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Research Article

A Two-Stage Algorithm for the Closed-Loop Location-Inventory Problem Model Considering Returns in E-Commerce

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Facility location and inventory control are critical and highly related problems in the design of logistics system for e-commerce. Meanwhile, the return ratio in Internet sales was significantly higher than in the traditional business. Focusing on the existing problem in e-commerce logistics system, we formulate a closed-loop location-inventory problem model considering returned merchandise to minimize the total cost which is produced in both forward and reverse logistics networks. To solve this nonlinear mixed programming model, an effective two-stage heuristic algorithm named LRCAC is designed by combining Lagrangian relaxation with ant colony algorithm (AC). Results of numerical examples show that LRCAC outperforms ant colony algorithm (AC) on optimal solution and computing stability. The proposed model is able to help managers make the right decisions under e-commerce environment.

1. Introduction

The increasing progress of information and prevalence of internet in the 21st century has forced the e-commerce to develop in a world-wide range. In 2012, B2C e-commerce sales grew 21.1% to top $1 trillion for the first time in history in the whole world [1]. Comparing with traditional commerce, customers are more liable to return goods under e-commerce environment. Note that many customer returns online account for 35% of original orders [2, 3]. Therefore, logistics systems as an important support system in e-commerce need to be adjusted and improved. To adapt to the reality of e-commerce market environment, it is critical to conduct the research on the reverse logistics network and highly integrated logistics process.

Facility location and inventory control are critical problems in the design of logistics system. There is much previous work in these two areas. In fact, there is a mutually dependent relationship among these problems in logistics system. Comprehensive optimizing and logistics activities management should be based on this relationship [4]. According to this idea, besides location allocation problem and inventory optimization, the location-inventory problem (LIP) starts to be researched.

Many papers about the LIP are studied deeply and have made some abundant achievements. In recent years, intelligent algorithms and heuristic algorithm have been used to solve LIP model [5–7]. In the reverse logistics research field, LIP attracts researchers' attention. Lieckens and Vandaele [8] applied a queuing mode in reverse logistics network to solve the facility location problem while considering the impact of inventory costs. Srivastava [9] established a reverse logistics network optimization model to optimize the location-allocation problem and capacity decisions, and he used heuristic algorithm to solve the model. Wang et al. [10] proposed a location-inventory policy in Chinese B2C electronic market as a bilevel programming model. Tancrez et al. [11] studied the LIP in three-level supply chain networks including reverse logistics; they developed an iterative heuristics approach to solve the model. Diabat et al. [12] built a mixed integer nonlinear programming (MINLP) model to minimize the total reverse logistics cost by finding out the number and location of initial collection point and centralized return center considering the inventory cost. Two solution approaches, namely, genetic algorithm (GA) and artificial immune system, are implemented and compared. However, research on the LIP of closed-loop logistics system

is limited. Sahyouni et al. [13] designed three generic facility location models that account for the integrated distribution and collection of products in the closed-loop supply chain networks; the authors described a Lagrangian relaxation-based solution algorithm to solve the models. Easwaran and Üster [14] offered a mixed integer linear programming model to optimize the total cost that consists of location, processing, and transportation costs of the multimerchandise in closed-loop supply chains; they introduced a heuristics solution approach that combines Benders decomposition and tabu search to solve the model. Abdallah et al. [15] presented the uncapacitated closed-loop location-inventory model; a sensitivity analysis for different parameters of the model reveals that the value of recovered products is a major factor in the economic feasibility of the closed-loop network. For dealing with returned merchandise without quality problems in e-commerce, Li et al. [16] developed a practical LIP model with considering the vehicle routing under e-supply chain environment and provided a new hybrid heuristic algorithm to solve this model.

Previous researches on the closed-loop logistics system optimization mainly focus on the minimization of the total cost of the network. To our best knowledge, few researches on manufacturing/remanufacturing system consider returns and concept of green logistics recycling in logistics network. Since customers may be dissatisfied with merchandise and return it, the cost of processing returns, the cost of inventory and shipping, order time, and size are changed. Furthermore, research on the LIP with return of closed-loop logistics system is limited.

The aim of this study is to develop a practical LIP model with the consideration of returns in e-commerce and provide a new two-stage heuristics algorithm. To our best knowledge, this work is the first step to introduce returns into the LIP in e-commerce, which makes it become more practical. We also provide an effective algorithm named Lagrangian relaxation combined with ant colony algorithm (LRCAC) to solve this model. Lagrangian relaxation algorithm (LR) can obtain a near-optimal solution by analyzing the upper bound and lower bound of objective function. But its effectiveness mainly relies on the performance of subgradient optimization algorithm. On the other hand, AC has great ability of local searching. If there is an appropriate initial solution, the performance of AC will be good. To adopt their strong points while overcoming their weak points, we combine the two algorithms. Results of numerical examples show that LRCAC outperforms ant colony algorithm (AC) on optimal solution and computing stability.

The remainder of the paper is structured as follows. In Section 2, a nonlinear integrated programming model about LIP considering returns in e-commerce is designed. Section 3 proposes the heuristic algorithm named LRCAC based on Lagrangian relaxation and ant colony algorithm. Section 4 shows and analyzes the results of different experiments. Section 5 concludes this paper and discusses the future research directions.

2. Problem and Mathematic Model

2.1. Problem Description. In e-commerce, some returned merchandise has a high integrity, which makes it usually not in need of being repaired and can reenter the sales channels after simply repackaging [17]. Some returned goods have quality problems; they have to be sent back to factory for repair. Therefore, we merge the recycling center with distribution center as merchandise centers (MCs) with an additional inspection function. MC is responsible for distributing normal goods to the sale regions; meanwhile the returned goods are collected to MCs. After inspecting at MCs, the returned goods with quality problems are sent back to factory, and the other returned goods are resalable as normal goods after simply repackaging. Customers can choose to return goods in e-commerce, and quantity of the returns is uncertain [18]. However, for a certain sale region (SR), the quantity of the returns can be usually seen as stochastic variable.

The objective of this paper is to determine the quantity, locations, order times, and order size of MCs in the closed-loop logistics network in e-commerce. The final target is to minimize the total cost and improve the efficiency of logistics operations. The involved decisions are as follows: (1) location decisions, the optimal number of MCs, and their locations; (2) allocation decisions, the corresponding service relationship between MCs, and sale regions; (3) inventory decisions, the optimal order times, and order size.

2.2. Assumptions. (1) There is a single type of merchandise; (2) the capability of factory is unlimited; (3) the capability of MCs is unlimited; (4) the demand and return of each sale region comply with the normal distribution, whose parameters are fixed; (5) the demands of regions are mutually independent; (6) returned merchandise is inspected and repackaged at MCs.

2.3. Notations

Sets

I: Set of SR;

J: Set of candidate MC.

Constants

f_j: Fixed cost (annual) administrative and operational cost of MC_j;

t_j: Shipping cost per unit of merchandise between factory and MC_j;

c_{ij}: The delivering cost per unit of merchandise between SR_i and MC_j;

h_j: The inventory holding cost per unit of merchandise per year at MC_j;

p_j: Ordering cost per time at MC_j;

l_j: Lead time at MC_j;

μ_i: Mean of annual demand at SR_i;

σ_i^2: Variance of annual demand at SR_i;

z_{α_j}: Standard normal deviate such that $p(z \le z_{\alpha_j}) = \alpha_j$;

α_j: Service level of MC_j;

r_i: The quantity of return at SR_i;

w: The probability of quality problem product in return goods;

d: Repacking cost per unit returned merchandise.

Decision Variables

X_j: 1, if the candidate MC_j is selected as a MC and 0 otherwise;

Y_{ij}: 1, if SR_i is served by MC_j and 0 otherwise;

Q_j: Optimal order size at MC_j;

N_j: Optimal order times at MC_j.

2.4. Model Formula

(1) Location Cost. The construction cost of MC_j is given by $\sum_{j=1}^{n} f_j X_j$.

(2) Inventory Cost. The total annual inventory cost consists of ordering cost and inventory holding cost, according to literatures [19, 20]; it is given by $p_j N_j + h_j(D_j/2N_j)$.

(3) Safety Stock Cost. The demand in the lead time l_j at MC_j is $\sqrt{l_j \sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}}$, so the safety stock is $z_{\alpha_j}\sqrt{l_j \sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}}$, and the safety stock cost is given by $h_j z_{\alpha_j}\sqrt{l_j \sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}}$.

(4) Transportation Cost. The transportation cost consists of cost from factory to MC, cost from MC to customer region for forward logistics, cost from customer region to MC, and cost from MC to factory for reverse logistics. So, the transportation cost is given by $\sum_{j\in\mathbf{J}} t_j \sum_{i\in\mathbf{I}}[\mu_i - r_i(1-w)]X_j Y_{ij} + \sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} c_{ij} w r_i X_j + \sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} t_j w r_i X_j + \sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} c_{ij}\mu_i Y_{ij}$.

(5) Repacking Cost. The returned goods without quality problems need to be repacked before reentering to sale channel, so the repacking cost is given by $\sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} d(1-w) r_i Y_{ij}$.

To sum up, the location-inventory model with returned merchandise (RLIP) is

$$\begin{aligned}\min Z = &\sum_{j\in\mathbf{J}}\left(f_j X_j + p_j N_j X_j + h_j \frac{D_j}{2N_j} X_j + h_j z_{\alpha_j}\sqrt{l_j \sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}}\right)\\ &+ \sum_{j\in\mathbf{J}} t_j \sum_{i\in\mathbf{I}} [\mu_i - r_i(1-w)] X_j Y_{ij} + \sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} c_{ij} w r_i X_j + \sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} t_j w r_i X_j\\ &+ \sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} c_{ij}\mu_i Y_{ij} + \sum_{j\in\mathbf{J}}\sum_{i\in\mathbf{I}} d(1-w) r_i Y_{ij},\end{aligned} \tag{1}$$

s.t.

$$\sum_{j\in\mathbf{J}} Y_{ij} = 1, \quad i \in \mathbf{I}, \tag{2}$$

$$Y_{ij} - X_j \le 0, \quad i \in \mathbf{I},\ j \in \mathbf{J}, \tag{3}$$

$$X_j = \{0, 1\}, \quad j \in \mathbf{J}, \tag{4}$$

$$Y_{ij} = \{0, 1\}, \quad i \in \mathbf{I},\ j \in \mathbf{J}, \tag{5}$$

$$N_j \ge 0, \quad j \in \mathbf{J}, \tag{6}$$

$$Q_j \ge 0, \quad j \in \mathbf{J}. \tag{7}$$

The objective function (1) is to minimize the system's total cost. Constraint (2) ensures that each sale region must be assigned to a MC. Constraint (3) stipulates that the assignment can only be made to the selected MC. Constraints (4) and (5) are standard integrality constraints. Constraints (6) and (7) are nonnegative constraints.

3. Solution Approach

On the one hand, Lagrangian relaxation algorithm (LR) is used to solve the complex optimization problem very often. It can obtain a near-optimal solution by analyzing the upper bound and lower bound of objective function. But its effectiveness mainly relies on the performance of subgradient optimization algorithm. The speed of convergence becomes more and more slow with the increasing of the number of iterations. On the other hand, AC has great ability of local searching. If there is an appropriate initial solution, the performance of AC will be good. To adopt their strong points while overcoming their weak points, we design a two-stage algorithm. In the first stage, we use LR algorithm to get a near-optimum solution. In the second stage, let the solution obtained from the first stage be the initial solution; we use AC to further improve it.

The abstract idea of solution approach is described as follows. Firstly, we give the formula for solving optimal order quantity Q_j and optimal order times N_j, which also rely on the decision variables X_j and Y_{ij}. Secondly, we use LR algorithm to get a near-optimal solution by computing the lower bound and upper bound of objective function. Then, let the near-optimum solution obtained from LR be the initial solution; we use AC to further improve it.

3.1. Finding the Optimal Order Quantity and Optimal Order Times. In the model (1)–(7), the decision variable N_j only has appeared in the objective function. Also, the objective function is convex for $N_j > 0$. Consequently, we can obtain the optimal value of N_j by taking the derivative of the objective function with respect to N_j as $N_j = \sqrt{h_j D_j / 2p_j} X_j$, where $D_j = \sum_{i\in\mathbf{I}}[\mu_i - r_i(1-w)]Y_{ij}$.

As we know the optimal order quantity $Q_j = D_j/N_j$, so there is

$$Q_j = \frac{D_j}{N_j} = \frac{D_j}{\sqrt{h_j D_j/2p_j}} = \sqrt{\frac{2p_j D_j}{h_j}} = \sqrt{\frac{2p_j \sum_{i\in\mathbf{I}} [\mu_i - r_i(1-w)] Y_{ij}}{h_j}}. \tag{8}$$

3.2. Transforming the Objective Function. In order to apply the LR algorithm, we transform the objective function as linear teams and nonlinear teams separately. The objective function can be rearranged as follows:

$$\begin{aligned}\min Z = &\sum_{j\in\mathbf{J}} \left[f_j + (t_j + c_{ij}) \sum_{i\in\mathbf{I}} wr_i \right] X_j \\ &+ \sum_{j\in\mathbf{J}} \left(p_j N_j + h_j \frac{D_j}{2N_j} \right) X_j \\ &+ \sum_{j\in\mathbf{J}} \sum_{i\in\mathbf{I}} \left[c_{ij}\mu_i + d(1-w) r_i \right. \\ &\qquad \left. + t_j\mu_i - t_j r_i (1-w) \right] Y_{ij} \\ &+ \sum_{j\in\mathbf{J}} h_j z_{\alpha_j} \sqrt{l_j} \sqrt{\sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}} \\ = &\sum_{j\in\mathbf{J}} \left(f'_j X_j + \sum_{i\in\mathbf{I}} c'_{ij} Y_{ij} + h'_j X_j + \pi_j \sqrt{\sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}} \right),\end{aligned} \tag{9}$$

where $f'_j = f_j + (t_j + c_{ij}) \sum_{i\in\mathbf{I}} wr_i$, $c'_{ij} = c_{ij}\mu_i + d(1-w)r_i + t_j\mu_i - t_j r_i(1-w)$, $h'_j = p_j N_j + h_j(D_j/2N_j)$, and $\pi_j = h_j z_{\alpha_j}\sqrt{l_j}$.

3.3. Lagrangian Relaxation

3.3.1. Finding a Lower Bound. To solve this problem, we intend to use Lagrangian relaxation embedded in branch and bound. In particular, we relax constraint (2) to obtain the following Lagrangian dual problem:

$$\begin{aligned}\max_{\lambda} \min_{Z} \longrightarrow &\sum_{j\in\mathbf{J}} \left(f'_j X_j + \sum_{i\in\mathbf{I}} c'_{ij} Y_{ij} + h'_j X_j \right. \\ &\qquad \left. + \pi_j \sqrt{\sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}} \right) + \lambda_i \sum_{i\in\mathbf{I}} \left(1 - \sum_{j\in\mathbf{J}} Y_{ij} \right) \\ = &\sum_{j=1}^{n} \left(f'_j X_j + \sum_{i\in\mathbf{I}} (c'_{ij} - \lambda_i) Y_{ij} \right. \\ &\qquad \left. + h'_j X_j + \pi_j \sqrt{\sum_{i\in\mathbf{I}} \sigma_i^2 Y_{ij}} \right) + \sum_{i\in\mathbf{I}} \lambda_i \\ \text{s.t. } &(3) - (7).\end{aligned} \tag{10}$$

For fixed values of the Lagrange multipliers λ_i, we want to minimize (10) over the location variables X_j and the assignment variables Y_{ij}. We separate the linear teams and nonlinear teams.

(1) For each MC_j, let $V_j = f'_j + \sum_{i\in I} \min(0, c'_{ij} - \lambda_i) + h'_j$, and let

$$X_j = \begin{cases} 1 & V_j \le 0 \\ 0 & V_j > 0. \end{cases} \tag{11}$$

If all V_j values are positive, we identify the smallest positive V_j and set the corresponding $X_j = 1$. The assignment variables are then easy to determine, setting as follows:

$$Y_{ij} = \begin{cases} 1 & X_j = 1,\ c'_{ij} - \lambda_i \le 0 \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

(2) However, the presence of the nonlinear terms makes finding an appropriate value of V_j difficult. So, we need to solve a subproblem as the following form for each candidate MC_j:

$$\begin{aligned}\mathrm{SP}(j) : V'_j = \min \quad &\sum_{i\in\mathbf{I}} b_i Z_i + \sqrt{\sum_{i\in\mathbf{I}} \varphi_i Z_i} \\ \text{s.t.} \quad &Z_i \in \{0,1\}, \quad i \in \mathbf{I},\end{aligned} \tag{13}$$

where $b_i = c'_{ij} - \lambda_i$, $\varphi_i = \pi_j^2 \sigma_i^2 \ge 0$.

In (13), we use Z_i to substitute Y_{ij}.

The solution of subproblem $\mathrm{SP}(j)$ refers to literature [19]; the solution of (10) is the summary of $\mathrm{SP}(j)$ and f'_j. To get the lower bound, we need to find the optimal Lagrange multipliers. We do so using a standard subgradient optimization procedure as illustrated in literatures [21, 22]. The optimal value of (10) is a lower bound of the objective function (1).

3.3.2. Finding an Upper Bound. We find an upper bound as follows.

We initially fix the MC locations at those sites for which $X_j = 1$ in the current Lagrangian solution. Then we assign SR to MCs in a two-phased process.

Step 1. For each SR_i, for which $\sum_{j\in\mathbf{J}} Y_{ij} \ge 1$, we assign the SR_i to the MC_j for which $Y_{ij} = 1$ and that increases the least cost based on the assignments made so far.

Step 2. We process SR_i, for which $\sum_{j\in\mathbf{J}} Y_{ij} = 0$; we assign each SR to the open MC which increases the least total cost based on the assignments made so far.

Hence, for these SRs, we consider all possible assignments to open MCs, and the cost of this stage is the upper bound.

3.4. Ant Colony Clustering. According to the clustering behavior of ant colony, we set the clustering probability $p_{ij}^k(t)$

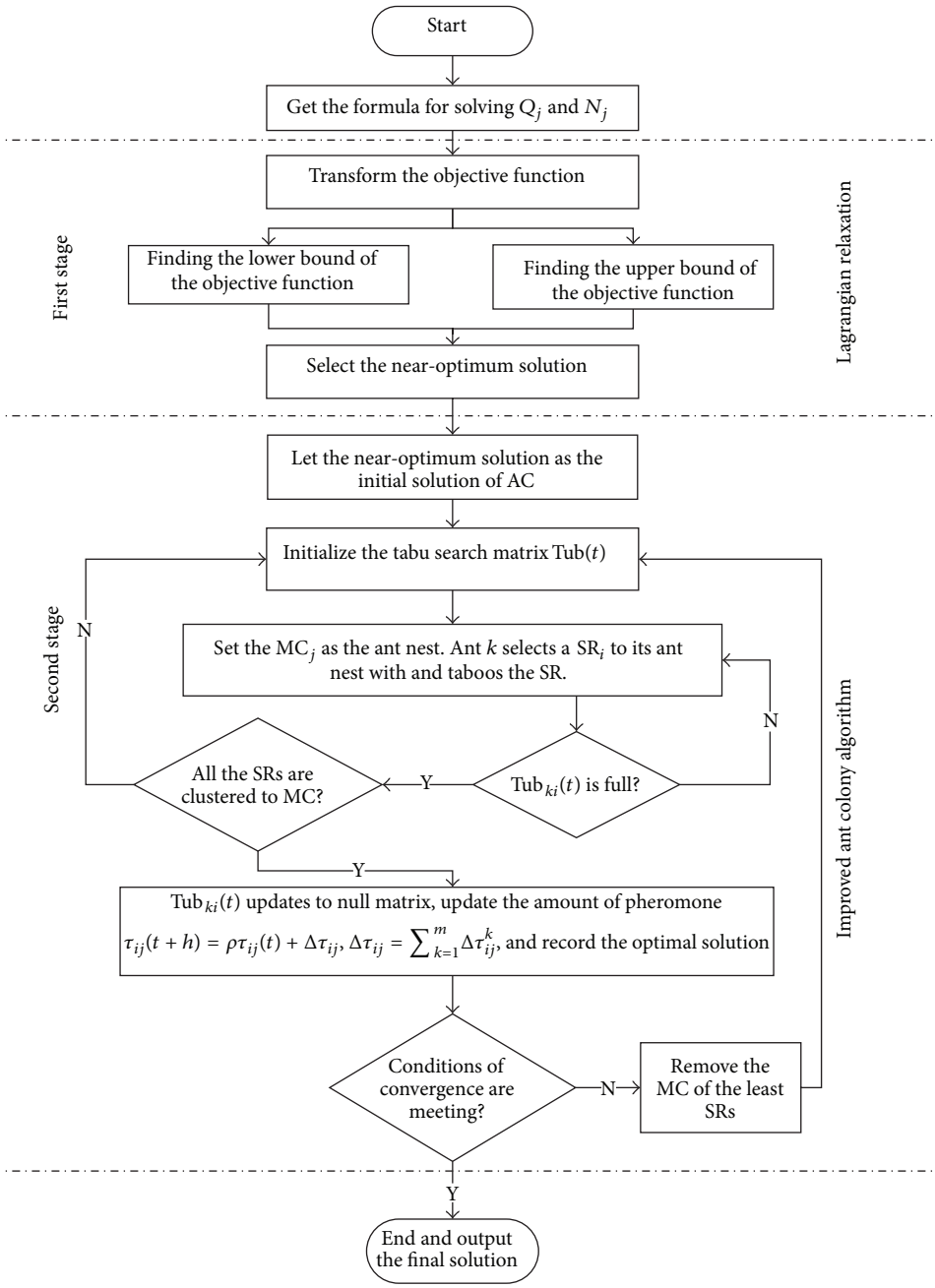

FIGURE 1: The working process of the integral two-stage algorithm.

to represent the probability of the SR_i and clustering center j at time t. The formula of $p_{ij}^{k}(t)$ is shown as follows:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{\mathrm{Tub}_{ks}(t)=0} \tau_{is}^{\alpha}\eta_{sj}^{\beta}}, & \mathrm{Tub}_{kj}(t) = 0; \\ 0, & \text{otherwise}, \end{cases} \tag{14}$$

where $\mathrm{Tub}_{kj}(t) = 0$ represents that ant k can cluster SR_i in next step; τ_{ij}^{α} is the amount of pheromone deposited for transition from state i to j; α is the parameter used to control the influence of τ_{ij}^{α}; η_{ij}^{β} is the desirability of state transition i and j; β is the parameter of controlling the influence of η_{ij}^{β}; d_{ij} is the distance from i to j.

And the following relationship exists:

$$\eta_{ij} = \begin{cases} \dfrac{1}{d_{ij}}, & \text{if } d_{ij} \neq 0, \\ 1, & \text{if } d_{ij} = 0. \end{cases} \tag{15}$$

Table 1: Parameters of MCs.

MC	Coordinate (km)	Fixed construction cost (Yuan)
Wuhan (j_1)	(3342, 38529)	50
Xiangyang (j_2)	(3322, 37609)	45
Xiaogan (j_3)	(3533, 38491)	40
Yichang (j_4)	(3397, 37528)	45
Jingzhou (j_5)	(3356, 37619)	40
Huanggang (j_6)	(3369, 38583)	35

Table 2: Parameters of SRs.

SR	Coordinate (km)	Demand (unit)
Wuhan (i_1)	(3342, 38529)	673
Xiangyang (i_2)	(3322, 37609)	514
Xiaogan (i_3)	(3533, 38491)	500
Yichang (i_4)	(3397, 37528)	465
Jingzhou (i_5)	(3356, 37619)	520
Huanggang (i_6)	(3369, 38583)	440
Huangshi (i_7)	(3342, 38604)	360
Shiyan (i_8)	(3614, 37480)	400
Suizhou (i_9)	(3468, 38361)	350
Xianning (i_{10})	(3305, 38527)	400
Enshi (i_{11})	(3271, 37357)	410
Jingmen (i_{12})	(3433, 37613)	510
Ezhou (i_{13})	(3362, 38583)	400

Table 3: Optimal results.

Number of MCs	N (unit)	Q (unit)	The SRs assigned to MC
j_1	2	1410	$i_1, i_3, i_6, i_7, i_{10}, i_{13}$
j_2	2	930	i_2, i_8, i_9
j_4	2	642	i_4, i_{11}
j_5	4	776	i_5, i_{12}

3.5. Algorithm Step. The integral two-stagealgorithm steps are shown below.

Step 0. We give the formula for solving Q_j and N_j, which also rely on the decision variables X_j and Y_{ij};

First Stage

Step 1. Transform the objective function as linear teams and nonlinear teams separately.

Step 2. Find the lower bound of objective function by using the LR.

Step 3. Find the upper bound of objective function by using the LR.

Step 4. Select the solution whose value is equal or approximately equal to the average value of the lower bound and upper bound as near-optimum solution.

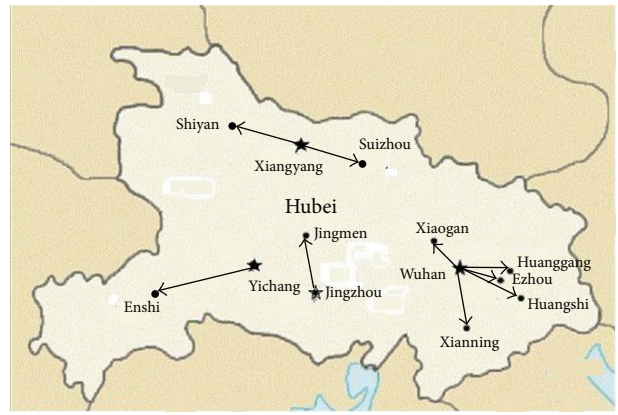

Figure 2: The logistics network obtained by LRCAC.

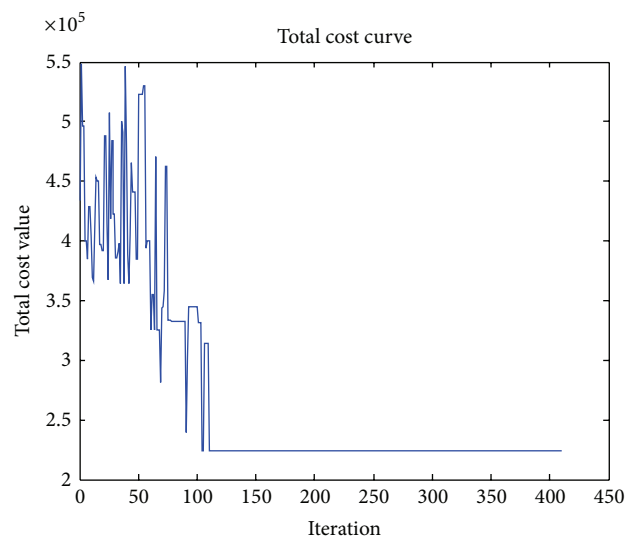

Figure 3: Trends of optimal objective function value by LRCAC.

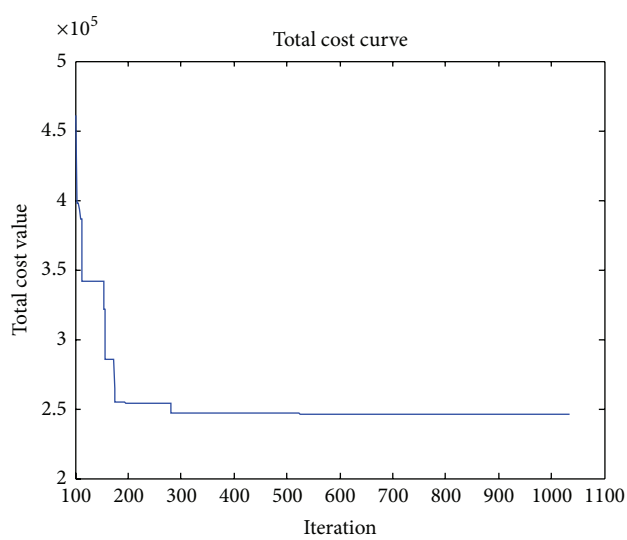

Figure 4: Trends of optimal objective function value by AC.

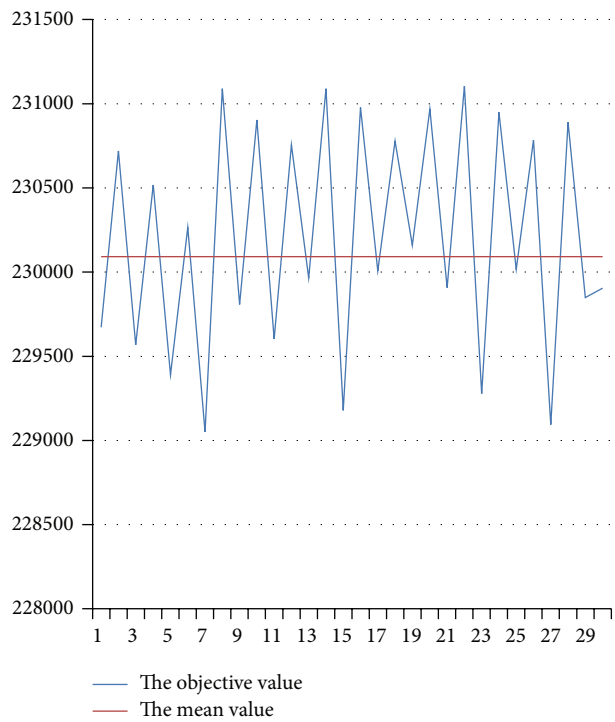

Figure 5: Fluctuation curve of total cost by LRCAC algorithm.

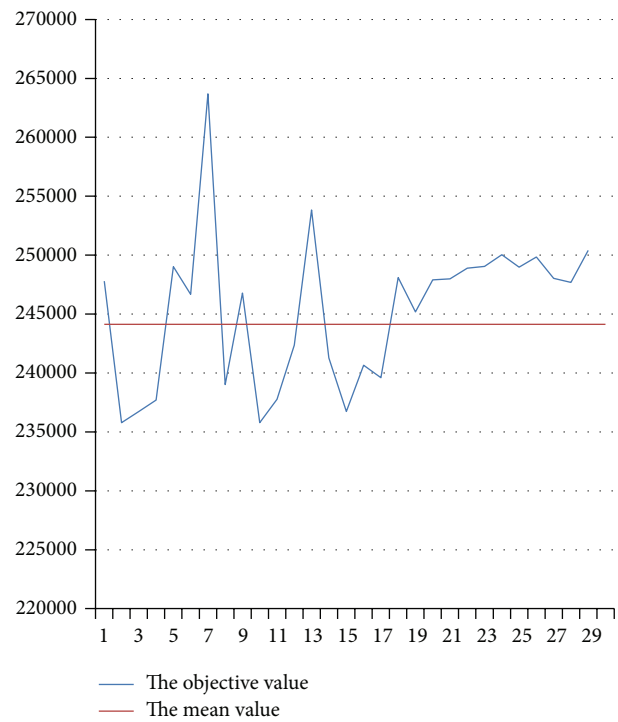

Figure 6: Fluctuation curve of total cost by AC.

Second Stage

Step 5. Let the near-optimum solution be the initial solution of AC.

Step 6. Initialize the tabu search matrix $\mathrm{Tub}(t)$, which is used to record the served SRs in the time $[t, t+1]$. Additionally, the $\mathrm{Tub}(t)$ is a 0-1 matrix, $\mathrm{Tub}_{ki}(t) = 1$, and SR_i is tabooed; $\mathrm{Tub}_{ki}(t) = 0$; SR_i is free.

Step 7. Set the MC_j as the ant nest z_j. Ant k selects a SR_i to its ant nest z_j with $p_{ij}^k(t)$ and taboos the SR. If $\mathrm{Tub}_{ki}(t)$ is full, go to Step 8; else repeat Step 7.

Step 8. If all the SRs are clustered to MC, the $\mathrm{Tub}_{ki}(t)$ updates to null matrix and goes to Step 9; else go to Step 6.

Step 9. Update the amount of pheromone $\tau_{ij}(t+h) = \rho\tau_{ij}(t) + \Delta\tau_{ij}$, $\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k$ and record the optimal solution.

Step 10. If the conditions of convergence are meeting, terminate the procedure and output the optimal solution; else remove the MC of the least SRs and go to Step 6.

The flowchart for our algorithm is shown in Figure 1.

4. Computational Experiments and Algorithm Analysis

4.1. Computational Experiment. We refer to the logistics network of company K in Hubei province of China as an example. We convert the latitude and longitude coordinates of some cities in Hubei province and the central meridian to Xi'an 80 geographic coordinate. They are shown in Tables 1 and 2, in which the values represent the actual kilometers. And other parameters' values are as follows: randomly generate the values between 100 and 160 as the μ_i, and assume that the σ_i^2 is equal to μ_i, $t_j = 1$, $p_j = 2$, $h_j = 1$, $l_j = 7$ (day), $\alpha_j = 97.5\%$, $w = 0.2$, and $d = 2$.

Table 4: Statistical results of optimal objective function value of two algorithms.

	Max	Min	Mean	Standard deviation	Coefficient of variation
AC	263678	235791	244118	135673	0.56
LRCAC	231104	224965	230092	93876	0.41

Based on MATLAB 7.0 platform, we programmed the LRCAC algorithm and run it 30 times on the computer (CPU: Intel Core2 P7570 @2.26 GHz 2.27 GHz; RAM: 2.0 GB; OS: Windows 7); the optimal result is in Table 3.

The optimal cost is 224965 yuan, and logistics network is shown in Figure 2.

For comparison, we programmed AC algorithm in the same platform and run 30 times on the same computer. The optimal objective function values of these two algorithms are shown in Table 4.

The two optimization trends of the two algorithms are shown in Figures 3 and 4.

The fluctuation curves of optimal objective function in 30 times are shown in Figures 5 and 6, respectively.

We can see that the LRCAC algorithm can converge more quickly than AC from Figures 3 and 4. Moreover, LRCAC

Table 5: Optimal objective function values of two algorithms.

Instance	Algorithm	Max	Min	Mean	Standard deviation	Coefficient of variation
Srivastava 86-8×2	AC	402316	336543	365784	196736	0.537847
	LRCAC	355215	306842	335765	158962	0.473432
Perl 183-12×2	AC	598173	528538	563184	257649	0.457486
	LRCAC	553785	498037	528764	149717	0.283145
Christofides 69-50×5	AC	696271	620975	667864	456287	0.683203
	LRCAC	633762	582867	619458	287392	0.4639411
Christofides 69-75×10	AC	890756	821789	867246	564782	0.651236
	LRCAC	843685	783804	810473	395647	0.488168
Daskin 95-88×8	AC	1102873	898483	926586	537862	0.5804771
	LRCAC	921587	873672	896926	407816	0.4546819
Daskin 95-150×10	AC	1516428	1256731	1478356	624638	0.422522
	LRCAC	1258904	1078396	1157832	428373	0.3699785

has better stability than AC, which can be easily found from Table 4 and Figures 5 and 6.

4.2. Algorithms Analysis. In this section, all the data in our experiments come from LRP database of the University of Aveiro [23]. A series of experiments show that LRCAC is more efficient and stable than AC. Results of numerical example in Section 4.1 show that the related parameters of LRCAC are reasonable. Thus, we employ these parameters in the remainder of this section. Each instance was calculated 30 times by LRCAC and AC, respectively; the results are shown in Table 5. In this table, *Srivastava* 86 is the name of this instance; 8×2 means there are 8 SRs and 2 candidate MCs, so do others. The coordinate of all nodes and the demands of SRs are given by the database. Table 5 shows that LRCAC can obtain better objective function value and stability than AC.

5. Conclusion

Customers have a higher return rate in the e-commerce environment. Some returned goods have quality problems and need to be sent back to the factory for repair. The others without quality problems can be reentered in the sales channels just after a simple repackaging process. This phenomenon puts forward high requirements to the logistics system that supports the operation of e-commerce. This study handles the above interesting problem and provides an effective heuristic. The main contributions are as follows.

(1) In reality, the cost of processing returned merchandise is produced by considering the condition that customers are not satisfied with products and return them. We firstly design a closed-loop LIP model to minimize the total cost which is produced in both forward and reverse logistics networks. It is able to help managers make the right decision in e-commerce, decreasing the cost of logistics and improving the operational efficiency of e-commerce.

(2) The above closed-loop LIP model with returns is difficult to be solved by analytical method. Thus, a two-stage heuristic algorithm named LRCAC is designed by integrating Lagrangian relaxation with AC to solve the model.

(3) Results of our experiments show that LRCAC outperforms AC on both optimal solution and computing stability. LRCAC is a good candidate to effectively solve the proposed LIP model with returns.

However, some extensions should be considered in further work. Considering the dynamic of the demand, a dynamic model should be established. Considering the fuzzy demand of customs or related fuzzy costs, more practical LIP model should be developed. Moreover, differential evolution algorithms (DEs) have turned out to be one of the best evolutionary algorithms in a variety of fields [24, 25]. In the future, we may use an improved DE to find better solutions for the LIPs. The integration research and practice of the management of e-commerce logistics system can be constantly improved.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publishing of this paper.

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