Journal of Southeast University (English Edition) Vol. 22, No. 4, pp. 570 – 576 Dec. 2006 ISSN 1003—7985

Integrated logistics facilities network design for 3PLS under uncertainty

Zhang Yong[1] Li Jian[2] Li Xuhong[1] Mao Haijun[1]

([1] School of Transportation, Southeast University, Nanjing 210096, China)

([2] College of Engineering, Nanjing Agricultural University, Nanjing 210031, China)

Abstract: According to the operational characteristics of the logistics networks for the third party logistics supplier (3PLS), the forward and reverse logistics networks together for 3PLS under the uncertain environment are designed. First, a fuzzy model is proposed by taking multiple customers, multiple commodities, capacitated facility location and integrated logistics facility layout into account. In the model, the fuzzy customer demands and transportation rates are illustrated by triangular fuzzy numbers. Secondly, the fuzzy model is converted into a crisp model by applying fuzzy chance constrained theory and possibility theory, and one hybrid genetic algorithm is designed for the crisp model. Finally, two different examples are designed to illustrate that the model and solution discussed are valid.

Key words: third party logistics supplier; integrated logistics facilities network design; fuzzy chance constrained model; hybrid genetic algorithm; uncertainty

With competence increasing, more and more enterprises are subject to outsourcing their logistics operations to the third party logistics suppliers (3PLS) in order to improve efficiency and decrease costs. The 3PLS is playing a significant role in many supply chain management fields, acting as an important partner in the supply chain to satisfy various and individual logistics needs including forward logistics and reverse logistics. Recent legislation in the United States, in particular, and in Europe and Japan, has refocused attention on recycling for the management of waste, especially electronic wastes[1]. Reverse logistics is actually involved in operational skills and can be extremely complex. Many companies with limited resources outsource their reverse logistics operation demands to third-party providers[2]. Reverse logistics networks design is one of the key subjects concerning reverse logistics, so many researchers have been paying much attention to it[3-8]. Specially, Jayaraman et al. [5] proposed the basic model and solution for reverse logistics; Rogers and Fleischmann et al. [4,6] reviewed the model and optimization about the reverse logistics system.

It is important and necessary for the 3PLS to design an optimal logistics facility network including the forward and reverse logistics facility at the same time. Only Ko[9] proposed a dynamic model about a forward and reverse logistics facility network and a hybrid genetic algorithm for the model.

Uncertainty is one of the characteristics of product recovery networks. In particular the strategic design of the logistic infrastructure has to take uncertain information into account[8], but the uncertainty is not considered by Ko[9]. This paper studies the forward and reverse logistics facility network together from the view of 3PLS.

1 Problem Definition and Model

1.1 Problem definition

The logistics network for 3PLS is shown in Fig. 1, consisting of two critical activities: ① The forward logistics process, which is delivering various types of products from the client plants of 3PLS to the client markets; ② The reverse logistics process, which is taking-back different types of products from the client markets to the client plants because of the reverse actions, e. g., direct reuse, repair, recycling and remanufacturing as options for the client under the economical and ecological motivations of their reverse logistics needs.

The logistics network design problem can be described as follows: Given the potential locations of the warehouses facilities, the client plants and markets, the capacities of these facilities, the demands of the client markets for the forward and reverse logistics services, the cost structure such as transporting, storing and fixed costs, and the characteristics of the products, it is necessary to find out which facilities should be opened and how the forward and reverse product flows should be stored and delivered so that the total costs of the logistics network are minimized.

Received 2006-02-22.

Biography: Zhang Yong (1976—), male, doctor, lecturer, zan7678@163.com.

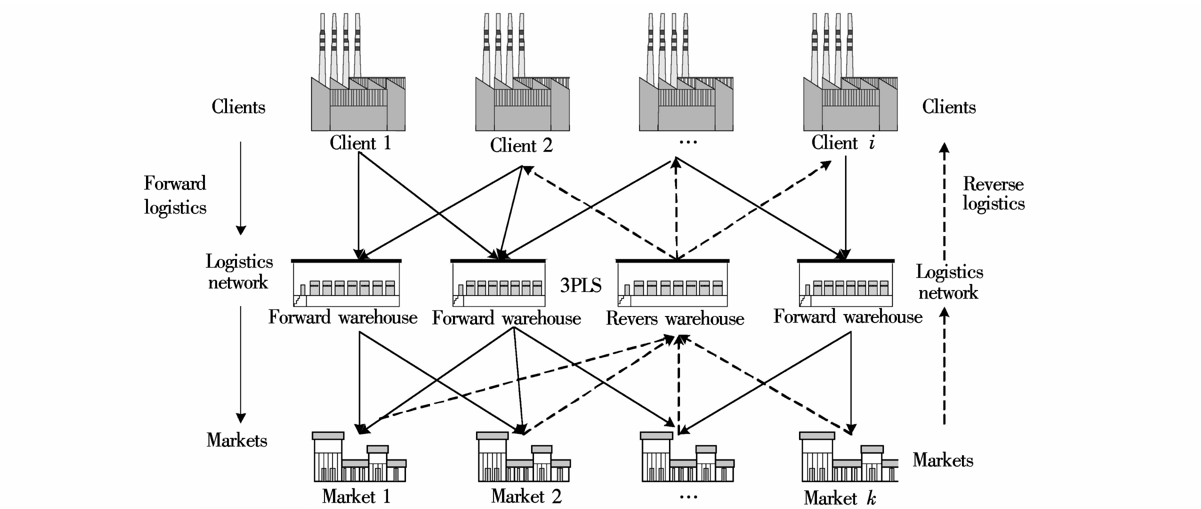

Fig. 1 Network topology for 3PLS under integration of forward and reverse logistics

In order to formulate a mathematical model for the logistics network design problem we make the following assumptions:

① The decision problem belongs to typical location-allocation problem. It is a strategic level operation for 3PLS, so the vehicle-routing problem and the location-routing problem concerned with the logistics network design are ignored in this paper.

② The network configurations for 3PLS are given. They include primarily geographical characteristics associated with the client plants, the client markets and the potential facilities, product characteristics and the potential facility characteristics in terms of the special activities for 3PLS.

③ 3PLS has endorsed the service contract with all clients for the same service period, and the logistics network with only one service period is designed. The products of every client can only satisfy the owner demands of the markets. Moreover, the products can be stored and transported in the same logistics facility.

④ The cost structures for transporting, storing and fixed costs are known.

⑤ The uncertainty of the transportation and the customer demands for the forward and reverse logistics are considered. It is necessary for 3PLS to evaluate the uncertain environment in the logistics operations so that the most effective design can be found. The triangular fuzzy numbers are applied to describe the uncertain parameters.

1.2 Model

The formulation of the problem for 3PLS to design an integrated logistics network as a fuzzy mixed integer linear programming problem is given by the fuzzy mixed integer model (FMIM).

$$\min z = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P} b_j(X^{\mathrm{f}}_{ijkp} + X^{\mathrm{r}}_{ijkp}) + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P} G_j\left(\frac{X^{\mathrm{f}}_{ijkp}}{T^{\mathrm{f}}_{ikp}} + \frac{X^{\mathrm{r}}_{ijkp}}{T^{\mathrm{r}}_{ikp}}\right) + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P} (\tilde{C}^{\mathrm{f}}_{ijkp} X^{\mathrm{f}}_{ijkp} + \tilde{C}^{\mathrm{r}}_{ijkp} X^{\mathrm{r}}_{ijkp})(D_{ij} + D_{jk}) + \sum_{j\in J} bw_j z_j + \sum_{j\in J} br_j y_j - \sum_{j\in J} wr_j z_j y_j \tag{1}$$

such that

$$\sum_{j\in J} X^{\mathrm{f}}_{ijkp} \cong \tilde{d}^{\mathrm{f}}_{ikp} \qquad \forall i\in I, p\in P, k\in K \tag{2}$$

$$\sum_{j\in J} X^{\mathrm{r}}_{ijkp} \cong \tilde{d}^{\mathrm{r}}_{ikp} \qquad \forall i\in I, p\in P, k\in K \tag{3}$$

$$\sum_{i\in I}\sum_{k\in K}\sum_{p\in P} \frac{\lambda_1 X^{\mathrm{f}}_{ijkp} s^{\mathrm{f}}_p}{T^{\mathrm{f}}_{ikp}} \leqslant M^{\mathrm{f}}_j z_j \qquad \forall j\in J \tag{4}$$

$$\sum_{i\in I}\sum_{k\in K}\sum_{p\in P} \frac{\lambda_2 X^{\mathrm{r}}_{ijkp} s^{\mathrm{r}}_p}{T^{\mathrm{r}}_{ikp}} \leqslant M^{\mathrm{r}}_j y_j \qquad \forall j\in J \tag{5}$$

$$X^{\mathrm{f}}_{ijkp}, X^{\mathrm{r}}_{ijkp} \geqslant 0 \qquad \forall i\in I, j\in J, k\in K, p\in P \tag{6}$$

$$z_j, y_j \in \{0,1\} \qquad \forall j\in J \tag{7}$$

where $I=\{1, 2, \ldots, I\}$ denotes the set of client plant locations; $J=\{1, 2, \ldots, J\}$ denotes the set of potential logistics crunodes for 3PLS; $K=\{1, 2, \ldots, K\}$ denotes the set of client markets; $P=\{1, 2, \ldots, P\}$ denotes the set of client product types; bw_j is the setup cost for installing a reverse warehouse in the potential logistics crunode j; br_j is the setup cost for installing forward warehouse in the potential logistics crunode j; wr_j represents the savings associated with opening an integrated forward-reverse warehouse in the potential logistics crunode j; $\tilde{C}^{\mathrm{f}}_{ijkp}$ is the fuzzy rate for per unit product p transportation from client i to market k by the potential logistics crunode j; $\tilde{C}^{\mathrm{r}}_{ijkp}$ is the fuzzy rate for per unit product p return from market k to client by the potential logistics crunode j; D_{ij} is the distance between client i and the potential logistics crunode j; D_{jk} is the distance between the potential logistics crunode j and market k; M^{f}_j is the maximum capacity of the forward warehouse j; M^{r}_j is the maximum capacity of the reverse warehouse j; s_p^{f} is the per unit storage capacity of product p in forward logistics; s_p^{r} is the per unit storage capacity of product p in reverse logistics; $\tilde{d}_{ikp}^{\mathrm{f}}$ is the fuzzy demand of product p by market k from client i; $\tilde{d}_{ikp}^{\mathrm{r}}$ is the fuzzy return demand of product p from market k to client i; b_j is the per unit truckage in the potential logistics crunode j; G_j is the per unit storage rate in the potential logistics crunode j; T_{ikp}^{f} is the average per unit inventory turnover of the product p from client i in market k; T_{ikp}^{r} is the average per unit inventory turnover of the product p from market k to client i; λ_1 is the space parameter for designing the forward warehouse; λ_2 is the space parameter for designing the reverse warehouse; X_{ijkp}^{f} is the amount of the product p from client i through the potential crunode j into client market k; X_{ijkp}^{r} is the amount of the product p from client market k through the potential crunode j into client i; z_j is the binary integer variable for the possible selection of crunode j as a forward warehouse, if the forward warehouse is opened in the potential crunode j, the value is 1, 0 otherwise; y_j is the binary integer variable for the possible selection of crunode j as a reverse warehouse, if the reverse warehouse is opened in the potential crunode j, the value is 1, 0 otherwise.

The first two terms of the above objective function in the model FMIM give the total storing costs, while the third term gives the sum of the transporting costs. Finally, the fourth, fifth and sixth terms correspond to the total fixed costs for setting up the forward and reverse warehouses. Eqs. (2) and (3) ensure that the total demands of the client markets are satisfied. Moreover, Eqs. (4) and (5) guarantee that the storage capacity of the maximum for the forward or reverse warehouse in potential facilities are not excessive. Finally, Eqs. (6) and (7) deal with the nature of the variables associated with the existing decision problem for 3PLS.

2 Model Changing

It is complicated to effectively solve the model FMIM. The way proposed in this study to solve the model FMIM consists of two steps as follows: First, the model FMIM is converted into a crisp model based on the fuzzy chance constrained theory and a possibility theory according to Refs. [10 – 11]; secondly, a hybrid genetic algorithm is designed to solve the crisp model.

Let these fuzzy parameters be expressed by the triangular fuzzy numbers of (C_{ijkp1}^{f}, C_{ijkp2}^{f}, C_{ijkp3}^{f}), (C_{ijkp1}^{r}, C_{ijkp2}^{r}, C_{ijkp3}^{r}), (d_{ikp1}^{f}, d_{ikp2}^{f}, d_{ikp3}^{f}) and (d_{ikp1}^{r}, d_{ikp2}^{r}, d_{ikp3}^{r}). That means fuzzy per unit transportation rate for the forward distribution, fuzzy per unit transportation rate for the reverse distribution, fuzzy total forward demands of the client markets and fuzzy total reverse demands of the client markets, respectively. Referring to the fuzzy chance constrained theory, the model FMIM is converted into the equivalence of the fuzzy chance constrained model FCCM given by

$$\min \bar{f}$$

such that

$$\mathrm{pos}\left\{ \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P}(\tilde{C}_{ijkp}^{\mathrm{f}}X_{ijkp}^{\mathrm{f}}+\tilde{C}_{ijkp}^{\mathrm{r}}X_{ijkp}^{\mathrm{r}})(D_{ij}+D_{jk})+ H_0(X_{ijkp}^{\mathrm{f}},X_{ijkp}^{\mathrm{r}},y_j,z_j)\leqslant \bar{f}\right\}\geqslant\alpha \tag{8}$$

$$\mathrm{pos}\{\sum_{j\in J}X_{ijkp}^{\mathrm{f}}\cong\tilde{d}_{ikp}^{\mathrm{f}}\}\geqslant\beta \qquad \forall i\in I,p\in P,k\in K \tag{9}$$

$$\mathrm{pos}\{\sum_{j\in J}X_{ijkp}^{\mathrm{r}}\cong\tilde{d}_{ikp}^{\mathrm{r}}\}\geqslant\delta \qquad \forall i\in I,k\in K,p\in P \tag{10}$$

Other constraints are the same as Eqs. (4) to (7).

$$H_0(X_{ijkp}^{\mathrm{f}},X_{ijkp}^{\mathrm{r}},z_j,y_j)= \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P}b_j(X_{ijkp}^{\mathrm{f}}+X_{ijkp}^{\mathrm{r}})+ \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P}G_j\left(\frac{X_{ijkp}^{\mathrm{f}}}{T_{ikp}^{\mathrm{f}}}+\frac{X_{ijkp}^{\mathrm{r}}}{T_{ikp}^{\mathrm{r}}}\right)+ \sum_{j\in J}bw_jz_j+\sum_{j\in J}br_jy_j-\sum_{j\in J}wr_jz_jy_j$$

where α,β and δ are predetermined confidence levels of the respective constraints, pos{·} denotes the possibility of the event in {·}. So it is feasible if and only if the possibility measure of Eqs. (8), (9) and (10) are at least the predetermined confidence level.

In order to solve the chance constrained programming FCCM with fuzzy parameters, Eqs. (8), (9) and (10) are converted into their respective crisp equivalents. According to Refs. [10 – 12], the crisp equivalent of chance constraints (8) is shown by Eq. (11). Similarly, chance constraints (9) and (10) are converted into equivalents, respectively expressed by Eqs. (12) and (13). The detailed procedures can be referred to in Refs. [10 – 12].

$$H_0(X_{ijkp}^{\mathrm{f}},X_{ijkp}^{\mathrm{r}},z_j,y_j)+ \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P}[(1-\alpha)(C_{ijkp1}^{f}X_{ijkp}^{\mathrm{f}}+C_{ijkp1}^{\mathrm{r}}X_{ijkp}^{\mathrm{r}})+ \alpha(C_{ijkp2}^{\mathrm{f}}X_{ijkp}^{\mathrm{f}}+C_{ijkp2}^{\mathrm{r}}X_{ijkp}^{\mathrm{r}})](D_{ij}+D_{jk})\leqslant\bar{f} \tag{11}$$

$$\left.\begin{aligned} &\sum_{j\in J}X_{ijkp}^{\mathrm{f}}\geqslant(1-\beta)d_{ikp1}^{\mathrm{f}}+\beta d_{ikp2}^{\mathrm{f}}\\ &\sum_{j\in J}X_{ijkp}^{\mathrm{f}}\leqslant(1-\beta)d_{ikp3}^{\mathrm{f}}+\beta d_{ikp2}^{\mathrm{f}}\\ &\forall i\in I,k\in K,p\in P \end{aligned}\right\} \tag{12}$$

$$\left.\begin{aligned}&\sum_{j\in J} X^{\mathrm{r}}_{ijkp} \geqslant (1-\delta)\, d^{\mathrm{r}}_{ikp1} + \delta d^{\mathrm{r}}_{ikp2}\\&\sum_{j\in J} X^{\mathrm{r}}_{ijkp} \leqslant (1-\delta)\, d^{\mathrm{r}}_{ikp3} + \delta d^{\mathrm{r}}_{ikp2}\\&\forall\, i\in I, k\in K, p\in P\end{aligned}\right\} \quad (13)$$

Finally, the equivalent crisp model (ECM) of the model FCCM is given as

$$\min \bar{f}$$

such that

$$H_0(X^{\mathrm{f}}_{ijkp}, X^{\mathrm{r}}_{ijkp}, z_j, y_j) + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P}[(1-\alpha)(C^{\mathrm{f}}_{ijkp1} X^{\mathrm{f}}_{ijkp} + C^{\mathrm{r}}_{ijkp1} X^{\mathrm{r}}_{ijkp}) + \alpha(C^{\mathrm{f}}_{ijkp2}X^{\mathrm{f}}_{ijkp} + C^{\mathrm{r}}_{ijkp2}X^{\mathrm{r}}_{ijkp})](D_{ij} + D_{jk}) \leqslant \bar{f} \quad (14)$$

$$\left.\begin{aligned}&\sum_{j\in J} X^{\mathrm{f}}_{ijkp} \geqslant (1-\beta)\, d^{\mathrm{f}}_{ikp1} + \beta d^{\mathrm{f}}_{ikp2}\\&\sum_{j\in J} X^{\mathrm{f}}_{ijkp} \leqslant (1-\beta)\, d^{\mathrm{f}}_{ikp3} + \beta d^{\mathrm{f}}_{ikp2}\\&\forall\, i\in I, k\in K, p\in P\end{aligned}\right\} \quad (15)$$

$$\left.\begin{aligned}&\sum_{j\in J} X^{\mathrm{r}}_{ijkp} \geqslant (1-\delta)\, d^{\mathrm{r}}_{ikp1} + \delta d^{\mathrm{r}}_{ikp2}\\&\sum_{j\in J} X^{\mathrm{r}}_{ijkp} \leqslant (1-\delta)\, d^{\mathrm{r}}_{ikp3} + \delta d^{\mathrm{r}}_{ikp2}\\&\forall\, i\in I, k\in K, p\in P\end{aligned}\right\} \quad (16)$$

Other constraints are the same as Eqs. (4) to (7).

3 Hybrid Genetic Algorithm Design

3.1 Framework of hybrid genetic algorithm

The concept of the genetic algorithm (GA) was first proposed by Holland in 1975[13], and then developed and described by Goldberg, which is a stochastic search procedure based on the mechanisms of natural selection and the biological reproduction of animal species. The GA has successfully been applied in various classical logistics network problems such as plant and distribution networks[14], vehicle-routing problems[15], reverse logistics networks[16] and supply chain design[17].

Due to the proven effectiveness of the GA for various NP hard problems, it is suitable for solving the logistics network design problems for 3PLS to meet the demands of forward and reverse logistics. In order to avoid the weakness of the basic GA in solving the combinational problems about location-allocation models, there are many types of hybrid GAS corresponding to the particular characteristics of the special problems by combining the basic GAS with the traditional algorithms. Therefore, a new hybrid GA is proposed for solving validly and effectively the fuzzy model converted into the crisp model ECM for 3PLS in this study.

According to the nature of the ECM, the hybrid GA presented in this paper is divided into two critical procedures: the first procedure is to solve the location decision sub-problem for 3PLS to determine which potential facility is to be opened by applying the basic GA; the second procedure is to solve the transportation decision sub-problem in order to arrange how the products for the forward and reverse logistics are to be distributed by combining the method of minimum elements and potentials methods with the first GA procedure. Furthermore, the decision variables of z_j and y_j are determined by the first procedure, and the decision variables of X^{f}_{ijkp} and X^{r}_{ijkp} are also achieved by the second procedure. The general structure of the hybrid GA for the logistics network design problem for 3PLS is shown in Fig. 2.

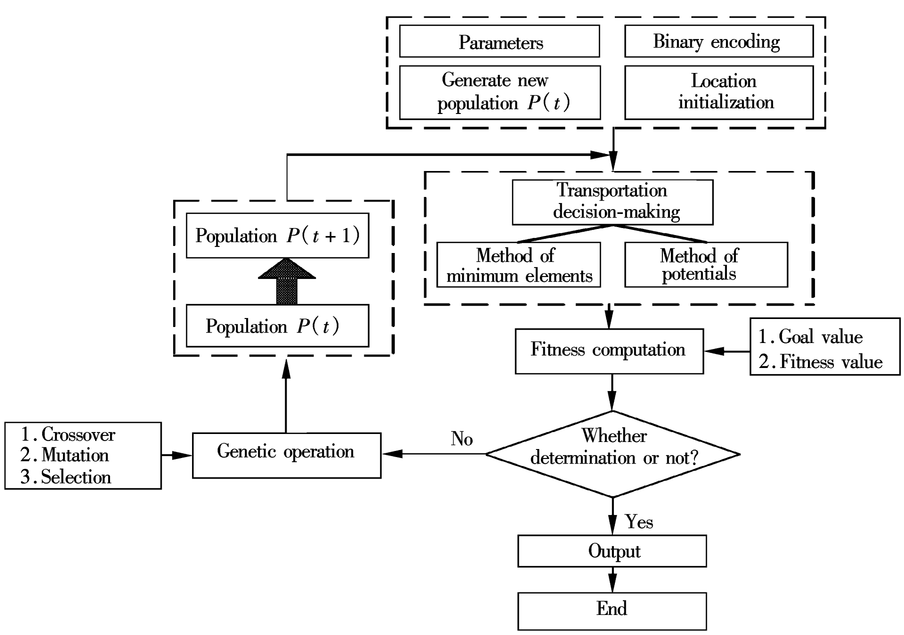

Fig. 2 Structure of the hybrid genetic algorithm

3.2 Encoding

The first step in designing a GA for a particular problem is to design a suitable chromosome representing a valid candidate solution in terms of the probabilistic transition rule. The chromosome developed is based on two-dimensional arrays which consist of binary values addressing the decision variables concerned with the forward and the reverse logistics facility location problems. The binary representation of a chromosome is illustrated in Fig. 3, the logistics network has six potential facility sites for the forward warehouses and the reverse warehouse, respectively. As shown in Fig. 3, the forward warehouses are set in potential facility sites 1, 2, 4 and 5; and the reverse warehouses are opened in potential facility sites 3, 4 and 6 at the same time.

Potential facility sites	1	2	3	4	5	6
Forward warehouses	1	1	0	1	1	0
Reverse warehouses	0	0	1	1	0	1

Fig. 3 Structure of two arrays chromosome

3.3 Fitness computer

The fitness value is a measure of the quality of a solution to the original objective function. In our hybrid GA, the fitness function is formed by adding a penalty to the original objective function. Let v_k^t be the k-th ($k = 1, 2, \dots, s$) chromosome in the current generation t. Then let the s be the total amount of the parent and offspring chromosomes in the current generation. So the procedure of the fitness computing is described as follows:

Step 1 Calculate the total cost of the k-th chromosome according to the following equation:

$$f_k(v_k^t) = H_0(X_{ijkp}^{\mathrm{f}}, X_{ijkp}^{\mathrm{r}}, z_j, y_j) + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P}[(1-\alpha)(C_{ijkp1}^{\mathrm{f}} X_{ijkp}^{\mathrm{f}} + C_{ijkp1}^{\mathrm{r}} X_{ijkp}^{\mathrm{r}}) + \alpha(C_{ijkp2}^{\mathrm{f}} X_{ijkp}^{\mathrm{f}} + C_{ijkp2}^{\mathrm{r}} X_{ijkp}^{\mathrm{r}})](D_{ij} + D_{jk}) \tag{17}$$

Step 2 Compute the total penalty value in terms of the penalty function, expressed as

$$\mathrm{pen}_k(v_k^t) = \sum_{j\in J} Ef(X_{ijkp}^{\mathrm{f}}, s_p^{\mathrm{f}}, T_{ikp}^{\mathrm{f}}, M_j^{\mathrm{f}}, z_j) + \sum_{j\in J} Ef(X_{ijkp}^{\mathrm{r}}, s_p^{\mathrm{r}}, T_{ikp}^{\mathrm{r}}, M_j^{\mathrm{r}}, y_j) \tag{18}$$

where E is the penalty value.

$$f(X_{ijkp}^{\mathrm{f}}, s_p^{\mathrm{f}}, T_{ikp}^{\mathrm{f}}, M_j^{\mathrm{f}}, z_j) = \sum_{i\in I}\sum_{k\in K}\sum_{p\in P}\frac{\lambda_1 X_{ijkp}^{\mathrm{f}} s_p^{\mathrm{f}}}{T_{ikp}^{\mathrm{f}}} - M_j^{\mathrm{f}} z_j,$$

if Eq. (4) is not satisfied; 0 otherwise.

$$f(X_{ijkp}^{\mathrm{r}}, s_p^{\mathrm{r}}, T_{ikp}^{\mathrm{r}}, M_j^{\mathrm{r}}, y_j) = \sum_{i\in I}\sum_{k\in K}\sum_{p\in P}\frac{\lambda_2 X_{ijkp}^{\mathrm{r}} s_p^{\mathrm{r}}}{T_{ikp}^{\mathrm{r}}} - M_j^{\mathrm{r}} y_j,$$

if Eq. (5) is not satisfied; 0 otherwise.

Step 3 Compute the fitness value of v_k^t by applying the fitness function, represented as

$$\mathrm{eval}(v_k) = \frac{1}{f_k(v_k^t) + \mathrm{pen}_k(v_k^t)} \tag{19}$$

3.4 Genetic operations

1) Crossover

The crossover operator is more capable of generating a new solution which will have the best parts of the parent solutions. There are various methods of crossovers such as single-point crossover, multi-point crossover and uniform crossover. A single-point crossover is applied to generate new generations (solution) for this study.

2) Mutation

Mutation is considered as the secondary mechanism in the operation of genetic algorithms to prevent solutions from being trapped in local optima. We applied a single-point mutation with a small probability.

3) Selection

Selection operator is a critical process to direct the GA search toward promising space near the optimal solution. We apply the selection operation combined roulette wheel selection with the optimal saving selection to select two parents from the current generation.

4 Numerical Examples[18]

Two different scale optimization problems are given to illustrate the feasibility of the fuzzy model and the solution for 3PLS to design the integration of the forward and reverse logistics facility network. Two numerical examples are described in detail in Ref. [18], but there are also the outputs of the numerical examples in this study. Numerical example 1 is the description of the logistics network design problem consisting of two clients, four potential facility sites, four client markets considering four typical products and the forward and reverse product flows. Compared with numerical example 1, numerical example 2 specially describes the logistics structure of ten potential facility sites. The input parameters in these optimization problems are not given in this study. A computing programming related to the hybrid genetic algorithm found in this paper is built to solve these numerical examples by applying the VB 6.0 soft language. The hybrid genetic algorithm procedures are executed on a Pentium Ⅳ computer equipped with a speed of 1.7 GHz, and 256 MB of memory. When the value of the population size is 50, the maximum number of generations is 600, the crossover rate is 0.4 and the mutation rate is 0.2, the genetic algorithm obtain the best results. The hybrid genetic algorithm outputs of these numerical experiments compared with the results of the branch and bound algorithm which is effective in solving a small size problems are shown respectively by Tab. 1 and Tab. 2 under various confidence levels $\alpha = \beta = \delta$.

Tab. 1 Computer results for numerical example 1 under various confidence levels $\alpha = \beta = \delta$ Dollar

Confidence level	0	0. 1	0. 2	0. 3	0. 4	0. 5	0. 6	0. 7	0. 8	0. 9	1. 0
Branch and bound algorithm	1 866 856	1 942 486	2 020 134	2 099 237	2 179 793	2 262 223	2 355 155	2 43 0194	2 516 571	2 598 537	2 697 419
Hybrid genetic algorithm	1 902 483	1 950 582	2 030 475	2 140 889	2 194 137	2 319 353	2 400 536	2 453 754	2 537 436	2 641 298	2 717 623

Tab. 2 Computer results for numerical example 2 under various confidence levels $\alpha = \beta = \delta$ Dollar

Confidence level	0	0. 1	0. 2	0. 3	0. 4	0. 5	0. 6	0. 7	0. 8	0. 9	1. 0
Branch and bound algorithm	1 343 423	1 375 644	1 423 304	1 470 984	1 519 169	1 567 614	1 615 730	1 664 385	1 734 748	1 783 555	1 833 260
Hybrid genetic algorithm for the worst result	1 364 584	1 419 923	1 469 722	1 515 991	1 567 998	1 617 149	1 656 979	1 702 675	1 787 413	1 828 757	1 883 113
Hybrid genetic algorithm for the best result	1 343 689	1 388 991	1 437 577	1 493 064	1 546 847	1 598 681	1 632 327	1 672 130	1 739 294	1 797 423	1 849 012
Hybrid genetic algorithm for the average result	1 352 058	1 398 864	1 451 081	1 502 328	1 559 306	1 600 583	1 647 739	1 691 231	1 760 910	1 810 141	1 859 298

The results represented in Tab. 1 and Tab. 2 show that the fuzzy model and the hybrid genetic algorithm are valid in solving the integrated logistics facility design problem under an uncertain environment. Therefore the hybrid genetic algorithm can be applied to solve larger size problems that are too complex and difficult for the branch and bound algorithm to solve.

5 Conclusion and Further Research

This paper presents a cost-minimization model for minimizing the total logistics costs of a multi-product and multi-client capacitated facility location-allocation problem for 3PLS to integrate the forward and reverse logistics facility under an uncertain operational environment. By identifying the critical activities and related basic characteristics involved in the logistics operations for 3PLS, a fuzzy mixed integer linear programming problem model coupled with six groups of constraints are formulated. Compared with early literature on addressing the logistics network design problem, the model formulated in this paper has three distinctive features. First, the model is found from the perspective of 3PLS itself according to the practical activities. Secondly, the integration and coordination between the forward and reverse logistics facilities are emphasized in this model. Thirdly, two fuzzy parameters are taken into account in the model which are often ignored in traditional literature.

The results from applying the model and the solution to two numerical examples suggest that the model and solution are feasible enough to support 3PLS to design an effective logistics network. In the future, the model will be improved by filling the gaps between the assumptions and the practical operations for 3PLS. Additionally, some new solutions to solve the model will be deeply and extensively discussed.

References

[1] Nagurney Anna, Toyasaki Fuminori. Reverse supply chain management and electronic waste recycling: a multitiered network equilibrium framework for e-cycling[J]. *Transportation Research*, *Part E*, 2005, **41**(1): 1 − 28.

[2] Krumwiedea Dennis W, Sheu Chwen. A model for reverse logistics entry by third-party providers[J]. *Omega*, 2002, **30**(5): 325 − 333.

[3] Fleischmann Moritz, Bloemhof-Ruwaard Jacqueline M, Dekker Rommert, et al. Quantitative models for reverse logistics: a review[J]. *European Journal of Operation Research*, 1997, **103**(1): 1 − 17.

[4] Rogers D S, Tibben-Lembke R S. Going backwards: reverse logistics trends and practices [R]. Reno: The University of Nevada, Center for Logistics Management, Reverse Logistics Council, 1998.

[5] Jayaraman Vaidyanathan, Patterson Raymond A, Erik Rolland. The design of reverse distribution networks: Models and solution procedures[J]. *European Journal of Operational Research*, 2003, **150**(1): 128 − 149.

[6] Fleischmann Mortiz, Krikke Hans Ronald, Dekker Rommert, et al. A characterization of logistics networks for product recovery [J]. *Omega*, 2000, **28**(6): 653 − 666.

[7] Yalabik Baris, Petruzzi Nicholas C, Chhajed Dilip. An integrated product returns model with logistics and marketing coordination[J]. *European Journal of Operational Research*, 2005, **161**(1): 162 − 182.

[8] Listes Ovidiu, Dekker Rommert. A stochastic approach to a case study for product recovery network design. [J]. *Eu-*

ropean Journal of Operational Research, 2005, **160**(1): 268 - 287.
[9] Ko Hyun Jeung. Optimization modeling for the design and operation of dynamic facility networks for 3PLS [D]. Louisville: Department of Industrial Engineering of University of Louisville, 2003.
[10] Liu Baoding, Iwamura Kakuzo. Chance constrained programming with fuzzy parameters [J]. *Fuzzy sets and Systems*, 1998, **94**(2): 227 - 237.
[11] Liu Baoding, Iwamura Kakuzo. A note chance constrained programming with fuzzy coefficients [J]. *Fuzzy Sets and Systems*, 1998, **100**(1 - 3): 229 - 233.
[12] Zhao Xiaoyu, Wang Dingwei. Fuzzy chance constrained programming model for bi-level distribution network design in the supply chain[J]. *Control Theory and Application*, 2002, **19**(2): 249 - 252. (in Chinese)
[13] Holland J H. *Adaptation in natural and artificial systems* [M]. MI: University of Michigan Press, 1975.
[14] Chan Felix T S, Chung S H, Wadhwa Subhash. A hybrid genetic algorithm for production and distribution [J]. *Omega*, 2005, **33**(4): 345 - 355.
[15] Hwang Heung-Suk. An improved model for vehicle routing problem with time constraint based on genetic algorithm[J]. *Computers & Industrial Engineering*, 2002, **42** (2 - 4): 361 - 369
[16] Min Hokey, Ko Hyun Jeung, Ko Chang Seong. A genetic algorithm approach to developing the multi-echelon reverse logistics network for product returns[J]. *Omega*, 2006, **34**(1): 56 - 69.
[17] Zhou Gengui, Min Hokey, Mitsuo Gen. The balanced allocation of customers to multiple distribution centers in the supply chain network: a genetic algorithm approach [J]. *Computers & Industrial Engineering*, 2002, **43**(1, 2): 251 - 261.
[18] Zhang Yong. Optimization methodology for the layout of the logistics crunodes for 3PLS [D]. Nanjing: School of Transportation of Southeast University, 2006. (in Chinese)

不确定条件下第三方物流企业一体化物流网络设计

张 永[1] 李 建[2] 李旭宏[1] 毛海军[1]

([1] 东南大学交通学院,南京 210096)
([2] 南京农业大学工学院,南京 210031)

摘要:针对第三方物流企业的运作特点,研究了不确定环境下第三方物流企业正逆向一体化物流网络的设计问题. 首先,应用三角模糊数描述客户需求和运输费用的不确定性,建立了一个考虑多产品、多客户、容量限制及一体化网络设计的模糊模型. 为求解模糊模型,应用模糊机会约束理论、可能度理论将其转化为确定型模型,然后设计出一个混合遗传算法求解确定型模型. 最后,利用 2 个不同规模的算例验证了所提出的模糊模型和求解算法的有效性.

关键词:第三方物流企业;一体化物流网络设计;模糊机会约束模型;混合遗传算法;不确定条件
中图分类号:U492. 3