

A Remanufacturing Logistics Network Model Based on Improved Multi-objective Ant Colony Optimization

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ABSTRACT

This paper attempts to optimize the location selection of processing centers, vehicle routing and carbon emissions in the remanufacturing logistics network. For this purpose, the author developed a novel optimization model to minimize the total cost of remanufacturing logistics, and designed an improved multi-objective ant colony optimization (MACO) algorithm to solve the model. The simulation results show the effectiveness and efficiency of our algorithm in solving the optimization problem. The research findings provide a reference for reducing reverse logistics cost considering environmental factors.

1. INTRODUCTION

With the growing constraints of resources and the environment, remanufacturing logistics has become a major concern in logistics management, especially reverse logistics management. The remanufacturing logistics generally involves the collection, detection, classification, disposal, remanufacturing and redistribution of waste products. This concept covers both the reverse logistics of products from the consumer to the remanufacturer, and the forward logistics of products from the remanufacturer to the seller. The reverse and forward logistical processes constitute a closed-loop logistics system. Compared with the traditional forward logistics, the reverse logistics network faces an immense difficulty in location allocation.

The location allocation problem has been tackled in many studies on the optimization of remanufacturing logistics network. For example, Lee and Dong [1] proposed a two-stage stochastic location model, considering the uncertainties in multi-period reverse logistics network. Alumur et al. [2] explored the multi-cycle static location allocation problem of multi-product recycling network, and suggested to reduce the transport cost by setting up network facilities like recycling centers and remanufacturing factories in the same city. Alshamsi and Diabat [3] constructed a mixed-integer linear model to configure the complex network in the reverse logistics system, aiming to optimize the site selection, the remanufacturing facilities and the capacities of inspection centers. Diabat et al. [4] developed an exact two-phase Lagrangian relaxation algorithm to solve a mixed integer nonlinear location allocation model in reverse supply chain. Radhi and Zhang [5] formulated a mixed integer nonlinear programming model to configure the remanufacturing production network, which takes account of the quality uncertainty, quantity of returns, total spending and transport cost. To minimize the total cost and maximize consumer satisfaction, Afshari et al. [6] proposed a multi-objective

model in integrated forward/reverse streams under uncertainty. To assist with decision-making by managers, Sangwan [7] designed various activities, decision variables and performance indices based on the four activities in reverse logistics. Liao [8] created a hybrid genetic algorithm (GA) to solve a generic mixed integer nonlinear programming model in reverse logistics network. Targeting recycled wood materials, Trochu et al. [9] developed a reverse logistics network model under environmental policies. Zorbakhshnia et al. [10] prepared a mixed integer linear program for green forward and reverse logistics networks.

Recent years saw the rising importance of environmental factors in remanufacturing logistics. Considering carbon emissions in the supply chain network, Elhedhli and Merrick [11] developed a facility location allocation model based on the relationship between carbon emissions and vehicle loads. Focusing on the associated costs of environmental contributions in reverse logistics, Bazan et al. [12] constructed a reverse logistics model covering the energy consumption and greenhouse gas emissions of manufacturing and remanufacturing. Accorsi et al. [13] examined the relationship between carbon emissions and total cost (production cost and logistics cost) in grain supply chain, arising from product transport distance and the agro ecosystem, and developed a mixed linear programming model for facility location allocation based on the relationship between transport distance and carbon emissions. Tornese et al. [14] constructed a linear programming model in light of the relationship between carbon emissions and pallet remanufacturing. Talaei et al. [15] studied the uncertainty of cost and demand based on fuzzy programming, and put forward a double objective mixed integer linear programming model to reduce the total network cost and the CO₂ emissions. John et al. [16] proposed network design model for reverse supply chain, which considers the emissions cost of transport.

Compared with general logistics optimization problems, the remanufacturing logistics optimization faces complicated

environmental factors. However, most studies have neglected the cost of environmental factors resulting from the product fabrication and transport in remanufacturing logistics network. In view of the growing resource and environmental constraints, it is highly reasonable and practical to consider the cost of carbon emissions in the optimization of remanufacturing logistics network. In other words, the remanufacturing logistics network should be optimized from the aspects of both economic and environmental costs.

This paper proposes an optimization model for remanufacturing logistics network, which includes decisions on location allocation, vehicle routing and carbon emissions. The goal is to minimize the total cost in remanufacturing logistics network. Moreover, an improved multi-objective ant colony optimization (MACO) algorithm was developed to optimize the total cost in remanufacturing logistics network. The effectiveness of the MACO was verified through a simulation on waste textile product remanufacturing logistics.

2. MODEL CONSTRUCTION

2.1 Problem description

This paper attempts to develop a remanufacturing logistics network model that optimizes the costs of location allocation, transport and carbon emissions. As shown in Figure 1, the products are transported from recycling centers to processing centers and remanufacturing centers. The three types of centers are linked up by transport vehicles and collection vehicles. The transport vehicles travel between remanufacturing centers and processing centers, while the collection vehicles visit processing centers and recycling centers. The main purpose of the model is select the processing centers and optimize the delivery routes that can optimize the total cost in remanufacturing logistics network.

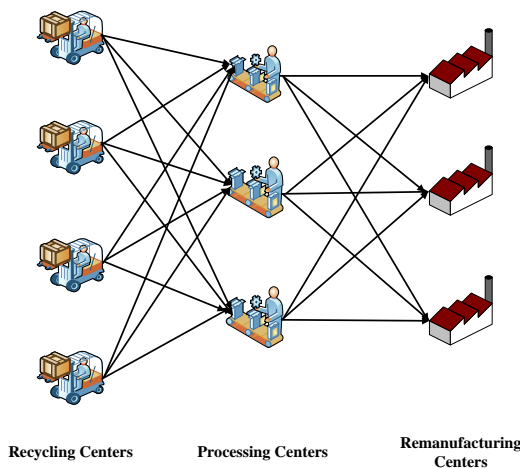


Figure 1. Remanufacturing logistics network

2.2 Assumptions

The following assumptions were put forward before model construction:

- (1) Each recycling center is served by only one collection vehicle.
- (2) Each collection vehicle starts from a processing center, then visits the recycling centers and eventually returns to the starting processing center.

(3) All collection vehicles are of the same type with the same capacity.

(4) All transport vehicles are of the same type with the same capacity.

(5) The capacity of an alternative processing center is limited.

(6) Carbon emissions is taxed at P yuan/t by the government.

2.3 Notations

(1) Sets

R: the set of recycling centers

I: the set of potential processing centers

J: the set of remanufacturing centers

K: the set of collection vehicles

G: the set of transport vehicles

(2) Parameters

BC_i: Construction cost of potential processing center i in a period

AC_r: Unit variable cost of recycling center r

Q_{ri}: Transport quantity from recycling center r to processing center i

C_w: Transport cost of collection vehicle per unit distance

C_u: Transport cost of transport vehicle per unit distance

D_{ri}: Transport distance from node r to node i

D_{ij}: Transport distance from node i to node j

λ_i: Carbon emissions coefficient of processing center i

β_i: Carbon emissions coefficient per unit distance from recycling centers to processing center i

Q_{ij}: Transport quantity from processing center i to remanufacturing center j

Q_k: Maximum capacity of collection vehicle k

Q_g: Maximum capacity of transport vehicle g

Q_r: Quantity of recycled products by recycling center r in a period

Q_i: Quantity of processed products by processing center i in a period

M_i: Maximum processing capacity of processing center i

p: Tax rate of carbon emissions

(3) Decision variables

$$X_i = \begin{cases} 1 & \text{If } i \text{ was chosen to be processing center } i \in B \\ 0 & \text{or else} \end{cases}$$

$$Y_{ri}^k = \begin{cases} 1 & \text{If collection vehicle } k \text{ travels from node } r \text{ to } i \\ 0 & \text{or else} \end{cases} \\ r \in A, i \in B, k \in D$$

$$Y_{ij}^g = \begin{cases} 1 & \text{If transport vehicle } g \text{ travels from node } i \text{ to } j \\ 0 & \text{or else} \end{cases} \\ i \in B, j \in C, g \in E$$

$$X_{ri} = \begin{cases} 1 & \text{If products of recycling center } r \text{ are} \\ 0 & \text{processed by processing center } i \\ & \text{or else} \end{cases} \\ r \in A, i \in B$$

2.4 Mathematical model

$$\min Z_1 = \sum_{i \in I} X_i BC_i + \sum_{r \in R} \sum_{i \in I} AC_r Q_{ri} X_i \quad (1) \\ + \sum_{k \in K} \sum_{r \in (R \cup I)} \sum_{i \in (R \cup I)} C_w D_{ri} Q_{ri} Y_{ri}^k + \sum_{g \in G} \sum_{i \in (I \cup J)} \sum_{j \in (I \cup J)} C_u D_{ij} Q_{ij} Y_{ij}^g$$

$$\min Z_2 = p \left(\begin{aligned} & \sum_{i \in I} \lambda_i X_i + \sum_{k \in K} \sum_{i \in I} \sum_{r \in (R \cup I)} \beta_i Q_{ri} D_{ri} Y_{ri}^k \\ & + \sum_{g \in G} \sum_{i \in (I \cup J)} \sum_{j \in J} \beta_{ij} Q_{ij} D_{ri} j Y_{ij}^g \end{aligned} \right) \quad (2)$$

Subject to:

$$\sum_{r \in (R \cup I)} \sum_{i \in (R \cup I)} Q_r Y_{ri}^k \leq Q_k \quad (3)$$

$$\sum_{i \in (I \cup J)} \sum_{j \in (I \cup J)} Q_i Y_{ij}^g \leq Q_g \quad (4)$$

$$\sum_{r \in R} \sum_{k \in K} Y_{ri}^k Q_{ri} \leq M_i \quad (5)$$

$$\sum_{i \in I} X_{ri} = 1, r \in R \quad (6)$$

$$\sum_{r \in (R \cup I)} Y_{rm}^k - \sum_{i \in (R \cup I)} Y_{mi}^k = 0, k \in K, m \in (R \cup I) \quad (7)$$

$$\sum_{i \in I} \sum_{r \in R} Y_{ir}^k \leq 1, k \in K \quad (8)$$

$$\sum_{k \in K} \sum_{r \in R} Y_{ri}^k - X_i \leq 0, i \in I \quad (9)$$

$$\sum_{k \in K} \sum_{r \in (R \cup I)} Y_{ri}^k = 1, i \in (R \cup I) \quad (10)$$

$$X_{ri} = \{0,1\}, \forall i \in (R \cup I), r \in (R \cup I) \quad (11)$$

$$Y_{ri}^k = \{0,1\}, \forall i \in (R \cup I), i \in (R \cup I), k \in K \quad (12)$$

$$Y_{ij}^g = \{0,1\}, \forall i \in (I \cup J), j \in (I \cup J), g \in G \quad (13)$$

$$X_i = \{0,1\}, \forall i \in I \quad (14)$$

Eq. (1) sets out the optimization objectives like the costs of location allocation, operation and transport. Eq. (2) defines the optimization objective of the carbon emissions cost in the remanufacturing logistics network. Constraints (3) and (4) specify the maximum capacities of collection vehicle and transport vehicle, respectively. Constraint (5) imposes the capacity limit on processing centers. Constraint (6) requires that each recycling center can only be served by one processing center. Constraint (7) assures that transport routes are continuous. Constraint (8) illustrates that each collection vehicle should only pass through one processing center. Constraint (9) stipulates that potential processing centers can be built when selected. Constraint (10) demands that each collection vehicle serves only one recycling center. Constraints (11)~(14) define the possible values.

3. AN IMPROVED MACO

The ant colony optimization (ACO) was improved to solve the discrete optimization problem of our remanufacturing logistics network. The ACO mimics the foraging behavior of ant colonies to find the optimal path based on shared special information. In the ACO, the ants in a colony can memorize

the shared information on each path and provide feedbacks about the correctness of the path. The path which has been repeatedly proved correct will attract more ants. In this way, more and more ants will make the optimal decision on path selection. However, the path selection may not output the optimal result due to the lack of pheromone, which slows down the convergence and even enters the local optimum trap. In this paper, the MACO is developed by integrating the ACO and the GA, aiming to optimize the remanufacturing logistics network more effectively.

3.1 MACO encoding

In the MACO, individual chromosomes are generated randomly through real number encoding. The chromosomes can be expressed as a n-dimensional vector $[m_1, m_2, \dots, m_n]$, $m_i \in \{1, 2, \dots, n\}$. Each m_i corresponds to a recycling center. Each collection vehicle starts from the alternative processing center 0. When the transport quantity exceeds its maximum capacity, the collection vehicle returns to the processing center 0, thus creating a path. Next, the collection vehicle leaves the alternative processing center 0 and arrives at the next recycling center. The above steps are repeated until the vehicle has traversed all recycling centers in all n-dimensional vectors.

3.2 State transition rule

The probability of node selection for each ant k moving from node i to node j can be expressed as:

$$p_k(i, j) = \begin{cases} \frac{[\sum_{m=1}^M w_m \tau_k^m(i, j)]^\alpha \eta_j^\beta}{\sum_{h \in L_k(i)} ([\sum_{m=1}^M w_m \tau_k^m(i, j)]^\alpha \eta_j^\beta)}, & q > q_0 \\ \arg \max_{j \in L_k(i)} \{ [\sum_{m=1}^M w_m \tau_k^m(i, j)]^\alpha \eta_j^\beta \}, & q \leq q_0 \end{cases} \quad (15)$$

where, w_m is the weight of M objectives in the initial phase; $\tau(i, j) = \sum_{m=1}^M w_m \tau_k^m(i, j)$ is the pheromone vector; q_0 is a random variable uniformly distributed in $[0, 1]$; η_j is the visibility factor; α is the cumulative pheromone released by individual ants in the colony; β represents relative importance of other shared information for path selection.

3.3 Pheromone update

If ant k decides to move to node j from node i, the pheromone of path (i, j) will be reduced to increase the probability for ants to choose other nodes. The pheromone intensity is updated by:

$$\tau^m(i, j) = (1 - \zeta) \tau^m(i, j) + \zeta \Delta \tau^m(i, j) \quad (16)$$

where ζ is a constant ($0 < \zeta < 1$); $(1 - \zeta) \tau^m(i, j)$ is the volatilization of representative pheromones; Q_m represents the size of the pheromone; F_m is the value of the m-th objective function.

3.4 Crossover operation

Based on the crossover rules in the ACO, the crossover

operator A was selected to perform the crossover of chromosomes in our problem. Firstly, two parent chromosomes were randomly selected. Then, two points were identified randomly in each parent chromosome. After that, the two parent chromosome swapped the segment between the two points.

To sum up, the AMCO can be implemented in the following steps:

Step 1: Initialize the parameters and place m ants on n alternative processing centers.

Step 2: Each ant k ($k=1, 2, \dots, m$) moves to the next point j according to Eq. (15). When the ant chooses all the nodes, an individual chromosome is generated. The chromosomes thus generated form the initial population.

Step 3: Calculate the m objective function values of each ant, and update the pareto frontier and Pareto optimal solution set.

Step 4: Perform crossover using the crossover operator A, and then conduct the mutation operation.

Step 5: Update the pheromone according to Equation (16).

Step 6: If the current number of iterations is smaller than the maximum number of iterations, return to Step 2.

Step 7: Terminate the algorithm.

4. SIMULATION ANALYSIS

The MACO was verified through a simulation on textile product remanufacturing logistics. Specifically, 23 large cities were selected from Guangdong Province, China, and the distances between them were obtained from Google Maps. The cities as potential processing centers were numbered by 1

to 5, the cities as recycling centers are numbered by 6 to 20, and the cities as remanufacturing centers are numbered by 21 to 23. The parameters were set as: $\alpha=1$, $\beta=5$, $\rho=0.1$, $\zeta=0.4$, $q_0=0.7$, the maximum number of iterations of 150, the crossover rate of 0.9 and the mutation rate of 0.1. The other parameters are listed in Table 1 below. The simulation results are recorded in Table 2. Three processing centers were selected and five distribution routes were taken as the best routes to optimize the total cost.

Furthermore, the performance of the MACO was compared with that of the ACO and the GA. The ACO parameters were configured as $\alpha=1$, $\beta=5$, $\rho=0.2$, $\zeta=0.3$, $q_0=0.8$, and the maximum number of iterations of 150. The GA parameters were configured as: the population size of 100, the crossover rate of 0.9, the mutation rate of 0.1 and the maximum number of iterations of 150. The convergence curves of the three algorithms are plotted as Figure 2. It can be seen that the optimal value of the MACO was smaller than that of the GA and that of the ACO. Moreover, the MACO only took 41 iterations to converge to the optimal value, while the GA and ACO respectively took 86 and 75 iterations. To sum up, the MACO outperformed the other two algorithms in finding the optimal solution to remanufacturing logistics network.

Table 1. Parameter setting

Parameter	Value	Parameter	Value
AC_r	350	β_i	U (0.03,0.1)
C_w	0.3	Q_k	2000
C_u	0.35	Q_g	2300
λ_i	U (730,810)	p	0.02

Table 2. Simulation results

Selected processing center	Distribution route	Location cost	Operating costs	Transportation cost	carbon emissions (kg)	Total cost
1	1-11-17-20-16-1 1-14-15-1	17900	1032500	327400	41150	1378623
2	2-9-6-7-2 2-8-10-12-2	19500	1172500	368990	38110	1561752
4	4-19-13-18-4	23000	892500	177165	4554	1092756

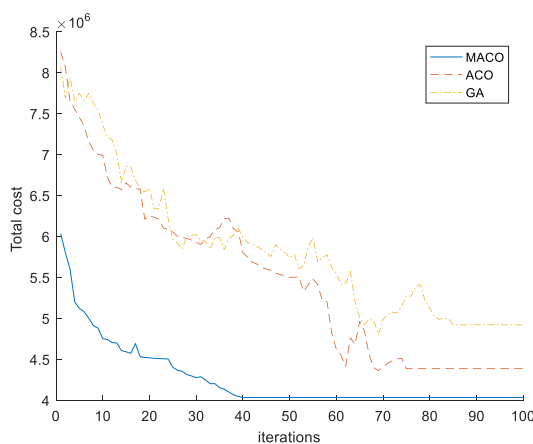


Figure 2. Comparison of convergence curves

5. CONCLUSIONS

This paper proposes an improved MACO for

remnufacturing logistics network. Through the integration between the ACO with the GA, the MACO enhances the uniformity of individual distribution and jumps out of the local optimum trap. The simulation results show that three processing centers were selected with five best distribution routes according to the MACO. The comparison with the ACO and the GA indicates that our algorithm is an effective way to optimize the remanufacturing logistics network.

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