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Research Article

Solving a Closed-Loop Location-Inventory-Routing Problem with Mixed Quality Defects Returns in E-Commerce by Hybrid Ant Colony Optimization Algorithm

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This paper presents a closed-loop location-inventory-routing problem model considering both quality defect returns and nondefect returns in e-commerce supply chain system. The objective is to minimize the total cost produced in both forward and reverse logistics networks. We propose a combined optimization algorithm named hybrid ant colony optimization algorithm (HACO) to address this model that is an NP-hard problem. Our experimental results show that the proposed HACO is considerably efficient and effective in solving this model.

1. Introduction

According to eMarketer, worldwide business-to-consumer (B2C) e-commerce sales reached $1.471 trillion in 2014, increasing by nearly 20% over 2013 [1]. Customers have grown accustomed to return unwanted products back to the store for any reasons. It is reported that the proportion of customer returns online range from 18% to 74% of original orders under e-commerce environment [2, 3]; thus enterprises take various measures to prevent the appearance of quality defects. However, quality defect is inevitable. So, it is necessary for us to take into account both quality defect returns and nondefect returns; we call it mixed quality defect returns (MQDR), when considering the closed-loop supply chain as a support system in e-commerce environment.

As a classic discrete dynamics problem, the customer service level is determined by three important decisions: facility location decision, inventory decision, and transportation decision [4]. Obviously, facility location, inventory control, and transportation optimization are highly related. For example, delivery in small lots and high frequency leads to reducing the in-inventory cost but increases the additional transportation cost. In addition, facility location decision needs to consider inventory decision and distribution decision. Perl and Sirisoponsilp [5] discuss the interdependence between the three key elements. Ballou and Masters [6] provide a schematic representation of the interrelationships among facility location, inventory control, and transportation optimization.

In the literature, many papers studied the integration and coordination of any two of the above three decisions: location-inventory problem (LIP), location-routing problem (LRP), and inventory-routing problem (IRP). For reviews on LIP, readers can refer to Erlebacher and Meller [7], Daskin et al. [8, 9], and Liao et al. [10]. For LRP, please refer to Balakrishnan et al. [11], Min et al. [12], and Nagy and Salhi [13]. Refer to Chan et al. [14], Kleywegt et al. [15], and Adelman [16] for IRP.

There are few researches about the integration optimization of location-inventory-routing problem (LIRP). Some researchers attempt to carry out research on LIRP [17]. Liu and Lee [18] firstly studied this interesting problem; they proposed a two-phase heuristic method to solve the multidepot location-routing problem (MDLRP) considering inventory optimization. In order to avoid the local optimal solution, Liu and Lin [19] designed a global optimizing heuristic method to find the solutions for LIRP. Shen and Qi [20] presented an algorithm based on Lagrangian relaxation to minimize the inventory and routing costs in strategic location models. They focused on the layout phase and used continuous approximation to get the approximate optimal routing cost, but the vehicle routing was not optimized in their models. Javid and Azad [21] presented a novel LIRP model and proposed heuristic method containing two stages: constructive stage and improvement stage. Ahmadi-Javid and Seddighi [22] presented a mixed-integer programming model and a three-phase heuristic to solve the LIRP with multisource distribution logistics network. Guerrero et al. [23] researched the LIRP with deterministic demand and provided the hybrid algorithm to solve the problem. Zhang et al. [24] proposed a hybrid metaheuristic solution to LIRP considering multiple depots and geographically dispersed customers. Nekooghadirli et al. [25] presented a novel biobjective model of LIRP model considering a multiperiod and multiproduct system. Based on Lagrangian relaxation and a column generation technique, Guerrero et al. [26] developed a relax-and-price heuristic to solve ILRP; they proposed two dependent constraint sets with an exponential nature: Lagrangian relaxation and a column generation technique.

However, little research has been conducted on the LIRP considering returns. Li et al. [27] presented the HGSAA algorithm to solve a LIRP model considering returns under e-supply chain environment. To be more consistent with reality, Liu et al. [28] introduced a stochastic demand into LIRP considering returns in e-commerce and proposed a PPGASA algorithm as the solving approach.

The above two researches mainly focus on the returns without quality defect but did not consider the MQDR. In this paper, we propose a model of closed-loop LIRP with MQDR. To the best of our knowledge, it is the first time to introduce the MQDR into LIRP in e-commerce. An effective hybrid algorithm named hybrid ant colony optimization (HACO) is provided to solve this model. Results of numerical instances indicate that HACO outperforms ant colony optimization (ACO) on optimal solution, iterations, and computing stability.

The remainder of this paper is organized as follows. Section 2 presents the mathematical model of LIRP with MQDR. Section 3 proposes the solution approach named HACO. Section 4 analyses the parameters of HACO and shows the results of different experiments. Section 5 gives the conclusion and future research directions.

2. Model Formulation

As we all know, customers' return in e-commerce is higher than traditional commerce. Because of personal dissatisfaction, or a mistaken purchase of the wrong product, some of the returns are without quality defects. These returns can reenter into the market after a simple repackaging process without being recovered [29]. While the other returns result from quality defects, which need to be sent back to the plant and be recovered.

In order to meet the needs of MQDR, the merchandise center (MC) is necessary to deliver normal merchandises to the demand points (DPs) of downstream and collect the returned merchandises. MC integrates the functions of distribution center and recycling center and provides quality inspection and repackaging services. Meanwhile the returned merchandises are collected to MCs. Returned merchandises without quality defects become resalable normal items after repackaging treatment at MCs. The plant will recover the returns with quality defects and bring them to the market again.

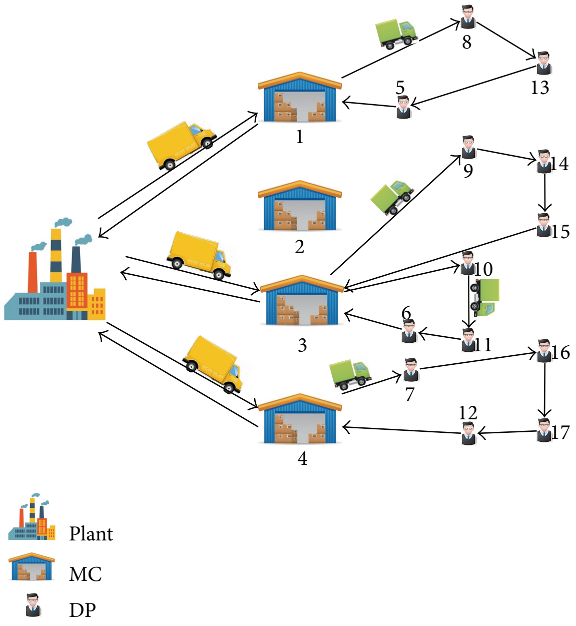


Figure 1: Closed-loop supply chain for a single product.

The operation mode of the system is shown in Figure 1. The closed-loop supply chain in this paper consists of one plant, multiple MCs, multiple DPs, and a single type of product with continuous inventory policy under the e-commerce environment.

The goal of this study is to decide the quantity and location of MCs and arrange the vehicle routes and determine the ordering times on each route. To minimize the total cost of logistics operations, this problem involves the following three decisions: (1) location decisions: obtain the optimal number of MCs and their locations; (2) inventory management: determine the ordering times on each route; (3) routing optimization: arrange the vehicles to delivery merchandises and collect returns.

To benefit from the risk of MQDR, we take assumptions (1)–(8) from Li et al. [27] into consideration: since the single-product system is researched in this paper, assumption (1) is necessary; in the capacitated vehicle routing problem, assumption (2) should be satisfied [30]; assumption (3) eliminates the indeterminacy from the different type of vehicle; assumption (4) means that each DP is well served by the only vehicle route [31]; assumption (5) ensures that each route will return to the same MC after traversing; assumption (6) follows the early published papers considering uncapacitated MCs [32]; assumption (7) takes MCs as the distribution center and recycling center; assumption (8) is a simplification of the reality [33].

The returned merchandises without quality defect are processed and repackaged at MCs, while others will be shipped back to the plant for reprocessing after a predetermined quantity at the MCs. Assume that the demand at each retailer is known and let $\mathbf{R}$ be the set of candidate MCs. Let $\mathbf{S}$ be the set of DPs and let M be the number of DPs. Let $\mathbf{V}$ be set of vehicles from the MCs to DPs. Let $\mathbf{U} = \mathbf{R} \cup \mathbf{S}$. Let the following notation denote the decisions of the firm:

N_{rv}: ordering times of MC$_r$ on routing v.

X_{ijr}^{v}: =1, if node j is served by MC$_r$ on routing v from node i, or 0 otherwise.

Y_{ir}^{v}: =1, if node i is assigned to MC$_r$ on routing v, or 0 otherwise.

Z_r: =1, if MC$_r$ is selected as an MC location, or 0 otherwise.

U_{jk}: auxiliary variable avoiding the subtour constraints in route k.

According to the aforementioned assumptions, the inventory levels depend on both demand and the quantity of MQDR. So, during each replenishment cycle, the holding cost of MCs is $\lambda h \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} ((d_i + q_i + w_i)/2N_{rv}) Y_{ir}^{v}$, where h is annual inventory holding per unit merchandises, d_i is mean (daily) demand for DP$_i$, and q_i and w_i are quantity of merchandises without and with quality defect returned by DP$_i$ per day.

In order to exactly describe the logistic distribution costs. Let c_r be the transportation costs per unit product from plan to MC$_r$. Let l be the delivering cost per unit distance. Let s_{ij} be the distance from node i to node j. And let λ be the working days per year. The total transportation costs from plant to DPs through MCs can be expressed, respectively, as $\lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} c_r (d_i - q_i + w_i) Y_{ir}^{v}$ and $\lambda l \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} \sum_{j\in\mathbf{U}} s_{ij} d_i X_{ijr}^{v}$.

So the cost of forward distribution is

$$\begin{aligned}
&\sum_{r\in\mathbf{R}} f_r Z_r + \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} b_r N_{rv} + \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} e_r N_{rv} \\
&\quad + \lambda h \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} \frac{(d_i + q_i + w_i)}{2N_{rv}} Y_{ir}^{v} \\
&\quad + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} c_r (d_i - q_i + w_i) Y_{ir}^{v} \\
&\quad + \lambda l \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} \sum_{j\in\mathbf{U}} s_{ij} d_i X_{ijr}^{v},
\end{aligned} \tag{1}$$

where e_r denote the fixed cost of dispatching vehicles per time at MC$_r$, f_r denote the fixed (annual) administrative and construction cost of MC$_r$, and b_r denote the ordering cost per unit product from plant to MC$_r$.

We let k to be the returning cost per unit of merchandise from DPs to MCs, so the total reverse transportation costs from DPs back to MCs are

$$\lambda k \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} (q_i + w_i) Y_{ir}^{v}. \tag{2}$$

The cost of deal with mixed quality defects is

$$\lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} p_r q_i Y_{ir}^{v} + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} a_r (q_i + w_i) Y_{ir}^{v}. \tag{3}$$

We adopt a_r as the inspecting cost per unit for the returned product and p_r as the repackaging cost of unit returned merchandise without quality problem at MCs.

In summary, the model is formulated as follows:

$$\begin{aligned}
\min Z = {} & \sum_{r\in\mathbf{R}} f_r Z_r + \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} b_r N_{rv} + \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} e_r N_{rv} \\
& + \lambda h \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} \frac{(d_i + q_i + w_i)}{2N_{rv}} Y_{ir}^{v} \\
& + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} c_r (d_i - q_i + w_i) Y_{ir}^{v} \\
& + \lambda l \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} \sum_{j\in\mathbf{U}} s_{ij} d_i X_{ijr}^{v} \\
& + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} p_r q_i Y_{ir}^{v} \\
& + \lambda k \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} (q_i + w_i) Y_{ir}^{v} \\
& + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} a_r (q_i + w_i) s Y_{ir}^{v}.
\end{aligned} \tag{4}$$

It is easy to find that the objective function (4) is convex in N_{rv}. We can simplify the objective function by solving N_{rv}. Consequently, the optimization solution of N_{rv} can be obtained by taking the derivative of the function with respect to N_{rv}; the result is as follows:

$$N_{rv}^{*} = \sqrt{\frac{\sum_{i\in\mathbf{S}} \lambda h (d_i + q_i + w_i) Y_{ir}^{v}}{2(e_r + f_r)}}. \tag{5}$$

The optimization problem (4) given a known N_{rv}^{*} can now be written as

$$\begin{aligned}
\min Z = {} & \sqrt{2\lambda h \sum_{r\in\mathbf{R}} \sum_{v\in\mathbf{V}} \sum_{i\in\mathbf{S}} (f_r + e_r)(d_i + q_i + w_i) Y_{ir}^{v}} \\
& + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} c_r (d_i - q_i + w_i) Y_{ir}^{v} \\
& + \lambda l \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{U}} \sum_{j\in\mathbf{U}} s_{ij} d_i X_{ijr}^{v} \\
& + \lambda k \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} (q_i + w_i) Y_{ir}^{v} \\
& + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} p_r q_i Y_{ir}^{v} \\
& + \lambda \sum_{v\in\mathbf{V}} \sum_{r\in\mathbf{R}} \sum_{i\in\mathbf{S}} a_r (q_i + w_i) Y_{ir}^{v} + \sum_{r\in\mathbf{R}} f_r Z_r
\end{aligned} \tag{6}$$

$$\text{s.t.} \quad \sum_{r\in\mathbf{R}} Z_r \geq 1, \quad r \in \mathbf{R} \tag{7}$$

$$\sum_{v\in\mathbf{V}}\sum_{i\in\mathbf{S}} Y_{ir}^{v} \leq Z_r, \quad r \in \mathbf{R} \tag{8}$$

$$\sum_{i\in\mathbf{S}} d_i Y_{ir}^{v} \leq g, \quad r \in \mathbf{R},\ v \in \mathbf{V} \tag{9}$$

$$\sum_{v\in\mathbf{V}}\sum_{r\in\mathbf{R}} Y_{ir}^{v} = 1, \quad i \in \mathbf{S} \tag{10}$$

$$\sum_{v\in\mathbf{V}}\sum_{r\in\mathbf{R}}\sum_{i\in\mathbf{U}} X_{ijr}^{v} = 1, \quad j \in \mathbf{S} \tag{11}$$

$$\sum_{i\in\mathbf{U}} X_{ikr}^{v} - \sum_{j\in\mathbf{U}} X_{kjr}^{v} = 0, \quad k \in \mathbf{S},\ r \in \mathbf{R},\ v \in \mathbf{V} \tag{12}$$

$$U_{lk} - U_{jk} + Mx_{ljk} \leq M - 1, \quad l, j \in \mathbf{S},\ k \in \mathbf{R} \tag{13}$$

$$-Y_{ij}^{v} + \sum_{k\in\mathbf{U}} \left(X_{ikr}^{v} + X_{kjr}^{v}\right) \leq 1, \quad i \in \mathbf{S},\ j, r \in \mathbf{R},\ v \in \mathbf{V} \tag{14}$$

$$Z_r = \{0, 1\}, \quad r \in \mathbf{R} \tag{15}$$

$$Y_{ir}^{v} = \{0, 1\}, \quad i \in \mathbf{S},\ r \in \mathbf{R},\ v \in \mathbf{V} \tag{16}$$

$$X_{ijr}^{v} = \{0, 1\}, \quad i \in \mathbf{U},\ j \in \mathbf{S},\ r \in \mathbf{R},\ v \in \mathbf{V}. \tag{17}$$

The objective function (6) is to minimize the total cost; (7) ensure the selected MC is not empty; (8) ensure each DP is traversed by a unique vehicle which belongs to a certain MC; (9) ensure the amount of each delivery from MC on each route must be within vehicle capacity; (10) ensure that each route has only one vehicle; (11) ensure each DP must be followed by exactly one note; (12) ensure every DP node of the system will be serviced before it gives services to the others; (13) ensure the subtour is eliminated. Equation (14) ensures that each DP is assigned to an MC when there exists a route that starts from the MC passing through the DP. Equations (15)–(17) ensure the nonnegativity and integrality of decision variables.

3. Solution Approach

Like the VRP, the closed-loop LIRP is also an NP-hard problem, since it includes the VRP and is more complex than VRP. Generally speaking, there does not exist a complete, efficient, and accurate analytic algorithm to address NP-hard problems; ant colony optimization (ACO) has been proved very successful and widely applied to solve the static and dynamic problems as an EC algorithm [34]. However, ACO does not distinguish ant behavior results. The pheromone concentration will distribute in every direction for the iteration. Therefore, this leads to low searching efficiency. The algorithm may get caught in local optimization if we do not take preventive measures. On the other hand, ABC provides an effective institution to find the global optimal solution from the trapping of local optimal solution [35]. So, in this study, we present a hybrid ant colony optimization algorithm based on the combination of ACO and ABC to solve the above LIRP model.

3.1. Initialize Solution. Since the natural number is an efficient coding method for these problems, the sequence of solutions is composed of candidate MCs $(1, 2, \ldots, R)$ and DPs, which are indicated by $(R + 1, \ldots, R + S)$. The candidate solution of our proposed model will be described well by those natural number sequences. As an example, Figure 1 fully interpreted the perceptions of our method, which refers to the individual feasible solution: {1 8 13 5 3 9 14 15 10 11 6 4 7 16 17 12}.

In the HACO, the moving strategy of the ant in node i is depending on the pseudorandom proportional rule. The rule indicates that the ant has both exploiting and exploration ability, which means the ant is guided by the pheromone trails as well as the heuristic information. In this case, the ant has a higher degree of exploring unknown knowledge. The connected function of the pheromone values τ_{ij} and the heuristic values η_{ij} is shown as

$$P_{ij}^{k} = \begin{cases} \dfrac{\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum_{k\in\text{allow}(k)}\left[\tau_{ik}\right]^{\alpha}\left[\eta_{ik}\right]^{\beta}} & j \in \text{allow}(k) \\ 0 & \text{otherwise,} \end{cases} \tag{18}$$

where τ_{ij} is the density of pheromone remaining on the edge (i, j), η_{ij} is the inverse value of distance between node i and node j, α and β are user-defined parameters for corresponding pheromone concentration and heuristic information, and allow(k) is the remaining nodes to be visited by ant k.

3.2. The ABC Phase. In order to improve the performance of global searching of our algorithm, the paper applied the scout bee searching phase into the ACO. Scout bees are free bees used for finding a new better solution from the neighbor known solution. As soon as a scout bee finds a new solution, she turns into an employed bee. If there is no improvement in the quality of solution, the bee will abandon that source and continue to search for another new solution.

The searching function of scout bees is as

$$\widehat{x}_i^{j} = x_{\max} - \text{rand}\,[0, 1] * \left(x_{\max} - x_i^{j}\right). \tag{19}$$

To meet the requirements for coding sequence type, we described two operations to complete scouts searching process, namely, random array reverse (RAR) and random swap (RS).

Step 1. Set the initial number of scout bee n and probability p_0.

Step 2. Generate two positions randomly named a and b, for each $a < b$.

Step 3. Get a random probability $0 < p < 1$; if $p > p_0$ turn to Step 4; otherwise, turn to Step 5.

```
Procedure: ABC
Input: the initial sequence, the number of scout bee $n$ and $p_0$
Output: the better sequence
Begin
Take $n$ and $p_0$
while $i < n$
    $p$ = rand[0, 1]
    take $a < b$
  if $p > p_0$
        Reverse the array between position $a$ and $b$
  else
        Swap the position of $a$ and $b$
Output: the better sequence
End
```

Pseudocode 1: Pseudocode of an ABC framework.

Step 4. Reverse the array between positions a and b as a new solution.

Step 5. Swap the position of a and b as a new solution.

Step 6. Calculate the cost of new solution.

Step 7. Keep the best solution to the next iteration and return to Step 2.

The pseudocodes of ABC are shown in Pseudocode 1.

3.3. Global Pheromone Trail Update. The global pheromone updating rule is triggered at the end of iteration to reward tours that are in line with the objective of impedance minimization. This strategy is applied to reinforce the pheromone density on the sets of edges belonging to the inspect tour and to increase the likelihood that this tour will also be selected by other ant agents. The rule of global pheromone updating is given by

$$\tau_{ij} = (1-\rho)\,\tau_{ij} + \rho\Delta\tau_{ij}^{bs} \quad i, j \in T^{bs}, \tag{20}$$

where

$$\Delta\tau_{ij}^{bs} = \begin{cases} \dfrac{L}{L_{bs}} & i, j \in \text{global best tour} \\ 0 & \text{otherwise.} \end{cases} \tag{21}$$

L is a constant initial pheromone. L_{bs} is the cost of the best of all the tours produced by all m agents from the beginning of the iteration. $\rho \in (0, 1]$ is the pheromone evaporation coefficient. To improve the pheromone trail quality, a part of the worst result is removed.

3.4. Local Pheromone Trail Update. In addition to the global pheromone trail updating rule, the selected ants will update the local pheromone trail in the process of passing an arc(i, j). It is opposite to the normal pheromone trail updating rule that increases the pheromone density while ants cross over arcs. The purpose of using the local pheromone trail update rule is to prevent stagnation behavior because the arc becomes less desirable for the following ants. The rule of local pheromone updating is as follows:

$$\tau_{ij} = (1-\xi)\,\tau_{ij} + \xi\tau_0, \tag{22}$$

where τ_0 is a constant at the beginning of pheromone trails and ξ is a user-defined coefficient that lowers the pheromone density of arcs traversed by the intelligent ants.

3.5. Algorithm Flow

Step 1. Get the formulas for solving N_{rv}.

Step 2. Set the initial parameters for the model: set of candidate MCs **R**, set of DPs **S**, set of vehicles **V**, inspecting cost a_r, ordering cost b_r, transportation costs c_r, daily demand d_i, dispatching vehicles cost e_r, fixed (annual) administrative and construction cost f_r, vehicle capacity g, holding cost h, and returning cost k.

Step 3. Parameter setting for HACO is as follows: ants number m, evolution terminate iteration M, pheromone concentration impact factor α, heuristic information pheromones impact factor β, evaporation rate of the pheromone ρ, constant initial pheromone L, and mutation probability array reverse p_0.

Step 4. Using unit matrix τ_{ij}, calculate the probability

$$P_{ij}^{k} = \begin{cases} \dfrac{\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum_{k\in \text{allow}(k)}\left[\tau_{ik}\right]^{\alpha}\left[\eta_{ik}\right]^{\beta}} & j \in \text{allow}\,(k) \\ 0 & \text{otherwise.} \end{cases} \tag{23}$$

Step 5. Ant solutions generation module: each ant will generate a feasible solution after traversing the DPs.

Step 6. Best ant solution module: after calculating each ant's solution, select the best solution which is known as the iteration best to compare with the global best. Keep the next best solution as the next global best.

```
Procedure: HACO for LIRP
Input: coordinates of nodes, demands and returns of DPs, MC parameters, vehicle capacity, HACO parameters
Output: the best solution (include routes, MCs locations, order times and order size)
Begin
Take max $t$
while max $t < M$
    for 1 to $m$
         Foraging Behavior of Ants
           $\tau_{ij} = (1 - \xi)\tau_{ij} + \xi\tau_0$
        Calculate individual total cost Tcost($m$)
    end
        Tcost_best = min(Tcost($m$))
    for 1 to $m/2$ Neighbor range
      Scout bee searching the neighbor range
      $a$ = round(rand)
      $b$ = round(rand)
      make $a < b$
      if $p < 0.5$
        vech = [vech(1 : $a - 1$) vech($b$: − 1 : $a$) vech(($b + 1$) : end)];
      else
        exchange($a, b$)
      end
        if Tcost($m/2$) < Tcost_best
        Tcost_best = Tcost($m/2$)
        end
    end
       for 1 to $m$
          if Tcost($m$) > Tcost_ave
            for 1 to $n$
         $\tau_{ij} = (1 - \rho)\tau_{ij} + \rho\Delta\tau_{ij}^{\mathrm{bs}}$
            end
          end
       end
end
Output: the best solution
End
```

Pseudocode 2: Pseudocode of the proposed HACO.

Step 7. Scout bee module: random selection probability $0 < p < 1$; if $p > p_0$, turn to random array reverse operation. Otherwise, turn to random swap operation.

Step 8. Pheromone updating module: update the information pheromones as follows:

$$\begin{aligned}\tau_{ij} &= \left(1 - \rho\right)\tau_{ij} + \rho\Delta\tau_{ij}^{bs} \quad i, j \in T^{bs},\\ \tau_{ij} &= (1 - \xi)\,\tau_{ij} + \xi\tau_0.\end{aligned} \tag{24}$$

Step 9. Termination module: if the parent optimal solution and offspring optimal solution are equal during continuous M generations, stop the algorithm. Otherwise, return to Step 3 after M increments.

Step 10. Output.

The pseudocodes of HACO are shown in Pseudocode 2.

4. Computational Experiments and Results Analysis

In this section, numerical simulations are given to illustrate the performance of HACO compared with the traditional ACO. Both algorithms in this paper are compiled by *Matlab R2014a* and run on a computer with 8 GB main memory and 3.6 GHZ CPU. All instances come from the LRP database in University of Aveiro [36].

4.1. Parameters Discussion. Parameter values selection is crucial to the efficiency of algorithms. An example named Gaskell 67-22 × 5 from the database, which contains the nodes coordinate and the DPs demand, is used to determine the optimal parameter. Gaskell 67 is the instance's name and 22 × 5 means 5 candidate MCs for 22 DPs. The inventory holding cost $h = 2$, the vehicle capacity $g = 500$, transportation costs $c_r = 2$, returning cost $k = 2$, working days $\lambda = 300$, and the delivering cost per unit distance $l = 0.7$. The other parameters of the instance are as follows: $a_r \sim U(16, 20)$;

Table 1: Results with different m (cost: million CNY; iterations: times).

m		Cost			Iterations		
		Mean	Std. dev.	C.V.	Mean	Std. dev.	C.V.
30	ACO	32.4	0.96	0.0295	168.6	30.64	0.1817
	HACO	33.46	1.12	0.0336	125.72	29.02	0.2308
40	ACO	32.13	0.96	0.03	173.48	32.95	0.1899
	HACO	33.37	0.93	0.0277	117.82	15.4	0.1307
50	ACO	32.22	0.74	0.0229	157.19	40.58	0.2581
	HACO	32.96	0.96	0.0292	119.26	17.47	0.1465
60	ACO	32.21	0.67	0.0208	158.12	39.39	0.2491
	HACO	32.72	0.86	0.0263	121.86	17.37	0.1425
70	ACO	31.96	0.71	0.0223	162.88	32.48	0.1994
	HACO	32.77	1.13	0.0344	121.06	23.7	0.1958

$\alpha = 1$, $\beta = 5$, $\rho = 0.1$, $L = 150$, and $p_0 = 0.5$.

Table 2: Results with different α (cost: million CNY; iterations: times).

α		Cost			Iterations		
		Mean	Std. dev.	C.V.	Mean	Std. dev.	C.V.
0.25	ACO	31.92	0.54	0.0168	189.3	73.28	0.3871
	HACO	31.63	0.79	0.025	189.38	69.64	0.3677
0.5	ACO	31.85	0.78	0.0246	181.86	57.34	0.3153
	HACO	31.52	0.91	0.029	182.24	63.94	0.3509
1	ACO	32.22	0.74	0.0229	157.19	40.58	0.2581
	HACO	33.06	1.04	0.0315	123.28	14.02	0.1137
1.25	ACO	32.13	0.79	0.0247	154.24	30.12	0.1953
	HACO	33.11	1.09	0.0331	115.78	11.61	0.1002
1.5	ACO	32.14	0.9	0.0279	154.96	25.68	0.1658
	HACO	32.97	1.11	0.0335	116.2	10.23	0.0881

$m = 50$, $\beta = 5$, $\rho = 0.1$, $L = 150$, and $p_0 = 0.5$.

Table 3: Results with different β (cost: million CNY; iterations: times).

β		Cost			Iterations		
		Mean	Std. dev.	C.V.	Mean	Std. dev.	C.V.
3	ACO	31.91	0.91	0.0286	192.78	42.08	0.2183
	HACO	33.06	1.19	0.0359	148.8	54.84	0.3686
4	ACO	32.19	0.8	0.0249	170.2	41.89	0.2461
	HACO	33.05	1.14	0.0344	126	42.17	0.3347
5	ACO	32.22	0.74	0.0229	157.19	40.58	0.2581
	HACO	32.96	0.96	0.0292	119.26	17.47	0.1465
6	ACO	32.1	0.77	0.0241	159.38	31.99	0.2007
	HACO	33.12	1.19	0.0358	119.86	22.4	0.1869
7	ACO	32.42	0.84	0.0258	154.69	23.92	0.1546
	HACO	33.25	1.07	0.0322	111.68	8.62	0.0772

$\alpha = 1$, $m = 50$, $\rho = 0.1$, $L = 150$, and $p_0 = 0.5$.

$b_r \sim U(16, 20)$; $c_r \sim U(6, 10)$; $e_r \sim U(21, 25)$; $q_i \sim U(12, 25)$; and $w_i \sim U(2, 5)$.

The parameters of algorithm are initialized as follows: ant's number $m = 50$, evolution terminate iteration $M = 100$, pheromone concentration impact factor $\alpha = 1$, heuristic information pheromones impact factor $\beta = 5$, evaporation rate of the pheromone $\rho = 0.1$, constant $L = 150$, mutation probability array reverse $p_0 = 0.5$.

We run the program 50 times on the same computer. The performance of ACO and HACO varies with the different values of the parameters, which are shown in Tables 1–6. In these tables, the symbol C.V. means the coefficient of variation.

Tables 1–6 represent the parameters' effect on the objective function values. The data was normalized through two dimensions, that is, cost and iterations, and three indicators,

Table 4: Results with different ρ (cost: million CNY; iterations: number).

ρ		Cost			Iterations		
		Mean	Std. dev.	C.V.	Mean	Std. dev.	C.V.
0.1	ACO	32.22	0.74	0.0229	157.19	40.58	0.2581
	HACO	32.12	0.93	0.0289	138.4	21.02	0.1518
0.2	ACO	32.38	0.87	0.0269	133.27	20.57	0.1543
	HACO	32.7	0.97	0.0296	124.12	13.01	0.1048
0.3	ACO	32.65	0.94	0.0289	132.8	31.09	0.2341
	HACO	32.75	1.45	0.0443	122.1	13.09	0.1072
0.4	ACO	33.03	0.94	0.0284	131.86	28.76	0.2181
	HACO	33.31	1.1	0.033	122.98	20.2	0.1643
0.5	ACO	33.41	0.87	0.0261	157.27	67.72	0.4306
	HACO	33.55	1.08	0.0323	116.24	15.44	0.1328

$\alpha = 1$, $m = 50$, $\beta = 5$, $L = 150$, and $p_0 = 0.5$.

Table 5: Results with different L (cost: million CNY; iterations: times).

L		Cost			Iterations		
		Mean	Std. dev.	C.V.	Mean	Std. dev.	C.V.
50	ACO	31.99	0.72	0.0224	159.72	33.39	0.21
	HACO	33.07	1.22	0.0369	123.7	25.96	0.2098
100	ACO	31.9	0.67	0.0209	159.8	30.73	0.19
	HACO	32.88	1.09	0.033	121.63	18.91	0.1555
150	ACO	32.22	0.74	0.0229	157.19	40.58	0.2581
	HACO	33.02	1.05	0.0319	121.14	23.2	0.1915
200	ACO	32.11	0.8	0.0251	167.66	38.61	0.23
	HACO	32.9	1.12	0.0339	120.8	22.05	0.1825
250	ACO	32.08	0.87	0.0271	164.08	34.16	0.21
	HACO	33.1	1.09	0.033	121.87	28.95	0.2376

$\alpha = 1$, $m = 50$, $\beta = 5$, $\rho = 0.1$, and $p_0 = 0.5$.

Table 6: Results with different p_0 (cost: million CNY; iterations: times).

p_0	Cost			Iterations		
	Mean	Std. dev.	C.V.	Mean	Std. dev.	C.V.
0.3	33.07	1.22	0.0369	123.70	25.96	0.2098
0.4	32.88	1.09	0.0330	121.63	18.91	0.1555
0.5	33.02	1.05	0.0319	121.14	23.20	0.1915
0.6	32.90	1.12	0.0339	120.80	22.05	0.1825
0.7	33.10	1.09	0.0330	121.87	28.95	0.2376

$\alpha = 1$, $m = 50$, $\beta = 5$, $\rho = 0.1$, and $L = 150$.

that is, mean, standard deviation, and coefficient of variation. Actually, in order to find the minimal cost, we usually take the parameter values, where the cost is lower and more stable. From the discussion, we found that HACO reaches the best performance when $m = 60$, $\alpha = 0.5$, $\beta = 5$, $\rho = 0.1$, $L = 100$, and $p_0 = 0.4$, while ACO reaches the best performance when $m = 70$, $\alpha = 0.5$, $\beta = 3$, $\rho = 0.1$, and $L = 100$.

4.2. Computational Experiment. To get a reliable conclusion, we run another 50 times on the same computer with the best parameter values in Gaskell 67-22 × 5. One of the best solutions of objective function in the 50 experiments of HACO is 30.2 million CNY. Table 7 shows the solution. MCs were established at MC1, MC2, and MC5 with five vehicles distribution routes. Figure 2 shows topological structure of the closed-loop supply chain.

Figure 3 shows their trend of optimal objective function values along with iterations. The fluctuation curves of optimal objective function value are varied by different algorithm, which are shown in Figures 4(a) and 4(b).

As shown in Figure 3, the cost and iterations of HACO are lower than ACO; and in Figure 4, the range and mean value of

Table 7: The solution of Gaskell 67-22 × 5.

MC	Routing number	Routing	Order times
MC1	V1	1 → 12 → 13 → 9 → 10 → 26 → 1	17
	V2	1 → 16 → 15 → 18 → 14 → 1	18
MC2	V3	2 → 23 → 24 → 27 → 25 → 17 → 2	37
MC5	V4	5 → 22 → 20 → 21 → 8 → 19 → 5	24
	V5	5 → 7 → 6 → 11 → 5	18

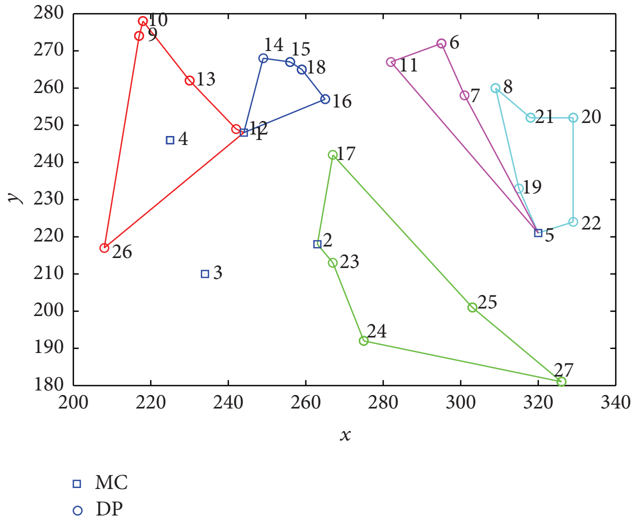


Figure 2: Topological structure of the network.

the minimum cost of HACO are also lower than ACO, which both imply that HACO is more efficient than ACO in solving the LIRP.

4.3. Extended Experiments. In this section, a series of instances are given to show that HACO is more efficient and stable than classical software and ACO. In order to ensure the demands of DPs are not more than the vehicle capacity, we need to enumerate some instances. In this paper, the daily demands are set as 1/10 of corresponding demands of the database.

As we know, Lingo is a representative classical optimization software tool. Thus we used *Lingo 11.0* to solve the problem by using a small-sized instance named Peal 183-12 × 2 and two medium-sized instance named Gaskell 67-22 × 5 and Gaskell 67-36 × 5; the results are shown in Table 8.

Each instance was run 50 times by HACO and ACO with their optimized parameters values, respectively; the results are shown in Tables 9 and 10.

4.4. Result Analysis. According to Table 8, we found that (1) for the small-sized instance, HACO can obtain better result than Lingo within less time and (2) for medium-sized instances, Lingo cannot get the global optimization within 1 hour, while HACO can solve the problem in a short time.

Observe, from Tables 9 and 10, that HACO is more efficient than ACO for the following reasons. (1) The cost of HACO is significantly lower than ACO ($p < 0.05$); (2) the difference of the number of iteration between HACO and ACO is not significant ($p > 0.05$); (3) HACO is more stable than ACO as the coefficient of variation (C.V.) is lower. To sum up, our algorithm reduces the cost with the same number of iterations compared with ACO.

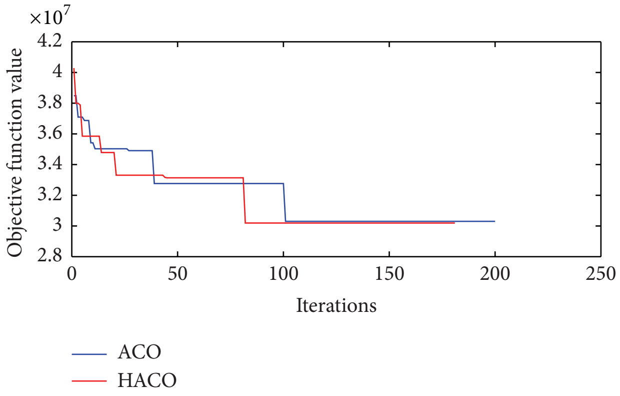
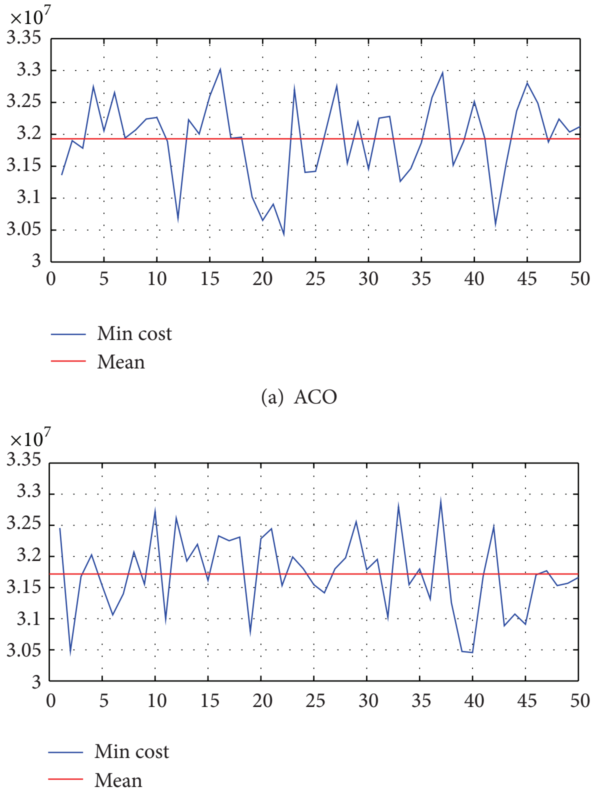


Figure 3: Trends of objective function value.



(a) ACO

(b) HACO

Figure 4: The fluctuation curve of optimal objective function value.

By improving pheromone updates and bee colony searching, we improve the solution quality of the algorithm and make it useful as a guide for the ant searching process. Observed from the results of numerical simulations, HACO can get better result with a fewer number of iterations. Hence,

Table 8: Comparisons between HACO and Lingo.

Instance name	Perl 183-12 × 2		Gaskell 67-22 × 5		Gaskell 67-36 × 5	
	CPU time	Cost	CPU time	Cost	CPU time	Cost
Lingo	523 s	715392	>1 hour	\	>1 hour	\
HACO	24.5 s	709152	44 s	32691202	99 s	31550446

Table 9: Optimal objective function values of two algorithms (CNY).

Instance name	Algorithm	Mean	Std. dev.	C.V.	t value	Significance test p value (sig. 1-tailed)
Perl 183-12 × 2	ACO	711347.1	6979.11	0.0098	1.6838	0.048
	HACO	709237.9	5454.48	0.0077		
Gaskell 67-22 × 5	ACO	31929818.3	627210.66	0.0196	1.7118	0.045
	HACO	31718084.1	609606.04	0.0192		
Gaskell 67-36 × 5	ACO	3288921.3	43585.25	0.0133	1.6602	0.050
	HACO	3275052	39868.81	0.0122		
Perl 183-55 × 15	ACO	285145.3	3779.15	0.0133	1.8391	0.034
	HACO	283831.6	3351.00	0.0118		
Christofides 69-75 × 10	ACO	419695.8	4948.15	0.0118	2.5020	0.007
	HACO	417298.6	4627.32	0.0111		
Perl 183-85 × 7	ACO	486011.0	4503.39	0.0093	1.8080	0.037
	HACO	484424.1	4270.44	0.0088		
Christofides 69-100 × 10	ACO	458235.6	6387.00	0.0139	1.6796	0.048
	HACO	456441.6	5317.70	0.0117		

Table 10: Iterations of two algorithms (times).

Instance name	Algorithm	Mean	Std. dev.	C.V.	t value	Significance test p value (sig. 1-tailed)
Perl 183-12 × 2	ACO	193.32	78.70	0.4071	0.6323	0.264
	HACO	183.90	70.04	0.3808		
Gaskell 67-22 × 5	ACO	191.34	86.36	0.4513	0.7831	0.218
	HACO	180.70	43.32	0.2397		
Gaskell 67-36 × 5	ACO	254.44	76.84	0.3020	0.2012	0.421
	HACO	251.84	49.42	0.1962		
Perl 183-55 × 15	ACO	241.74	77.29	0.3197	0.1000	0.460
	HACO	240.46	47.33	0.1968		
Christofides 69-75 × 10	ACO	245.24	79.10	0.3226	1.2340	0.110
	HACO	229.92	62.30	0.2710		
Perl 183-85 × 7	ACO	247.18	94.89	0.3839	0.4355	0.332
	HACO	240.80	65.75	0.2730		
Christofides 69-100 × 10	ACO	248.06	97.18	0.3918	0.2627	0.397
	HACO	244.08	65.48	0.2681		

comparing with ACO, HACO is adopted as a better approach in solving this LIRP with MQDR.

5. Conclusion and Future Research

With the development of e-commerce, customers' return keeps a high rate with MQDR, which can be reentered into markets after being repackaged or recovered. In this research, we built a closed-loop LIRP model considering both quality defect returns and nondefect returns; we call it MQDR in this paper. We perform an extensive computational study and observe the following interesting results.

(1) Considering MQDR are computationally beneficial for the formulation presented, the MQDR and closed-loop pattern with returns are features of the proposed

problem in e-commerce, which is never considered in previous work.

(2) Since the evolutionary computation algorithm has been proved successfully in tackling NP-hard problem, a hybrid algorithm is proposed by combining ACO algorithm and ABC algorithm to solve the LIRP. HACO integrated the scout bee searching phase into the ACO to improve the global searching ability.

(3) The performance of HACO is evaluated by using the instances in the LRP database, and HACO outperforms ACO on convergence, optimal solution, and computing stability. This numerical study shows the efficiency and effectiveness of the solution method.

However, developing other elements for the LIRP will lead to further research directions. And analyzing the model under the dynamic demand of customs and a time-varying demand can be a valuable subject. The design of experiments and verification by discrete dynamics simulation should be established. Fruit fly optimization algorithm (FOA) as one of the best EC algorithms has attracted the attention of various researchers [37]. It is important to apply these models and algorithms to the operation and management of enterprises to improve the decision-making efficiency of e-commerce logistics system.

Competing Interests

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

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References

[1] "Ecommerce sales worldwide reach $1.471 trillion in 2014," http://www.emarketer.com/Article/Worldwide-Ecommerce-Sales-Increase-Nearly-20-2014/1011039.

[2] J. Mostard and R. Teunter, "The newsboy problem with resalable returns: a single period model and case study," *European Journal of Operational Research*, vol. 169, no. 1, pp. 81–96, 2006.

[3] F. Zeng, Y. Chi, and J. Zheng, "The newsvendor problem with different delivery time, resalable returns, and an additional order," *Mathematical Problems in Engineering*, vol. 2015, Article ID 505268, 10 pages, 2015.

[4] R. H. Ballou, *Business Logistics Management*, Prentice Hall, New York, NY, USA, 1992.

[5] J. Perl and S. Sirisoponsilp, "Distribution networks: facility location, transportation and inventory," *International Journal of Physical Distribution & Materials Management*, vol. 18, no. 6, pp. 18–26, 1988.

[6] R. H. Ballou and J. M. Masters, "Commercial software for locating warehoused and other facilities," *Journal of Business Logistics*, vol. 14, no. 2, pp. 70–107, 1993.

[7] S. J. Erlebacher and R. D. Meller, "The interaction of location and inventory in designing distribution systems," *IIE Transactions*, vol. 32, no. 2, pp. 155–166, 2000.

[8] M. S. Daskin, C. R. Coullard, and Z. J. Shen, "An inventory-location model: formulation, solution algorithm and computational results," *Annals of Operations Research*, vol. 110, no. 1–4, pp. 83–106, 2002.

[9] Z.-J. M. Shen, C. Coullard, and M. S. Daskin, "A joint location-inventory model," *Transportation Science*, vol. 37, no. 1, pp. 40–55, 2003.

[10] S.-H. Liao, C.-L. Hsieh, and P.-J. Lai, "An evolutionary approach for multi-objective optimization of the integrated location-inventory distribution network problem in vendor-managed inventory," *Expert Systems with Applications*, vol. 38, no. 6, pp. 6768–6776, 2011.

[11] A. Balakrishnan, J. E. Ward, and R. T. Wong, "Integrated facility location and vehicle routing models: recent work and future prospects," *American Journal of Mathematical and Management Sciences*, vol. 7, no. 1-2, pp. 35–61, 1987.

[12] H. Min, V. Jayaraman, and R. Srivastava, "Combined location-routing problems: a synthesis and future research directions," *European Journal of Operational Research*, vol. 108, no. 1, pp. 1–15, 1998.

[13] G. Nagy and S. Salhi, "Location-routing: issues, models and methods," *European Journal of Operational Research*, vol. 177, no. 2, pp. 649–672, 2007.

[14] L. M. A. Chan, A. Federgruen, and D. Simchi-Levi, "Probabilistic analyses and practical algorithms for inventory-routing models," *Operations Research*, vol. 46, no. 1, pp. 96–106, 1998.

[15] A. J. Kleywegt, V. S. Nori, and M. W. P. Savelsbergh, "The stochastic inventory routing problem with direct deliveries," *Transportation Science*, vol. 36, no. 1, pp. 94–118, 2002.

[16] D. Adelman, "A price-directed approach to stochastic inventory/routing," *Operations Research*, vol. 52, no. 4, pp. 499–514, 2004.

[17] N. H. Moin and S. Salhi, "Inventory routing problems: a logistical overview," *Journal of the Operational Research Society*, vol. 58, no. 9, pp. 1185–1194, 2007.

[18] S. C. Liu and S. B. Lee, "A two-phase heuristic method for the multi-depot location routing problem taking inventory control decisions into consideration," *International Journal of Advanced Manufacturing Technology*, vol. 22, no. 11, pp. 941–950, 2003.

[19] S. C. Liu and C. C. Lin, "A heuristic method for the combined location routing and inventory problem," *International Journal of Advanced Manufacturing Technology*, vol. 26, no. 4, pp. 372–381, 2005.

[20] Z.-J. M. Shen and L. Qi, "Incorporating inventory and routing costs in strategic location models," *European Journal of Operational Research*, vol. 179, no. 2, pp. 372–389, 2007.

[21] A. A. Javid and N. Azad, "Incorporating location, routing and inventory decisions in supply chain network design," *Transportation Research Part E: Logistics and Transportation Review*, vol. 46, no. 5, pp. 582–597, 2010.

[22] A. Ahmadi-Javid and A. H. Seddighi, "A location-routing-inventory model for designing multisource distribution networks," *Engineering Optimization*, vol. 44, no. 6, pp. 637–656, 2012.

[23] W. J. Guerrero, C. Prodhon, N. Velasco, and C. A. Amaya, "Hybrid heuristic for the inventory location-routing problem with deterministic demand," *International Journal of Production Economics*, vol. 146, no. 1, pp. 359–370, 2013.

[24] Y. Zhang, M. Y. Qi, L. X. Miao, and E. Liu, "Hybrid metaheuristic solutions to inventory location routing problem," *Transportation Research Part E: Logistics and Transportation Review*, vol. 70, no. 1, pp. 305–323, 2014.

[25] N. Nekooghadirli, R. Tavakkoli-Moghaddam, V. R. Ghezavati, and S. Javanmard, "Solving a new bi-objective location-routing-inventory problem in a distribution network by metaheuristics," *Computers and Industrial Engineering*, vol. 76, no. 1, pp. 204–221, 2014.

[26] W. J. Guerrero, C. Prodhon, N. Velasco, and C. A. Amaya, "A relax-and-price heuristic for the inventory-location-routing problem," *International Transactions in Operational Research*, vol. 22, no. 1, pp. 129–148, 2015.

[27] Y. H. Li, H. Guo, L. Wang, and J. Fu, "A hybrid genetic-simulated annealing algorithm for the location-inventory-routing problem considering returns under E-supply chain environment," *The Scientific World Journal*, vol. 2013, Article ID 125893, 10 pages, 2013.

[28] B. L. Liu, H. Chen, Y. H. Li, and X. Liu, "A pseudo-parallel genetic algorithm integrating simulated annealing for stochastic location-inventory-routing problem with consideration of returns in e-commerce," *Discrete Dynamics in Nature and Society*, vol. 2015, Article ID 586581, 15 pages, 2015.

[29] J. A. Petersen and V. Kumar, "Perceived risk, product returns, and optimal resource allocation: evidence from a field experiment," *Journal of Marketing Research*, vol. 52, no. 2, pp. 268–285, 2015.

[30] Y. Niu, S. Wang, J. He, and J. Xiao, "A novel membrane algorithm for capacitated vehicle routing problem," *Soft Computing*, vol. 19, no. 2, pp. 471–482, 2014.

[31] M. Ball, L. Bodin, and R. Dial, "A matching based heuristic for scheduling mass transit crews and vehicles," *Transportation Science*, vol. 17, no. 1, pp. 4–31, 1983.

[32] M. Dror, G. Laporte, and P. Trudeau, "Vehicle routing with stochastic demands: properties and solution frameworks," *Transportation Science*, vol. 23, no. 3, pp. 166–176, 1989.

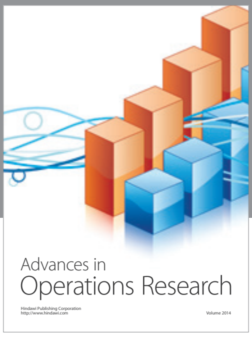
[33] Y. Dumas, J. Desrosiers, and F. Soumis, "The pickup and delivery problem with time windows," *European Journal of Operational Research*, vol. 54, no. 1, pp. 7–22, 1991.

[34] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 53–66, 1997.

[35] K. Dervis and B. Bahriye, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," *Journal of Global Optimization*, vol. 39, no. 3, pp. 459–471, 2007.

[36] "Location-Routing Problems (LRP)," http://sweet.ua.pt/~iscf143/_private/SergioBarreto HomePage.htm.

[37] L. Wang, Y. Shi, and S. Liu, "An improved fruit fly optimization algorithm and its application to joint replenishment problems," *Expert Systems with Applications*, vol. 42, no. 9, pp. 4310–4323, 2015.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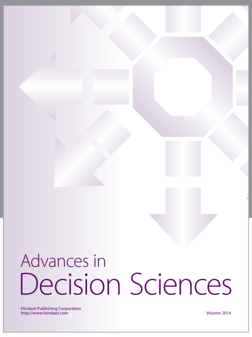
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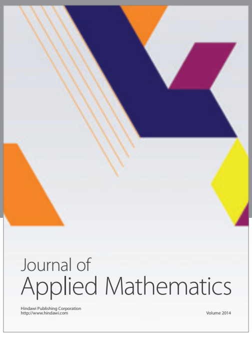
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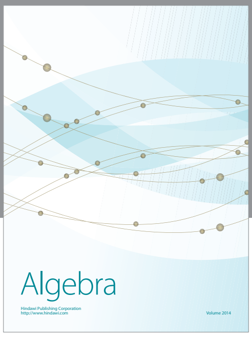
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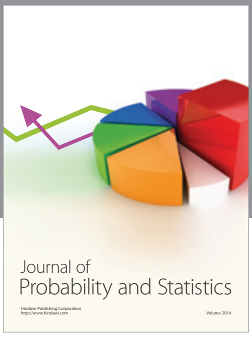
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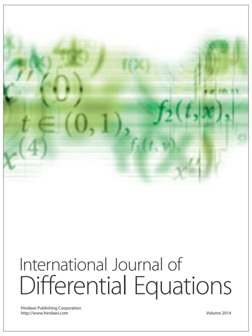
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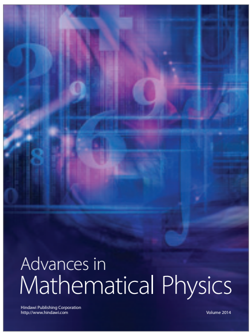
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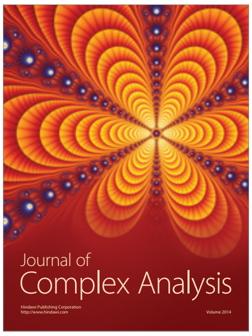
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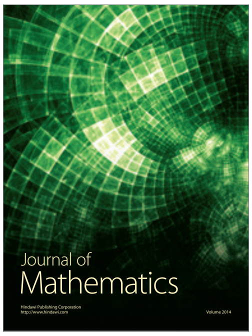
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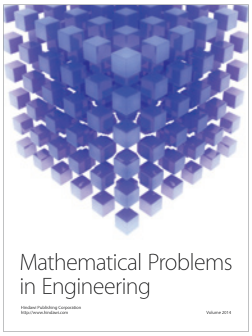
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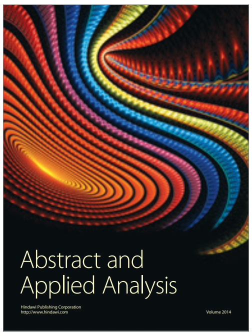
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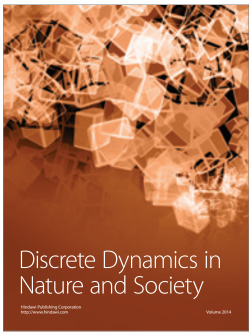
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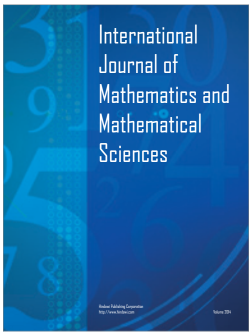
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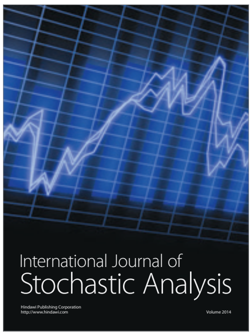
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