Research on Heuristics Logistics Distribution Algorithm Based on Parallel Multi-ant Colonies

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Abstract—**Logistics distribution problem is an important part of the modern logistics system. Suppliers need to plan a route scheme for each customer in goods distribution, which is a multi-point to multi-point problem. It is NP-hard. Through analysis of characteristics of the existing logistics system, mathematical models are constructed, by introducing the order request and the return request with multiple suppliers. With these models, we present multi-vendor logistics distribution optimized algorithm and heuristic logistics distribution algorithm based on parallel multi-colonies. The first algorithm takes into account customer requests, make full use of vehicle loading and reasonably choose delivery route, so that transportation costs are lower, but the time cost is higher. The second algorithm add heuristic factor and introduce metrizable ratio, which get a faster convergence rate and higher-quality global optima. Simulation results show that both of the proposed algorithms can be adapted to this problem, but the heuristic logistics distribution algorithm based on parallel multi-colonies is more effective, which can keep balance between the time overhead and the best route.**

Index Terms—**logistics distribution problem, delivery route, ant colony algorithm, metrizable ratio, heuristic information**

I. INTRODUCTION

Goods distribution is an important part of modern logistics distribution services. In the logistics distribution process, more and more manufacturers are confronted to the problem of "Reverse Logistics", multiple suppliers are possible to delivery goods, or many customers apply the order request and the return request at the same time[1]. Then suppliers process customers' requests in time, and plan the corresponding independent routes. It leads manufacturers to design a reverse logistic system. Suppliers need to plan a route scheme for each customer in goods distribution. This is a typical multipoint to multipoint relation, which is NP-hard. Therefore, it is an necessary that scientific and reasonable method is used to determine vehicle scheduling and distribution route.

Logistics and distribution problem comes down to a vehicle routing problem (VRP) for constraint condition with parameters. VRP was first proposed by Dantzig and Ramser in 1959, is an extension of the well known Traveling Sales Problem and has many practical applications in the field of logistics distribution. VRP consist of designing vehicle routes through a set of nodes (supplies, customers) subject to given side conditions and restrictions. The objective is to minimize total routing cost while satisfying all customers demand and suppliers are met. VRP and its variants is one of the most studied combinational optimization problems[2-6]. The previous works on the VRP can be divided into two classes, exact algorithms and heuristic algorithms. As VRP is a class of NP-hard problem, it is difficult to use exact algorithm solving. Heuristic algorithm is the main method to solve VRP. Several families of heuristics have been proposed for VRP, such as savings method, which is first proposed by Clarke and Wright, Sweep method is proposed by Gillett and Miller, Tabu search method is proposed by Glover and so on. They are widely used in the logistics and distribution problem.

Ant colony algorithm (ACA) is a recent developed, distributed, population-based approach, first proposed by Dorigo and Gambardella in 1997, take full advantage of the characteristic of the foraging behavior of ant colonies, which has been successfully applied to several NP-hard combinatorial optimization problems, and gets better results[7-9]. As the name suggests, ACA has been inspired by the behavior of real ant colonies, in particular, by their foraging behavior. ACA can get a faster convergence rate and higher-quality global optima in problems of solving multi-node, multi-constrained.

In this work, we analyze the characteristic of the logistics and distribution problem, present corresponding mathematical models. Multi-vendor logistics distribution optimized algorithm (MVLDOA) is proposed, but time overhead for solving this problem is higher. Base on the inherent parallelism of the ant colony algorithm, we introduce a heuristic logistics distribution algorithm based on parallel multi-colonies (PMC-HLDA). The objective is to find the best possible solutions. Through the practical application of a region, the empirical evidence indicate that PMC-HLDA can be applied with success to VRP optimization by using parallelism, and is more feasible and effective with simulation by

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consideration between the time overhead and routing cost.

The paper has the following structure: in section 2 we give a problem formulation of VRP under investigation. Section 3 describes the mathematical model using the whole method, and a multi-vendor logistics distribution optimized algorithm. In section 4 we present the heuristic logistics distribution algorithm based on parallel multi-colonies. Section 5 analyzes the most important experimental results achieved. Finally, in section 6, we draw some overall conclusions and suggest directions for future work.

II. PROBLEM FORMULATION

In the vehicle routing problem, a set of customers require some kind of service, which is offered by a fleet of vehicles. The goal is find routes for the vehicles, each starting from given suppliers to which they must return, such that every customer is visited exactly once. Usually there is also an objective that needs to be optimized, minimizing the cost [10-12].

The extended VRP is focus on distribution of multi-suppliers, processing of return requests and order requests. It captures capacities, time windows, split delivery and more, which all try to make richer and more useful formulations.

Logistics distribution problem which is a modification of the well-known VRP with time windows can be formulated as follow: suppose an undirected graph G=(V, E) as a logistics and distribution net, where $V = S \cup H$ is a set of supplies and customers, $E = \{(i, j), i \neq j, i, j \in V\}$. d_{ij} is the distance from location i to location j. Customers is delivered from a certain supplier. K is a set of vehicles. Each vehicle serves a subset of customers on the route which begins and ends at the supplier, where vehicles have the same capacity Max_Load. q_i is the weight of goods that is sent to location i, l_i is the weight of goods that locations i returns. For each customer, a service time window $[et_i, lt_i]$. The vehicle can arrive at the customer before the time et_i. The latest time for arrival of the vehicle at customer i is lt_i. Meanwhile it consists of designing a set of least-cost vehicle routes in such a way that

(1) routes guarantee the delivery of goods to all customers.

(2) Each customer is only delivered by one vehicle.

(3) All vehicle routes start and end at the same suppliers.

(4) The current capacity serve by a vehicle on route cannot exceed Max_Load after leave any customer.

(5) The distribution task is completed in time window $[et_i, lt_i]$.

(6) The size of the route set less than the number of vehicles needed.

(7) The total travel time distance should be minimum.

III. MULTI-VENDOR LOGISTICS DISTRIBUTION OPTIMIZED ALGORITHM

Ant colony algorithm is a new inspired optimization algorithm based nature-inspired behavior [13-17]. Ants left pheromone on the that they passed in the feeding process, apperceived the existence and intensity of pheromone and guide their own movement direction that is apt to the higher intensity. Therefore, the collective foraging behavior expressed a positive feedback phenomenon: the shorter a route, the more ants which passed, the higher the pheromone intensity, the larger the probability. Ants through this exchange of information to choose the shortest and achieve the purpose of searching food.

In order to get the best delivery route, a multi-vendor logistics distribution optimized algorithm is presented by using whole method to solve this problem.

The mathematical model describes as follow:

Let $|M_{sk}|$ is the quantity of locations which is distributed by vehicle k of vendor s, m_{ski} expresses the order of location which is distributed by vehicle k of vendor s is i , n_s is the quantity of customers distributed by vendor s. In a word, we can reduce the cost of transportation by adopting shorter route. It is helpful that the total cost of the logistics and distribution net could be reduced. The model can be described as follows:

Objective function:.

$$Min\ z = \sum_{s \in G} \sum_{k \in R} \sum_{i \in M_{sk}} d_{m_{sk(i-1)}, m_{ski}} \tag{1}$$

Subject to

$$M_{sk} = \begin{cases} m_{ski} \in S, i = 1, \\ m_{ski} \in H, i = 2, .., |M_{sk}|, \\ m_{ski} = m_{sk1}. \end{cases} \tag{2}$$

$$(M_{sk_1} - m_{sk_1} - m_{sk|M_{sk_1}|}) \cap (M_{sk_2} - m_{sk_2} - m_{sk|M_{sk_2}|}) = \varnothing, \forall k_1 \neq k_2 \tag{3}$$

$$0 \leq |M_{sk}| - 2 \leq n_s\ , \ \sum_{k \in R} (|M_{sk_1}| - 2) = n_s\ , \ \sum_{s \in G} n_s = C \tag{4}$$

$$c = \sum_{i \in M'} l_{m_{ski}} + \sum_{i \in (M_{sk} - M')} q_{m_{ski}}\ , \ c \leq Max\_Load,\ M' \subset M_{sk} \tag{5}$$

$$at_j = at_i + t_{ij} \quad \forall i, j \in V, i \neq j \tag{6}$$

$$t_{ij} = d_{ij} / v \quad \forall i, j \in V, i \neq j \tag{7}$$

$$et_i \leq at_i \leq lt_i \quad \forall i \in V \tag{8}$$

Equation (1) is the objective function. It achieve to the least cost as the final objective.

Equation (2)ensure that each vehicle must depart from a certain supplier, and finally return to the supplier. Each customer is only delivered by one vehicle. m_{ski} shows the delivery route, M_{ski}s the set of m_{ski}.

Equation (3), (4) are restriction of each vehicle. Each customer is from a vehicle route. The quantity of customers which is from each route should not exceed the quantity of customers distributed by vendor s, the quantity of customers distributed by vendor s should not exceed the total quantity of customers and each customer should be distributed.

Equation (5) is restriction of vehicle load capacity, and ensures the current load capacity is no more than the maximum load capacity while vehicles are departing any customer.

Equation (8) is restriction of the vehicle arrival time. Each vehicle must be delivered in time window $[et_i, lt_i]$.

The MVLDOA is described as follows:

A. State Transition Rules

In ACA $\tau_{ij}(t)$ is the intensity of trail on edge (i, j) at time t. Initially, the pheromone of each edge is the same. z ants are placed on vendors chosen customers. In each construction step, each ant moves, based on the pheromone trail $\tau_{ij}(t)$, to a customer it has not yet visited, by a locally available heuristic information η_{ij} and a additional heuristic information γ_{ij}. Ants prefer customers which are close and connected by edges with a high pheromone trail and ant k currently located at customer i chooses to go to customer j with (9):

$$P_{ij}^{k}=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}\left[\gamma_{ij}\right]^{\theta}}{\sum\limits_{l\in allowed_k}\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}\left[\gamma_{ij}\right]^{\theta}}, j\in allowed_k \text{ and } c_k\le Max\_Load,\\ 0, \qquad\qquad otherwise.\end{cases} \quad (9)$$

where α, β and θ are three parameters which determine the relative importance of the pheromone trail and the heuristic information, and $allowed_k$={S H-$tabu_k$} is the feasible neighborhood of ant k, that is, the set of locations which ant k has not visited yet. Each ant k stores the locations visited in its current partial route in $tabu_k$. Additionally, it allows the ant to retrace its route, once it is completed, so that it can deposit pheromone on the edges it contains.

B. Heuristic Information Value

In solving different combinatorial optimization problems by using ant colony system, the heuristic information is different in different situation. η_{ij} is a function of the edge length, here use $\eta_{ij}=1/d_{ij}$, γ_{ij} reflects the importance of the customers. It is expressed as the ratio, which is the weight of goods that is sent to the j-th customer, and the weight of the goods that the j-th customer returns, that is, $\gamma_{ij}= q_i/l_i$. The larger q_i, the higher the probability of the j-th customer that is selected, whereas the higher l_i, which means the j-th customer will be distributed after other customers unload, the lower the probability of the j-th customer that is selected. when γ_{ij} is smallest, d_{ij} is largest, the j-th customer would not select in the next time.

C. Pheromone Update

After all ants have completed the route construction, the pheromone trails are updated according to the following formula. It lowers the pheromone trails by a constant factor and then allows the ants to deposit pheromone on the edges they have visited.

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\sum_{i=1}^{z}\Delta\tau_{ij}^{k}. \quad (10)$$

where the parameter ρ (with $\rho\in[0, 1]$) is the trail persistence and $\Delta\tau_{ij}^{k}$ is the quantity per unit of length of pheromone laid on the edge (i, j) by the k-th ant it has used in its cycle. $\Delta\tau_{ij}^{k}$ is defined as follows:

$$\Delta\tau_{ij}^{k}=\begin{cases}Q/L_k, if\ (i,j) \text{ is used by ant } k \text{ in this cycle},\\ 0, otherwise.\end{cases} \quad (11)$$

where Q is a constant and L_k is the route length of the k ant. By (11), the better the ant's route is, the more pheromone is received by the edges belonging to this route. Here the amount of pheromone $\Delta\tau_{ij}^{k}$ represents the j-th customer will be selected more often to move when an ant is in customer i.

D. Local Optimization

The 2-Opt algorithm is probably the most basic and widely used local search heuristic [18]. The 2-Opt algorithm starts with an arbitrary initial route and incrementally improves this route by exchanging two of the edges in the route with two other edges. More precisely, in each improving step, the 2-Opt algorithm selects two edges (i, j) and (i+l, j+l) from the route, and the algorithm replaces these edges by the edges (i, j+1) and (j, i+1). when d(i, j) + d(i+1, j+1) < d(i, i+1) + d(j, j+1), it is the current feasible solution to decrease the length of the route. The algorithm terminates in a local optimum in which no further improving step is possible or fixed cycles reach.

E. Algorithm Description

Input: the related datas and parameters
Output: the optimal delivery routes and the total length

Procedure Multi-vendor Logistics Distribution Optimized Algorithm

begin
Initialize, all the ants are divided into k ant colonies, each ant colony has z ants. Set the initial pheromone of edge (i, j) is $\tau_{ij}=c$, T=0.
Calculate heuristic information η_{ij}, γ_{ij}.
While $T<T_{\max}$ do
for a=1 to z do
place z ants on vendors randomly,
if customers and suppliers are not completely visited
Calculate the current load
if the current load is less than the vehicle maximum load and is distributed in time window
Choose the next node according to state transition rule p_{ij}^{k} given by (9)
else the next node is supplier
end if
end if

```
        end for
        Record the delivery route length
        if this delivery route is the best
            use the 2-opt algorithm to optimize the current optimal solution.
            Record routes ants passed, update the pheromone according to Equation(11)
        end if
        update the pheromone according to global update rule Equation(10)
        T=T+1
    end while
    Output the optimal delivery route and the total length
end
end procedure
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IV. MULTI-COLONIES PARALLEL HEURISTIC LOGISTICS DISTRIBUTION ALGORITHM

With the development of logistics, MVLDOA is difficult to consistently solve problems with more than just a few customers. In some case, even evaluation of routing cost function can be extremely difficult, depending on the distribution of random variables. Hence, the need for practical heuristic solution method is evident[19-20].

Multi-colonies parallel heuristic logistics distribution algorithm (PMC-HLDA) is presented based on solving this problem. It is a plan that would be possible to execute given that the scenario would actually happen, which could have higher optimization ability and it iteration is reduced due to its high convergence speed.

In the case of multipoint to multipoint, the objective of logistics distribution is the routing cost is least. In order to predigest calculation, we use the total travel distance as the objective function value. With the analysis, we divide the multipoint-to-multipoint up into one-to-multipoint, and unify to achieve the total objective function.

Let $M_{sk} = \{m_{k0}, m_{k1}, ..., m_{ks}, m_{ks}\}$ presents the route that vehicle k is delivered, where m_{ki} is the order of location which is delivered by vehicle k is i in the current distribution route, m_{k0} is supplier. $|M_k|$ is the quantity of locations which is distributed by vehicle k, t_{ij} is the transport time from location i to location j, v is vehicles running speed, at_i is the arrival time of the vehicle. All the routes sets are $M = \bigcup_{s\in G, k\in K} M_{sk}$.

The mathematical model is as follows:

$$\min \sum_{s\in G} \sum_{k\in K} \sum_{i\in M_{sk}} d_{m_{k(i-1)}m_{ki}} \quad (12)$$

Subject to

$$0 \le |M_{sk}| \le C-2 \qquad \forall k \in K, s \in S \quad (13)$$

$$\sum_{k} |M_{sk}| = C-2K \qquad \forall k \in K, s \in S \quad (14)$$

$$M_{sk} = \begin{cases} m_{ki} = s, i = 1 \\ m_{ki} \in H, i = 2, ..., |M_k| - 1 \\ m_{ki} = m_{ki}, i = |M_k| \end{cases} \quad \forall k \in K, s \in G \quad (15)$$

$$M_{sk_1} \cap M_{sk_2} = \varnothing, \qquad \forall k_1, k_2 \in K \quad (16)$$

$$\sum_{i=1}^{r} l_{m_{ki}} + \sum_{i=r}^{|M_{sk}|} q_{m_{ki}} \le Max\_Load \quad (17)$$

$$at_j = at_i + t_{ij} \quad \forall i, j \in V, i \ne j \quad (18)$$

$$t_{ij} = d_{ij} / v \quad \forall i, j \in V, i \ne j \quad (19)$$

$$et_i \le at_i \le lt_i \quad \forall i \in V \quad (20)$$

Equation (12) is the objective function. It is constituted by vehicles driving distance, and achieve to the least cost.

Equation (13), (14) are restriction of each vehicle, and ensure the customers' quantity is no more than the total customers' quantity. Each customer must be delivered.

Equation (15), (16) ensure that each vehicle must depart from a certain supplier, and finally return to the supplier. Each customer is only delivered by one vehicle.

Equation (17) is restriction of vehicle load capacity, and ensures the current load capacity is no more than the maximum load capacity while the vehicle is departing any customer.

Equation (20) is restriction of the vehicle arrival time. Each vehicle must be delivered in time window $[et_i, lt_i]$.

The PMC-HLDA is described as follows

A. Initialization

We describe the logistics distribution to the form of ant colony algorithm, and keep the delivery routes to the route that ants passed. All the ants are divided into k ant colonies. That has k×z ants participate in routes in a iterative procedure. The pheromone which ants released is only affected the identical ant colony, and is not interfere with each other. In order to construct different initial solutions, each ant selects the first node randomly. In the movement process of ants, nodes which are not visited make up customers' distributed set. Then ants complete a search, a solution is got.

B. Path Construction

When every ant choose the next customer, we need to consider the follow factors on the premise of vehicle load restriction and time window restriction:

(1) The route length that chose the next customer, and the pheromone of routes.

(2) The demand quantity of the next selected customer the return quantity of the next selected customer. The customer had more demand quantity is distributed as the first. When vehicle is unloaded, it is convenient for customers had the higher return quantity to return goods. The priority rule is customers had the higher demand quantity and the less return quantity.

C. State Transition Rules

In the movement process, ant z in the k-th ant colony decides whether move location j from location i on the basis of state transition rules p_{ij}^{k}, that is:

$$P_{ij}^{kz} = \begin{cases} \dfrac{\left[\tau_{ij}{}^{k}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}\left[\gamma_{ij}\right]^{\theta}}{\sum\limits_{l\in allowed_k}\left[\tau_{ij}{}^{k}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}\left[\gamma_{ij}\right]^{\theta}}, j \in allowed_k \\ 0 \qquad\qquad ,otherwise \end{cases} \tag{20}$$

Where η_{ij} is the heuristic information, that is, $\eta_{ij} = 1/d_{ij}$, it shows the expected degreed. γ_{ij} is the heuristic information depended on the characteristic of this problem, it show the ratio of demand quantity and return quantity, that is $\gamma_{ij} = q_j / l_j$. α, β reflect the accumulative pheromone and the relative importance that ants chose routes. θ is the relative importance of heuristic information. $allowed_k = \{0,1,...C\}/tabu_k$ expresses nodes which ant k chose next allowable nodes. $tabu_{kx}$ records the visited node that ant k distributed the route. $allowed_k$, $tabu_{kx}$ could have the dynamic adjustment with process.

D. Introducation of Metrizable Ratio

With the multi-colonies parallel algorithm, it will appear ants chose the same node as the next node along different routes at the same time. In order to reduce the computer and intensify the search in specific regions of search, this algorithm introduces metrizable ratio to choose the next node. Let metrizable ratio is α, which expressed the priority chose customers, here use $\alpha = (Load_i / d_{ij})^{\omega_j}$, where $Load_i$ is the current load, w_j indicates that the importance of location. The request should be priority in one sense when the location j have emergency, the value of w_j set a large number. Then the request of customer j is the first with no influence to the whole distribution problem. To the above situation, it gives preference to nodes had the higher metrizable ratio, and ensures the optimal route to choose.

E. Pheromone Update

After all ants have completed the route construction, the pheromone trails are updated according to the following formula. It lowers the pheromone trails by a constant factor and then allows the ants to deposit pheromone on the edges they have visited.

$$\tau_{ij}{}^{k}(t+1) = (1-\rho)\tau_{ij}{}^{k}(t) + \Delta\tau_{ij}{}^{k} \tag{21}$$

where the parameter ρ (with ρ∈[0, 1]) is the trail persistence and $\Delta\tau_{ij}{}^{k}$ is the quantity per unit of length of pheromone laid on the edge (i, j) by the k-th ant colony it has used in its cycle. $\Delta\tau_{ij}{}^{k}$ is defined as follows:

$$\Delta\tau_{ij}{}^{k} = \sum_{z=1}^{m}\Delta\tau_{ij}{}^{kz} \tag{22}$$

where $\Delta\tau_{ij}{}^{kz}$ represents the quantity of pheromone laid on the edge (i, j) by the z-th ant of the k-th ant colony it has used in its cycle.

The basic ant colony algorithm is that all the routes ants passed had pheromone update after every cycle. Then the worse ant had affect the distribution of pheromone, these optimal routes is not embodied. In order to enhance the effect of optimal ants, every cycle only has pheromone update to the optimal ants in current cycle. The update rule is as follows:

$$\Delta\tau_{ij}{}^{kz} = \begin{cases} 1/L^{best} & if\ (i,j)\ is\ on\ the\ optimal\ route \\ 0 & otherwise \end{cases} \tag{23}$$

where L^{best} is the route length of the current optimal route. By (23), the better the ant's route is, the more pheromone is received by the edges belonging to this route. Here the amount of pheromone $\Delta\tau_{ij}{}^{k}$ represents the j-th customer will be selected more often to move when an ant is in customer i.

F. Algorithm Description

Input: the related datas and parameters
Output: the optimal delivery routes and the total length

Procedure Multi-Colonies Parallel Heuristic Logistics Distribution Algorithm

begin
  Intialize, all the ants are divided into k ant colonies, each ant colony has z ants. Set the initial pheromone of edge(i, j) is $\tau_{ij} = c$, T=0.
  Calculate heuristic information η_{ij}, γ_{ij}.
  While $T < T_{\max}$ do
    for a=1 to z do
      Place a ant from k-th ant colony on suppliers, set $tabu_{kx}$, $allowed_{kx}$ for every ant.
      k ants randomly choose either customer as the next node
      for b=1 to k do
        if customers and suppliers are not completely visited
          Calculate the current load
          if the current load is less than the vehicle maximum load and is distributed in time window
            Choose the next node according to state transition rule p_{ij}^{k}
          else the next node is supplier
          end if
        end if
        if k ants have the same customer j as the next node
          Calculate metrizable ratio, and choose the node had higher metrizable ratio as the next node. Modify $tabu_{kx}$, $allowed_{kx}$
        end if
      end for
    end for
    Record the delivery route length

if this delivery route is the best
Record routes ants passed, update the pheromone according to Equation(22)
end if
update the pheromone according to global update rule Equation(23)
T=T+1
end while
Output the optimal delivery route and the total length
end
end procedure

V. EXPERIMENTAL SIMULATION

In order to check up the result of PMC-HLDA, the test chose a distribution region, which had four suppliers and thirty-two customers to distribute. The multi-colonies parallel heuristic logistics distribution algorithm is applied on route planning. The delivery route solved is shown as thick line in figures. the parameters set as follows in the test:

$v = 6\text{km}/\text{h}$, $\alpha = 1$, $\beta = 2$, $\theta = 1$, $\rho = 0.15$, $T_{\max} = 30$, $z = 10$, $k = 5$.

The test problems tests on the Intel Pentium Dual processors using 2GB memory. MATLAB are used in the experiment. The result is compared with results got from the basic ant colony algorithm. The following Tab.1 compares the computional results for PMC-HLDA and ACA.

TABLE I.
SIMULATION RESULTS COMPARISON

Algorithm	Length	Vehicle	Iteration got the best length
PMC-HLDA	48.3km	13	12
ACA	52.6km	14	21

From Tab.1, it show that reasonable good solution can be obtained by the ant colony algorithm. From the computational results, we can see that PMC-HLDA has more trails getting the theoretical optimums, the length of the best length and the quantity of vehicle are much smaller than ACA. This indicates that our parallel algorithm has higher optimization ability, the iteration of the algorithm decreases due to its high convergence speed. Through the problem specific features described in PMC-HLDA for the selection probabilities, a further reduction of route lengths is achieved. PMC-HLDA uses metrizable ratio to choose the next node, while ant colonies choose the same customer as the next node. But only the optimal routes have pheromone update. Then it can lead to a significant reduction in the computational time, and a favorable solving to large scale optimization problem.

In order to analyze delivery routes of the result better, Fig.1, Fig.2 shows vehicle scheduling and route choice in the test to compare the performance of our PMC-HLDA with ACA. In Fig.1, the red triangle represents the customer who need the priority.

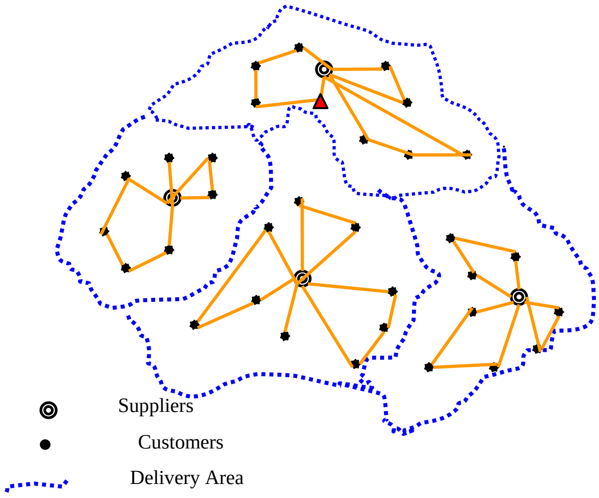

Figure 1. Simulation result of PMC-HLDA

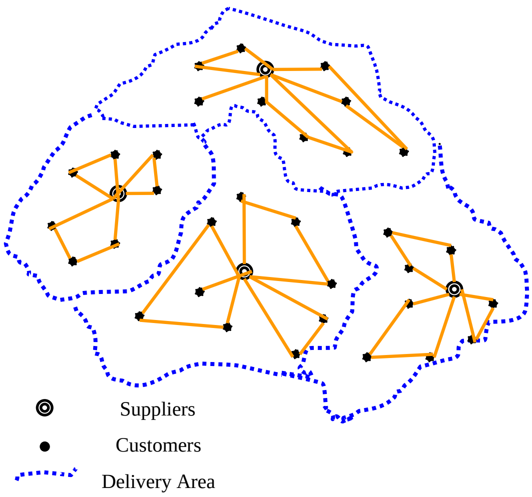

Figure 2. Simulation result of ACA

From Fig.1, Fig.2, we can see that the delivery length of the ACA is longer, the vehicle is more, the interval returned suppliers is larger. These are mainly attributed that the ACA only consider the delivery length. In this paper, our PMC-HLDA changes constraint conditions in routes construction, uses optimization strategy to improve its constraint conditions further, and gets more optimal solution. It can even process the emergency of customer.

Tab.2 shows the experimental results on MCP-HCP and MVLDOA. MCP-HCP algorithm represents the algorithm of adapting parallel strategy, and MVLDOA is based on whole method.

TABLE II.
SIMULATION RESULTS COMPARISON

Algorithm	Length	Vehicle	Iteration got the best length
PMC-HLDA	48.km	13	12
MVLDOA	47.8km	13	18

From Tab.2, we can see that the total length of MVLDOA is better than PMC-HLDA. MVLDOA takes suppliers and customers into account. But on the other hand, the iteration got the best length of PMC-HLDA is less than MVLDOA. PMC-HLDA with the parallel ant algorithms with fixed time interval of information exchange by using the corresponding strategy to solve the best route, PMC-HLDA can keep balance between the computer time and the quality of the solution so as to higher quality solutions in shorter time.

Fig.3 shows vehicle scheduling and route choice of MVLDOA.

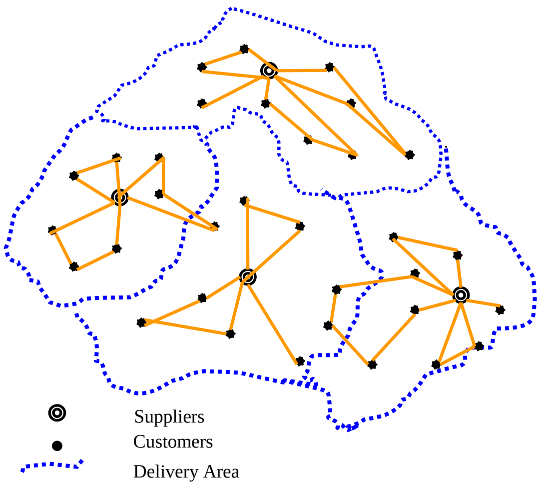

Figure 3. Simulation result of MVLDOA

In the experiment, we also compare the results of MVLDOA with PMC-HLDA. In Fig.2, we divides region into four areas, and call PMC-HLDA to solve. It ingore the actual relation of customers. MVLDOA considers all existent relation, but the time cost is larger. It is difficult to consistently solve problems with more than just a few customers. Compared with three algorithms, PMC-HLDA can keep balance between the time overhead and the best routing cost.

VI. CONCLUSION

To solve realistic routing problems, it is often essential to extend the classical VRP formulation. Vehicle routing and scheduling models aim to minimize cost (usually related to the number of vehicles, distance and time)[21-23]. In logistics distribution problem, reasonable choice of routes is an important means to improve the quality of service, and reduce the routing cost. We introduce the corresponding algorithms to solve this problem.

The Multi-vendor logistics distribution optimized algorithm take the relation between suppliers and customers into account from the overall optimal perspective, but the time overhead is higher. Base on the analysis of logistics distribution characteristic, we consider the actual situation, break the multipoint-to-multipoint up into one-to-multipoint, and unify to achieve the total objective function, and present a a multi-colonies parallel heuristic logistics distribution algorithm by introducing metrizable ratio. Several parameters in the heuristic could be tuned, which may lead to other insights The results show that PMC-HLDA can be a better optimization to vehicle scheduling and routes choice in a shorter time, plan a relative independent and reasonable delivery route for all customers, so that it might be suitable to customers' actual demand.

We would also like to expand our stochastic to support other stochastic variables, for instance running distance, service quantity, as well as add other extensions to the model. This would allow for a extended VRP to be solved using the same framework.

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