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Multiple vehicle routing problem integrated reverse logistics with fuzzy reverse demands

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Abstract: A new type of vehicle routing problem (VRP), multiple vehicle routing problem integrated reverse logistics (MVRPRL), is studied. In this problem, there is delivery or pick-up (or both) and uncertain features in the demands of the clients. The deliveries of every client as uncertain parameters are expressed as triangular fuzzy numbers. In order to describe MVRPRL, a multi-objective fuzzy programming model with credibility measure theory is constructed. Then the simulation-based tabu search algorithm combining inter-route and intra-route neighborhoods and embedded restarts are designed to solve it. Computational results show that the tabu search algorithm developed is superior to sweep algorithms and that compared with handling each on separate routes, the transportation costs can be reduced by 43% through combining pickups with deliveries.

Key words: reverse logistics; pickup and delivery; credibility measure theory; tabu search algorithm; fuzzy simulation

With the increasingly serious pollution of the environment, reverse logistics has attracted more and more attention. How to integrate forward logistics and reverse logistics to reduce transportation costs is a problem logistics enterprises concern highly. In this paper, the problem is called vehicle routing problem integrated reverse logistics (VRPRL). It is often encountered in practice, for example, firms delivering products on pallets recover the pallets for reuse. Retail stores delivering appliances may take away old appliances as a service to their customers. Firms leasing office equipment may pick up and recycle used equipment to be refurbished and leased again or sold. Products previously sold and delivered may need to be returned for inspection, rework, and resale as in the case of auto engines which experience quality problems. Bottlers may recover the container portion of their products when deliveries of the fresh product are made. Some countries, such as Germany, have gone as far as to legislate that some industries must take back all sales packaging materials. Japan has similar legislation and the United States has numerous laws on solid waste reclamation[1]. China has also some laws on electronic waste reclamation[2]. Frequently, some or all recovered materials are handled in conjunction with deliveries.

Compared with general vehicle routing problems (VRP), there are three features for VRPRL: 1) Each client requires either a delivery or a pick-up operation (or both) of a certain amount of goods or waste. That is to say, the vehicle may deliver and pick-up simultaneously. 2) The quantity of the delivery of each client is uncertain[2-3]. In this research it is assumed that the quantity of the delivery is a triangular fuzzy variable. 3) The computational complexity has greatly increased. It is known that the VRP is NP-hard. However, VRPRL is much more difficult than VRP. VRP under certainty is a special example of VRP under uncertainty. So feasible solutions space under uncertainty is much larger than under certainty.

In many researches only the objective of the traveling distance is minimized. In fact, it is necessary that the number of vehicles should be reduced as much as possible to decrease the fixed costs and the number of drivers. To minimize the objectives of the number of vehicles and traveling distances, a programming model fuzzy-theory-based credibility measure is constructed in this study. Contrasted with the possibility measure, the credibility measure plays a probability role[4].

In vehicle routing problems under uncertainty, the planned routing solution is generally derived from a given confidence level. However, additional costs will be generated, because the planned routes fail in practical environments. For this, the decision-maker hopes more to find a solution which minimizes the sum of planned costs and additional costs. Therefore, in this paper the additional costs are also involved in the objective function.

Aimed at the computation complexity of the problem, the tabu search algorithm is employed to solve the VRPRL, since it possesses very good qualities regarding combination optimization. In this paper, complex neighborhoods combining inter-route and intra-route neighborhoods and restarts are embedded in the tabu search algorithm. Then the developed tabu search algorithm and fuzzy simulation are integrated to solve the problem.

1 Related Literature Review

To our knowledge, the VRPRL in which each customer has both a pick-up demand and a fuzzy delivery demand has rarely been researched. Related works with VRPRL are vehicle routing problems with simultaneous pick-up and delivery under certainty (VRPSPD) and forward vehicle routing problems without pick-up or reverse vehicle routing problems without delivery under uncertainty. As for the former, Min[5] first introduced vehicle routing problems with simultaneous pick-up and delivery and proposed a cluster first and secondly a route approach to solve a problem of transporting books between libraries by two vehicles. Dethloff[6] studied the problem from the perspective of reverse logistics. He pro-

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posed a mathematical formulation for VRPSPD and developed insertion heuristics based on the concept of residual capacities. Salhi and Nagy[7] proposed a local search heuristic that considered solutions with a certain degree of infeasibility. Chen et al.[8] presented a heuristic based on the record-to-record travel and tabu lists. In those researches mentioned above, simultaneous pick-up and delivery are considered, but uncertainty has not been taken into account.

As far as the vehicle routing problem under uncertainty is concerned. It includes stochastic vehicle routing and fuzzy vehicle routing. There are a few papers which used fuzzy theory to research them. Teodorović and Pavković[9] first used fuzzy variables to deal with these uncertain parameters in the vehicle routing problem (VRP) and designed the sweep algorithm to solve it. Zheng et al.[10] modeled the vehicle routing problem with time windows (VRPTW) with credibility measures and proposed a hybrid genetic algorithm. Teodorović et al.[11-12] studied stochastic vehicle routing problems. Although they researched vehicles routing problems under uncertainty, reverse logistics is not integrated into forward vehicle routing.

In addition, Alshamrani et al.[1] studied VRPRL with single vehicles under stochastic environments and developed a heuristic procedure for it. Nevertheless, in some new systems, it is hard to describe the parameters of the problem as random variables because there are not enough data to analyze. On the other hand, multiple vehicle routing problems are in fact often encountered.

So aimed at the lack of the past researches, VRPRL with multiple vehicles under fuzzy conditions is presented. Then the developed tabu search algorithm and fuzzy simulation are integrated to solve it.

2 Fuzzy Model for MVRPRL

2.1 Descriptions of MVRPRL

Multiple vehicle routing problem integrated reverse logistics (MVRPRL) is described as that of a set of vehicles dispatched from the distribution to clients who need deliveries or pickups (or both). The aim is to find a route plan which minimizes both the number of vehicles and the sum of planned routing costs and the additional costs due to failure. In order to make the model, we assume that: 1) Positions of distribution centers and clients are known; 2) Neither the pickups nor the deliveries of every client are greater than the capacity of the vehicle where the former is certain but the latter is uncertain which is expressed as triangular fuzzy numbers; 3) All the vehicles have the same capacity; 4) When the vehicle arrives at client i, it will return to the distribution center to unload if its surplus space is less than the net delivery amounts of client i. Then it returns to continue to serve client i; 5) The requirements of every client must be satisfied, visited only once and served by only one vehicle.

2.2 Computation based on credibility theory

Some basic concepts and results on fuzzy variables were introduced by Zheng et al.[10]. Now a triangular fuzzy variable $\varepsilon = (r_1, r_2, r_3)$ is considered. From the definitions of possibility, necessity and credibility, it is easy to obtain

$$\operatorname{Poss}(\varepsilon \geqslant r) = \begin{cases} 1 & \text{if } r \leqslant r_2 \\ \dfrac{r_3 - r}{r_3 - r_2} & \text{if } r_2 \leqslant r \leqslant r_3 \\ 0 & \text{if } r \geqslant r_3 \end{cases} \tag{1}$$

$$\operatorname{Nec}(\varepsilon \geqslant r) = \begin{cases} 1 & \text{if } r \leqslant r_1 \\ \dfrac{r_2 - r}{r_2 - r_1} & \text{if } r_1 \leqslant r \leqslant r_2 \\ 0 & \text{if } r \geqslant r_2 \end{cases} \tag{2}$$

$$\operatorname{Cr}(\varepsilon \geqslant r) = \begin{cases} 1 & \text{if } r \leqslant r_1 \\ \dfrac{2r_2 - r_1 - r}{2(r_2 - r_1)} & \text{if } r_1 \leqslant r \leqslant r_2 \\ \dfrac{r_3 - r}{2(r_3 - r_2)} & \text{if } r_2 \leqslant r \leqslant r_3 \\ 0 & \text{if } r \geqslant r_3 \end{cases} \tag{3}$$

An arrangement of L client is generated randomly, as $(i_1, i_2, \dots, i_{L-1}, i_L)$. Then the client is assigned in turn to the vehicle. After it has served i' clients, whether the vehicle serves the next client i or not depends on whether the sum of forward delivery amounts is less then the capacity of the vehicle and the sum of net delivery amounts is less than surplus capacity S_k or not. We obtain constraints (4) and (5).

$$S_k = Q - \sum_{j=1}^{L} p_j y_{jk} \geqslant 0 \qquad k \in K \tag{4}$$

$$\operatorname{Cr}\left(S_Q - \sum_{j=1}^{i} (\tilde{d}_j - p_j) y_{jk} \geqslant 0 \right) \geqslant \alpha \qquad k \in K; i = 1, 2, \dots, L \tag{5}$$

where Q is the capacity of the vehicle; p_i is the pickup demand of the client i; $\tilde{d}_i$ is the delivery demand of the client i; K is the set of vehicles or routes, $K = \{1, 2, \dots, m\}$; and y_{ik} is the decision variable.

If both constraints (4) and (5) are satisfied, the vehicle continues to serve client i. Eq. (5) is computed based on Eq. (3). Consequently, we have the following fuzzy model for MVRPRL.

2.3 Fuzzy model for MVRPRL

The corresponding mathematical formulation is given by

$$\min \sum_{k=1}^{m} \sum_{i=0}^{L} \sum_{j=0}^{L} C_{ij} x_{ijk}, \ \min m \tag{6}$$

$$Q - \sum_{j=1}^{L} p_j y_{jk} \geqslant 0 \qquad k \in K \tag{7}$$

$$\operatorname{Cr}\left(S_k - \sum_{j=1}^{i} (\tilde{d}_j - p_j) y_{jk} \geqslant 0 \right) \geqslant \alpha \qquad k \in K; i = 1, 2, \dots, L \tag{8}$$

$$\sum_{k=1}^{m} y_{ik} = 1 \qquad i = 1, 2, \dots, L; k \in K \tag{9}$$

$$\sum_{i=0}^{L} x_{ijk} = y_{jk} \qquad j = 1, 2, \dots, L; k \in K \tag{10}$$

$$\sum_{j=0}^{L} x_{ijk} = y_{ik} \qquad i = 1, 2, \dots, L; k \in K \tag{11}$$

$$U_{ik} - U_{jk} + Lx_{ijk} \leqslant L - 1 \qquad i,j \in L; k \in K \quad (12)$$

$$\sum_{k=1}^{m} \sum_{j=0}^{L} \tilde{t}_{ijk} - \sum_{k=1}^{m} \sum_{j=0}^{L} \tilde{t}_{jik} = \tilde{d}_i - p_i \quad (13)$$

$$x_{ijk} = 0 \text{ or } 1 \qquad i,j = 0,1,\ldots,L; k \in K \quad (14)$$

$$y_{ik} = 0 \text{ or } 1 \qquad i = 1,2,\ldots,L; k \in K \quad (15)$$

$$U_{ik} \geqslant 0 \qquad i \in 1,2,\ldots,L; k \in K \quad (16)$$

$$\mathrm{Cr}(\tilde{t}_{ijk} \geqslant 0) = 1 \qquad i,j = 0,1,\ldots,L; k \in K \quad (17)$$

where L is the total number of clients; $\tilde{d}_i = (d_{i1}, d_{i2}, d_{i3})$ is the delivery demand of client i; C_{ij} is the traveling distance from client i to j, $i, j = 0, 1, \ldots, L$; $x_{ijk} = 1$, if point i immediately precedes point j on route k, otherwise 0; $y_{ik} = 1$, if client i is served by vehicle k, otherwise 0; t_{ijk} is the load on arc ij of vehicle route k; U_{ik} is the auxiliary variable for sub-tour elimination constraints on route k.

The objective function seeks to minimize the total traveling distances and the number of vehicles. Constraints (7) and (8) are forward delivery and reverse pickup constraints, respectively. Constraint (9) ensures that each client is visited by only one vehicle; constraints (10) and (11) denote that each client is visited only once. Constraint (12) guarantees that sub-tours are eliminated. Constraint (13) is a flow conservation equation. Constraints (14) to (17) define the nature of the decision variables.

3 Simulation-Based Tabu Search Algorithm

Since the MVRPRL is the NP-hard problem, the tabu search algorithm is employed to solve it. First an initial feasible solution is created using a sequential insertion method that constructs one route at a time until all the customers have been included on the route. Then it is improved by the tabu search algorithm. In order to minimize the number of vehicles, a penalty value is added to the objective value when the number of vehicles increases. If the best solution is not updated before a certain number of iterative times are completed, a restart will be applied to the solution.

3.1 Initial solutions

Step 1 Randomly generate vertex v_i and form the vertex sequence $(v_0, v_i, v_{i+1}, \ldots, v_L, v_1, v_2, \ldots, v_{i-1})$.

Step 2 According to constraints (4) and (5), starting with v_0, create routes by following the above vertex sequence and repeat this process until all the vertices are included into the routes (see Fig. 1).

Step 3 Compute the objective function value. It is computed as section 3.2.

Step 4 Repeat step 1 to step 3 for N cycles and choose a solution for which the objective function value is the smallest.

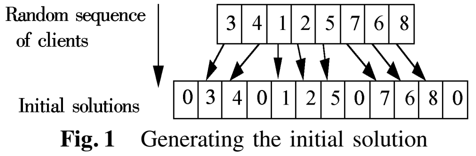

Fig. 1 Generating the initial solution

3.2 Evaluation of solutions

The objective value of the traveling distance is the sum of the planned cost and failed cost. It is possible that the planned routing cannot satisfy the actual constraint at client i because the delivery amount of client i is a fuzzy variable. If the planned routing fails, the vehicle will return to the depot to unload. Then the vehicle arrives at client i from the depot again to continue. The additional cost is regarded as failed cost (f_c, in short).

The failed value is calculated by a fuzzy simulation method. The procedure of calculating the failed value is described in more detail below.

Set f_c = 0 and Sum = 0
For $i = 1$ to N
Do
generate randomly a value d in (d_{i1}, d_{i3}) and calculate membership values u.
generate randomly a value r in $(0, 1)$.
If $u > r$ then d is accepted.
Loop until all the clients generate actual delivery values.
Calculate the failure cost according to the actual values generated above;
Sum = Sum + f_c;
Next i
Set Sum = Sum/N.
Note that N is set to be 10 in this paper.

3.3 Tabu search

The tabu search algorithm is a heuristic method designed to guide other methods, including local search algorithms, to escape local optima. It has shown superiority over other heuristic algorithms in classical vehicle routing problems. Therefore, the tabu search algorithm we developed is employed for the MVRPRL in this paper. And inter-route and intra-route neighborhoods, including four types of movements: swap move, shift move, 2-opt and Or-opt, are applied to it. After each neighborhood search is finished, the best non-tabu candidate solution is put into the tabu lists and the current solution and best solution which is generated in all the iterations so far are updated. If the best solution is not updated before a certain number of iterations are completed, a restart is applied to continue to complete the surplus iterations.

3.3.1 Neighborhood structure

In our implementation, four different classes of neighborhood moves are applied to the current solution. (1, 1) swap move and (1, 0) shift move are introduced by Fu et al. [13]. They are selected for inter-route improvement and 2-opt and Or-opt for intra-route improvement.

1) (1, 1) swap move. Exchange the positions of two selected vertices on two different routes.

2) (1, 0) shift move. Remove the first selected vertex from its current position on a tour and insert it into some position on another one.

3) 2-opt. This method was introduced by Lin[14]. In this procedure, two links which are not adjacent to each other are removed from the same route and the segments are reconnected in all possible ways.

4) Or-opt. This procedure was introduced by Or[15]. In this procedure, a sequence of three consecutive clients, two consecutive clients, or a single client on a tour is removed and inserted to another location on the same route.

3.3.2 Tabu lists

Tabu lists are established for every movement. The tabu lists contain the move attributes of solutions during the last three to seven iterations.

3.3.3 Stopping criterion

The search is terminated when the total specified number of iterations has elapsed.

3.3.4 Restarts

If the current solution is not improved after certain number of iterations, the best solution so far is set as the current solution and continues to be searched.

3.3.5 Tabu search algorithm procedures

The following variables are used in the description of the tabu search algorithm:

Iter is the current number of iterations; max_iter is the maximum number of iterations; cons_iter is the current number of consecutive iterations without any improvement to the best solution so far; max_cons_iter is the maximum number of consecutive iterations without any improvement to the best solution so far. The tabu search algorithm is described in pseudo-codes by VB language as follows:

```
Set iter and cons_iter to 0;
Generate an initial feasible solution and set this solution as the current solution and the best solution so far.
Do While(iter≤max_iter)
    Select one of the four types of the neighborhood methods randomly;
    Add the solution produced by the selected move to the candidate list;
      Select the best non-tabu candidate solution
      Set the new solution as the current solution, update the tabu list and increment iter;
   If the new solution improves the best solution so far, update the best solution so far; and set cons_iter to 0; otherwise, increment cons_iter;
   End if
   If cons_iter≥max_cons_iter
      Restarts
   End if
Loop
```

4 Numerical Experiments

This TS heuristic has been programmed using Visual Basic 6.0 and implemented on a Pentium Ⅵ PC running at 1.60 GHz with 128MB RAM. To test the computational performance of the heuristic, we compare it with the sweep algorithm[9].

In square [0, 40 km] × [0, 40 km], 20 clients are generated randomly. The sum of delivery and pick-up of each client is generated randomly at [0, 3.5 t], then the delivery and pick up of each client is distributed as follows: for each customer j, a ratio $r_j = \min\{x_j/y_j, y_j/x_j\}$ is calculated, where x_j and y_j are the coordinates of customer j. The pickup level of client j is then set to be $(1 - r_j)t_j$, where t_j is the total demand of client j. In this paper, d_{i1} is set to be $\frac{1}{3}r_jt_j$, d_{i2} is set to be $\frac{2}{3}r_jt_j$; d_{i3} is set to be r_jt_j; x and y coordinates of the depot are (0, 0). The capacity of the vehicle is 6 t. These basic data are described in Tab. 1 in detail. Computational parameters are set as follows: max_iter = 500; max_cons_iter = 100.

Tab. 1 Basic data of the clients

Client number	x/km	y/km	Delivery levels of clients/t	Pickup levels of clients/t
1	32.1	28.7	(0.36, 0.72, 1.08)	0.13
2	12.3	17.6	(0.14, 0.28, 0.42)	0.18
3	23.4	2.0	(0.04, 0.09, 0.13)	1.37
4	25.6	38.5	(0.11, 0.22, 0.33)	0.17
5	10.8	39.9	(0.21, 0.42, 0.62)	1.68
6	30.3	25.8	(0.60, 1.20, 1.79)	0.31
7	14.8	9.4	(0.49, 0.97, 1.46)	0.84
8	3.5	23.8	(0.16, 0.31, 0.47)	2.73
9	35.6	22.3	(0.58, 1.17, 1.75)	1.05
10	34.9	32.4	(1.02, 2.04, 3.06)	0.24
11	2.9	0.9	(0.14, 0.29, 0.43)	0.97
12	2.1	8.2	(0.22, 0.44, 0.67)	1.93
13	14.6	32.0	(0.33, 0.67, 1.00)	1.20
14	337.0	81.0	(0.18, 0.35, 0.53)	1.67
15	16.0	31.3	(0.14, 0.27, 0.41)	0.39
16	23.7	24.3	(0.29, 0.59, 0.88)	0.02
17	34.3	13.4	(0.10, 0.21, 0.31)	0.49
18	1.3	5.9	(0.10, 0.19, 0.29)	1.01
19	12.3	3.0	(0.10, 0.20, 0.29)	0.91
20	15.6	3.2	(0.23, 0.46, 0.70)	2.70

Tab. 2 compares the average values, the best values and the worst values obtained by the tabu search algorithm we developed with the results obtained by the sweep algorithm

Tab. 2 Comparisons of computational results

Credibility level	Tabu search algorithm				Sweep algorithm			
	Average result	The best result	The worst result	Average number of vehicles	Average result	The best result	The worst result	Average number of vehicles
0	295.0	287.0	301.6	4	493.1	481.2	500.3	4
0.1	295.0	287.0	301.1	4	494.0	481.2	500.3	4
0.2	295.3	287.0	297.6	4	496.1	490.7	501.0	4
0.3	293.8	287.0	297.6	4	495.4	482.5	509.0	4
0.4	295.3	288.9	300.7	4	502.1	462.9	520.1	4.8
0.5	295.3	287.0	301.1	4	500.4	466.4	526.7	4.5
0.6	290.6	287.0	301.5	4	479.8	463.3	552.7	4.7
0.7	296.3	287.0	304.5	4	440.5	440.5	440.5	5
0.8	307.5	291.3	312.6	4	439.8	439.8	439.8	5
0.9	312.0	300.6	316.9	4	453.9	453.9	453.9	5
1.0	315.6	313.1	326.3	4	453.9	453.9	453.9	5

at various credibility levels. This table confirms the superiority of the developed tabu search algorithm. It is clear that the results obtained by the developed tabu search algorithm are superior to the results obtained by the sweep algorithm in the average values, the best values and the worst values at various credibility levels. As shown in Fig. 2, the differences in the results of the two algorithms are seen more clearly. The best objective value is 287.0. Corresponding to it, the best operational plan is

Vehicle 1 0→3→14→17→6→16→15→13→2→0;
Vehicle 2 0→12→18→0;
Vehicle 3 0→11→19→20→7→0;
Vehicle 4 0→8→5→4→10→1→9→0.

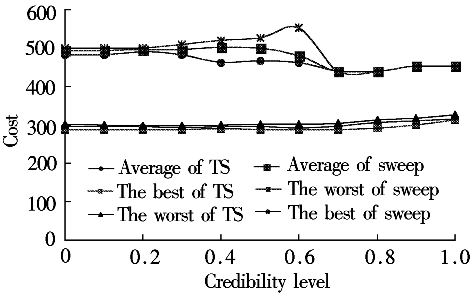

Fig. 2 Curves of comparisons of computational results

Furthermore, when the operational plan is performed, we have

$$\mathrm{Cr}\left(S_k - \sum_{j=1}^{i} (\tilde{d}_j - p_j) y_{jk} \geqslant 0, k \in K; i = 1,2,\ldots,L\right) \geqslant 0.73$$

And the runtime is less than 60 s.

Theoretically speaking, constraint(5) tells us that if the credibility level of the optimal solution is more than $\bar{\alpha}$ or equal to $\bar{\alpha}$, the optimal solution will be searched when the credibility level is set to be $\alpha \leqslant \bar{\alpha}$. The third column of Tab. 2 shows that the best solution is obtained at the credibility level from 0 to 0.7(except for 0.4). Although at the credibility level of 0.2 the best solution is not obtained, objective value (288.9) obtained is close to the best value(287.0). And Fig. 2 shows the stabilization of the solutions obtained by the tabu search algorithm we developed.

Tab. 3 computes respectively transportation costs of forward logistics and those of reverse logistics. Their total costs (503.2) are more than the transportation costs combining forward logistics and reverse logistics(287.0) according to Tab. 2. That is to say, through transportation integrating reverse logistics into forward logistics, transportation costs are reduced by 43%. So transportation integrating reverse logistics into forward logistics is economical.

Tab. 3 Respective transportation costs of forward logistics and reverse logistics

Total costs	Forward logistics		Reverse logistics	
	Cost	Number of vehicles	Cost	Number of vehicles
503.2	276.9	4	226.3	2

5 Conclusion

Multiple vehicle routing problem integrated reverse logistics is studied, in which each client requires either a delivery or a pick-up operation (or both) of a certain amount of goods or waste and the quantity of the delivery of each client is uncertain. Aimed at these features, a multi-objective fuzzy programming model with credibility measure theory is constructed to formulate MVRPRL where the objectives minimize the number of vehicles and the sum of the planned objective values and the failed values. Due to the computation complexity of the problem, the tabu search algorithm combining inter-route and intra-route neighborhoods and embedded restarts is proposed. Computational results show that the best solution and the stabilization of the solution obtained by the tabu search algorithm are obviously superior to the results obtained by the sweep algorithm. And it is necessary that reverse logistics be integrated into forward logistics because the performance can enhance the load ratio of the vehicle and save the cost of transportation.

Further research work may include MVRPRL with other constraints, such as with time windows, or with large scales.

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逆向需求模糊的多车辆集散货物路线问题

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摘要:研究了一类新的车辆路线问题(VRP)——整合逆向物流的多车辆路线问题(MVRPRL). 该问题的特点是客户可以同时取货和发货,而且客户发货量是在路线安排前是不确定的. 首先用三角模糊数表示客户发货量,建立了基于模糊置信度理论的多目标模型;然后设计了基于模拟的改进禁忌算法来求解该模型:用模拟的方法计算路线失败值,在路线搜索中采用路线内部改善和路线间改善两类邻域操作,而且采用了重起策略. 计算结果表明该方法优于传统的扫描算法,整合逆向物流的运输费用比正逆向分别运输之和减少了43%.

关键词:逆向物流;集散一体化;置信度理论;禁忌搜索算法;模糊模拟
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