the problem No.1 and 2 compared to the optimal solutions. Gaps in the test problems lie in the range of (0.23%, 7.0%) compared to lower bounds obtained from Lagrangian relaxation.

6. Conclusions

A growing number of companies begin to realize the importance of implementing integrated supply chain management since they are under pressure for filling customers' orders on time as well as for efficiently taking returned products back from customers after selling products. In terms of product flows, there are two flows in an integrated supply chain, which are forward logistics and reverse logistics. 3PLs are playing an increasing role in supporting such integrated supply chain management using sophisticated information systems and dedicated equipments. Up to date, most studies however have involved in either forward or reverse flows so that the objective of this paper aims to aid 3PLs in making strategic decisions with their network design, considering possible effects by integrating forward and reverse flows. This paper thus proposed a mixed integer programming model, and a solution methodology based on genetic algorithm since the mathematical model belongs to a class of NP hard problem. Finally, the validity of proposed algorithm was tested using numerical examples, and it provided a near optimal good solution compared to lower bound by Lagrangian algorithm. As a further research area, we suggest to apply this kind of approach in the real world situation with the cooperation of 3PLs.

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Table 7. The results of the test problems

No.	P	D	R	C	Genetic Algorithm	Lagrangian Relaxation	Gap
					Solution	Lower bound	(GA Solution-LB)/LB
1	1	5	5	20	131,981.9	131,667.5	0.002388
2	2	5	5	40	380,492.3	374,985.2	0.014686
3	3	10	10	60	741,319.2	710,850.6	0.042862
4	3	15	15	120	1,467,490.1	1,455,805.3	0.008026
5	3	20	20	180	2,168,320.6	2,027,076.6	0.069679

P: the total number of clients' products; D: the total number of distribution centers; R: the total number of collection centers; C: the total number of customer zones.

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