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Route Optimization for Last-Mile Distribution of Rural E-Commerce Logistics Based on Ant Colony Optimization

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ABSTRACT This paper aims to solve the last-mile distribution of rural e-commerce logistics (RECL) for the survival of third-party logistics enterprise. Considering the features of the RECL (long transport chain and low consumption density), A route optimization model is constructed for RECL's last-mile distribution to maximize the profit of the logistics enterprise, which is subsidized by the government. To solve the model, the ant colony optimization (ACO) was improved to suit the RECL's last-mile distribution by modifying the heuristic information, the update rule of pheromone, and the solution construction. Next, the optimal combinations of the default parameters in the improved ACO were determined through Matlab tests on five test datasets in different sizes. The other parameters were configured according to the scale of the RECL. On this basis, the improved ACO was proved effective through example analysis on the said test datasets. The analysis results also reflect how the number of vehicles affects the maximum profit of the logistics enterprise and the coverage of the RECL logistics network.

INDEX TERMS Rural e-commerce logistics (RECL), last-mile distribution, route optimization, ant colony optimization (ACO).

I. INTRODUCTION

The rural area is becoming the new blue ocean for online consumption, triggering a boom in rural e-commerce logistics (RECL). The Chinese Ministry of Transport proposed to speed up the construction of three-tier (county, town and village) distribution node system for rural logistics, offering infrastructure support for the "Express Delivery to the Countryside" project. Under the incentive policy, logistics enterprises start to set up outlets in easily accessible towns. However, the service network of most logistics enterprises has not yet covered villages, owing to their remote locations and poor transportation infrastructure. The economy in China's rural areas is increasingly bottlenecked by the incomplete network, high cost and slow speed of rural logistics.

The existing research on last-mile distribution mainly focuses on densely populated areas like cities, communities and business areas. The relatively few studies on the RECL manage to provide reference and theoretical basis for the last-mile distribution of rural logistics. Last-mile delivery has become a critical source for market differentiation, motivating retailers to invest in a myriad of consumer delivery innovations, such as buy-online-pickup-in-store, autonomous delivery solutions, lockers, and free delivery upon minimum purchase levels [1]. Consumers care about last-mile delivery because it offers convenience and flexibility [2]. For these reasons, same-day and on-demand delivery services are gaining traction for groceries, pre-prepared meals, and retail purchases [3]. To meet customer needs, parcel carriers are increasing investments into urban and automated distribution hubs [4]. However, there is a lack of understanding as to how best to design last-mile delivery models with retailers turning to experimentations that, at times, attract scepticism from industry observers [5]. Punakivi *et al.* [6] held that the last mile is one of the biggest challenges to e-commerce logistics, and proposed shared reception box to combine profitability and service level. Boyer *et al.* [5] pointed out that consumer-direct delivery of packages ordered over the

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Internet has grown at well over 25% per year in the last decade, while logisticians have faced a challenge in devising efficient and low-cost methods for last-mile delivery. Joress *et al.* [7] mentioned that the cost of global parcel distribution, excluding pickup, line-haul, and sorting, amounts to about €70 billion, more than half of which is incurred in the last mile, and that the last-mile distribution is not the focal point of express delivery enterprise. Considering the features of e-commerce logistics distribution, Durand and Gonzalez-Féliu [8] compared three common last-mile delivery modes: all home delivery, home delivery + pickup service, and pickup everything, and determined the most favorable last-mile distribution mode in urban environment. These studies show that logistics enterprises mainly face three problems in the last-mile distribution and the first-mile pickup, namely, sufficient demand, high distribution cost and imperfect facilities. These problems create a harsh environment for logistics enterprises to operate in rural areas, making it hard for them to earn profit and slowing down their penetration into rural areas.

The vehicle routing problem (VRP), a key issue in logistics distribution system, has long been a research hotspot. Many mature algorithms have been developed and applied to solve the VRP and its variants, laying a solid basis for optimizing the route of last-mile distribution in the RECL. The VRP first appeared in a paper by Dantzig and Ramser in 1959 [9], which is concerned with the optimum routing of a fleet of gasoline delivery trucks between a bulk terminal and a large number of service stations supplied by the terminal. Clarke and Wright [10] considered the VRP as a linear optimization problem, a common issue in logistics and transport and a hot topic in operational research. Azi *et al.* [11] proposed a single-vehicle, multi-route VRP with time window based on the home delivery of perishable goods, where vehicle routes are short and must be combined to form a working day, and solved the problem with an accurate algorithm with resource constraints. Ai *et al.* [12] put forward the VRP with simultaneous pickup and delivery (VRPSPD), solved it by a particle swarm optimization (PSO) algorithm with multiple social structures, and verified the solution using three benchmark datasets. Marinakis and Marinaki [13] successfully solved the VRP through the combination of the genetic algorithm (GA) [14] and the PSO [15]. Archetti [16] designed two exact branch-and-cut algorithms for the split delivery VRP (SDVRP), which excludes any feasible solution to relaxed constraints that does not satisfy the model constraints from the search space of the relaxed problem. Kalayci and Kaya [17] developed a hybrid algorithm based on an ant colony system (ACS) [18] and a variable neighborhood search (VNS) [19], in which the VNS releases pheromones instead of ants, solved the VRPSPD with the hybrid algorithm, and verified the high quality of the solution through numerical simulation.

Drawing on the above results and the features of the RECL (long transport chain + low consumption density), this paper thoroughly analyzes the cost and income of the RECL under fiscal subsidy, and puts forward an optimization model for the last-mile distribution of the RECL, according to the modelling practices for route optimization and vehicle orientation problems. Next, the ant colony optimization (ACO) was improved and applied to solve the established model, under the constraint of vehicle capacity (the maximum allowable quantity of goods onboard) and driver's working hours. The optimal parameters of the improved ACO for different numbers of distribution nodes were identified based on multiple groups of test data. Finally, the proposed model and algorithm were proved effective through example analysis.

The remainder of this paper is organized as follows: Section 2 establishes the optimization model for the last-mile distribution of the RECL, in the light of the RECL features, and improves the ACO algorithm; Section 3 verifies the proposed model and algorithm through example analysis, and discusses the verification results in details; Section 4 puts forward the main conclusions of this research.

II. METHODOLOGY

In China, the last-mile distribution of the RECL mainly takes places between the town level and the village level in the three-tier distribution node system. The following parameters are all known in advance: the number and location of all villages, the quantity of goods to be picked up (pickup quantity) from each village, and the quantity of goods to be delivered (delivery quantity) to each village. Each vehicle has a limited capacity, and each driver only works for a limited number of hours. To maximize its profit, the logistics enterprise needs to fully consider the cost and income of distribution, and rationally select the number of vehicles, under the constraint of vehicle capacity and driver's working hours. During the delivery process, the vehicles will leave from the logistics service center at the town (LSC-T), travel along the designed routes to deliver the goods to the selected villages in sequence, and return to the LSC-T after completing all distribution tasks.

From the perspective of graph theory, the last-mile distribution of the RECL can be described by a complete graph $G = (N, E)$, where $N = \{0, 1, 2, \ldots, n\}$ is the set of nodes (LSC-T and villages), and $E = \{(i, j)|i, j \in N\}$ is the set of edges (routes). Let $K = \{0, 1, 2, \ldots, m\}$ be the set of vehicles. Node 0 (LSC-T) is the fixed start and end points of each route. Each node $i \in N$ has a nonnegative income s_i and nonnegative service time t_i. The income and service time at node 0 (LSC-T) are both zero, i.e. $s_0 = t_0 = 0$. The transport cost per unit distance f and cost of each vehicle c_k are also nonnegative. The travel time of each route should not exceed the maximum travel time T_{max}, and the quantity of goods on each vehicle $k \in K$ should not surpass the maximum capacity Q_{max}.

The objective of the last-mile distribution of the RECL is to select m routes from the start point to the end point, each covering a subset of N, such that the total profit of vehicles travelling along these routes to the corresponding nodes, i.e. the total income of the visited nodes minus the total distribution cost of the vehicles, is maximized, without violating the constraints on vehicle capacity and driver's working hours.

A. HYPOTHESES

In China, the RECL mainly relies on a three-tier (county, town and village) distribution node system. All the vehicles must leave from the LSC-T, visit the selected villages in sequence and return to the LSC after completing all distribution tasks. For simplicity, the following hypotheses were put forward before modelling the last-mile distribution of the RECL.

Hypothesis 1. The pickup and delivery quantities of each village are fixed, and the two quantities of the selected villages can be fully satisfied.

Hypothesis 2. All the vehicles are of the same type and all the goods to be picked up and delivered belong to the same category.

Hypothesis 3. The cost and income of pickup and delivery at non-selected villages are not taken into account.

Hypothesis 4. The logistics enterprise receives no benefit from the distribution tasks from the LSC-T to the villages. The logistics network between the town level and village level is newly constructed. In this network, the only distribution income comes from fiscal subsidy.

Hypothesis 5. Each vehicle can serve multiple villages, but each village can only be served by one vehicle.

Hypothesis 6. Each vehicle only travels along one distribution route.

Hypothesis 7. Every vehicle leaves from the LSC-T at time 0.

Hypothesis 8. Every vehicle leaving from the LSC-T travels at a constant speed.

Hypothesis 9. All the villages are fixed at the same position and within the coverage of the LSC-T.

B. MODEL CONSTRUCTION

Considering the survival of third-party logistics enterprises, this subsection sets up a route optimization model for the last-mile distribution of RECL according to the modelling practices for route optimization and vehicle orientation problems. Under the abovementioned hypotheses, the following objective function of model was established to maximize the profit of the logistics enterprise:

$$\max Z = \sum_{i=1}^{n}\sum_{k=1}^{m}(s_1 q_i + s_2 p_i)\, y_{ik} - \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} f d_{ij} x_{ijk} - \sum_{j=1}^{n}\sum_{k=1}^{m} x_{0jk} c_k \quad (1)$$

where the first term is the distribution income; the second and third terms are the distribution cost. Here, the distribution income is replaced with fiscal subsidy.

The established model is subjected to the following constraints:

$$\sum_{j=1}^{n} x_{0jk} = 1, \quad k = 1, 2, \cdots m \quad (2)$$

$$\sum_{i=1}^{n} x_{i0k} = 1, \quad k = 1, 2, \cdots m \quad (3)$$

Formulas (2) and (3) requires each vehicle to leave from the LSC-T, visit the selected villages in sequence and return to the LSC after completing all pickups and deliveries, forming a closed loop.

$$\sum_{i=0}^{n} x_{ipk} - \sum_{j=0}^{n} x_{pjk} = 0, \quad p = 0, 1, \cdots n, \; k = 1, 2, \cdots m \quad (4)$$

Formula (4) ensures the continuity of the distribution route: the goods to be delivered to the selected villages must be loaded onto the same vehicle.

$$\sum_{k=1}^{m} y_{ik} \le 1, \quad i = 1, 2, \cdots n \quad (5)$$

Formula (5) stipulates that each village can only be visited once at most, which is consistent with the actual situation of rural logistics distribution. This is because the demand for rural logistics is small, and multiple traversals will increase the cost.

$$\sum_{i=0}^{n} x_{ijk} = y_{jk}, \quad j = 1, 2, \cdots n, \; k = 1, 2, \cdots m \quad (6)$$

$$\sum_{j=0}^{n} x_{ijk} = y_{ik}, \quad i = 1, 2, \cdots n, \; k = 1, 2, \cdots m \quad (7)$$

Formulas (6) and (7) define the relationship between two decision variables, which are explained later.

$$\sum_{i=1}^{n} q_i y_{ik} \le Q_{\max}, \quad k = 1, 2, \cdots m \quad (8)$$

$$\sum_{i=1}^{n} p_i y_{ik} \le Q_{\max}, \quad k = 1, 2, \cdots m \quad (9)$$

Formulas (8) and (9) limit the delivery quantity and pickup quantity, respectively. In the last-mile distribution of the RECL, pickup and delivery take place simultaneously at each village. Both delivery and pickup quantities should be constrained at each village, such that the quantity of cargoes onboard does not surpass the maximum capacity of the vehicle throughout the distribution process. Otherwise, the vehicle may be overloaded, when the pickup quantity is greater than the delivery quantity.

$$\sum_{i=1}^{n} L_i y_{ik} \le Q_{\max}, \; L_i = \max\{p_i, q_i\}, \quad k = 1, 2, \cdots m \quad (10)$$

where L_i is the maximum pickup and delivery quantities at node i. Formula (10) is integrated from formulas (8) and (9)

TABLE 1. Description of model parameters.

Symbol	Definition
N={0,1,2,…,n}	The set of n+1 nodes, including an LSC-T (node 0) and n villages
K={1,2,…,m}	The set of m vehicles
i,j	The serial number of nodes
k	The serial number of vehicles
(x_i,y_i)	The coordinates of each node
s_1	The income per unit pickup quantity (unit pickup income)
s_2	The income per unit delivery quantity (unit delivery income)
f	The transport cost per unit distance (unit distance cost)
c_k	The cost of each vehicle k
q_i	Delivery quantity at node i
p_i	Pickup quantity at node i
L_i	Maximum pickup and delivery quantities at node i
d_{ij}	Distance between nodes i and j
$Q_{\max}$	Maximum capacity of each vehicle
$T_{\max}$	Maximum working hours of the driver
t_i	Service time at node i
v	Travel time
x_{ijk}	Whether vehicle k travels directly from node i to node j
y_{ik}	Whether vehicle k passes through node i

to restrict the pickup and delivery quantities at each village. In this way, the two constraints are combined into a single constraint on vehicle capacity.

$$\sum_{i=0}^{n}\left(t_i y_{ik}+\sum_{j=0}^{n}\frac{d_{ij}}{v}x_{ijk}\right)\leq T_{\max},\quad k=1,2,\cdots m \tag{11}$$

Formula (11) sets the limit on driver's working hours. The maximum working hours of the driver must always be longer than the travel time on each route. Here, the travel time is the sum of the driving time and the pickup and delivery time (service time) at each village.

$$2\leq u_{ik}\leq n,\quad i=1,2,\cdots n,\ k=1,2,\cdots,m \tag{12}$$

$$u_{ik}-u_{jk}+1\leq n\left(1-x_{ijk}\right),\quad i,j=1,2,\cdots n,\quad k=1,2,\cdots,m \tag{13}$$

Formulas (12) and (13) are established based on Vansteenwegen P.'s subtour elimination constraint, aiming to eliminate secondary routes [15].

The two decision variables are defined below:

$$x_{ijk}=\begin{cases}1 & \textit{Vehicle k travels directly from nodeito node j}\\ 0 & \textit{Otherwise}\end{cases} \tag{14}$$

where x_{ijk} reflects whether vehicle k travels directly from node i to node j. If yes, $x_{ijk}=1$; otherwise, $x_{ijk}=0$.

$$y_{ik}=\begin{cases}1 & \textit{Vehicle k passes through node i}\\ 0 & \textit{Otherwise}\end{cases} \tag{15}$$

where y_{ik} reflects whether vehicle k passes through node i. If yes, $y_{ik}=1$; otherwise, $y_{ik}=0$.

The parameters of the model and their definitions are given in Table 1.

C. DESIGN OF SOLVING ALGORITHM

1) APPLICABILITY ANALYSIS

For the following reasons, the ACO was selected as the basis of the solving algorithm of our route optimization model for last-mile distribution in the RECL:

First, the ACO has been successfully applied to solve route optimization and vehicle orientation models. It only requires minor modifications to make the algorithm suitable for solving the last-mile distribution problem in the RECL.

Second, the ACO can preserve information well with its positive feedback mechanism. In the ACO, each ant releases pheromone on each route. The higher the pheromone concentration, the better the route, and the more likely for the route to be selected. The optimal route can be approximated iteratively through the update of pheromone concentration.

Third, the ACO boasts strong robustness. Through slight revisions, the algorithm will become suitable for various combinatorial optimization problems, and effectively tackle largescale problems that are non-deterministic polynomial-time (NP) hard.

Fourth, the ACO enjoys great potential of parallel search, for each ant in the colony can look for the optimal route at the same time. Through parallel search, the algorithm achieves a high efficiency, and the final result will not be affected by suboptimal choices of individual ants. With properly selected parameters, the ACO can be improved to shorten the search time, avoid early convergence and prevent the local optimum trap.

2) DESIGN OF THE IMPROVED ACO

The key to solving combinatorial optimization problems with the ACO lies in the construction of feasible solutions. In classic travelling salesman problem (TSP) and knapsack problem, the solutions are set up randomly: one of the unvisited nodes is selected as the next target according to the state transfer rules, until all the nodes have been visited once. In the

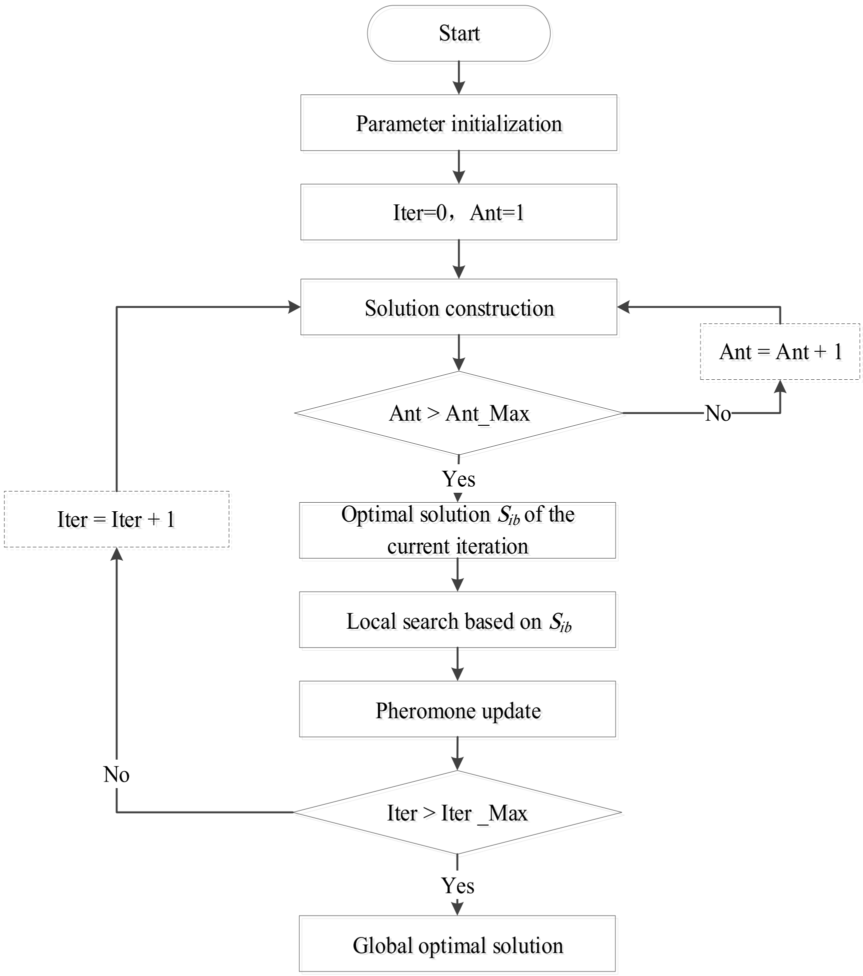


FIGURE 1. **The workflow of the improved ACO.**

last-mile distribution of the RECL, however, each ant needs to select a vehicle and its target node before each movement. To fulfil these needs, this paper decides to construct feasible solutions by the serial method in the literature [16]: each ant plans a feasible route for a vehicle, and then plans a feasible route for the next vehicle. This process continues until every vehicle has its feasible route. The workflow of the improved ACO is illustrated in Figure 1.

III. EXAMPLES

A. DATA

Standard route optimization and vehicle orientation problems are generally processed by the mathematical models and solving algorithms, which are developed based on the instances in the common test database (http://neo.lcc.uma.es/vrp/vrp-instances/capacitated-vrp-instances/). The common test data cannot be directly used to verify the effect of the improved ACO, because our research problem, i.e. the route optimization of last-mile distribution in the RECL, is not a standard VRP. Therefore, the datasets suitable to verify the improved ACO were developed based on five sets of standard test data (scales (A-n32-k5, B-n45-k5, B-n56-k7, B-n68-k9, and A-n80-k10) proposed by Augerat et al. with capacity constraint. Considering the actual conditions of the RECL's last-mile distribution, the pickup quantity at each node was added to the original data, and the start and end points of each vehicle were set to node 1.

B. EXPERIMENT RESULTS

1) PARAMETER SELECTION

Based on the test datasets, the optimal parameter combinations of the improved ACO were determined for node sets in different sizes. The values of model parameters are recorded in Table 2. During the verification, only one parameter was changed at a time to reflect its impact on algorithm performance. The improved ACO was applied to solve the established model on each test dataset ten times. The mean profit of the ten tests was computed for further comparison.

The impact of the colony size on test results was neglected. Relevant literature has shown that the ACO has the best convergence when the number of ants is 1.5 times that of nodes. Thus, the colony size was set to 60, according to the largest

TABLE 2. Parameter settings.

Description	Unit	Symbol	Value
Unit delivery income	RMB yuan	s_1	2
Unit pickup income	RMB yuan	s_2	3
Vehicle cost	RMB yuan	c	60
Unit distance cost	RMB yuan	f	0.1
Number of vehicles	each	m	1
Maximum capacity of each vehicle	each	Q_{max}	500
Maximum working hours of the driver	h	T_{max}	10
Travel speed	km/h	v	70
Service time at each node	h	t	0.5

node set (80 nodes) in the test datasets [17]. In addition, the probability P_{best} for an ant to find the optimal solution in each iteration was set to 0.05, and the maximum number of iterations was set to 100 [18].

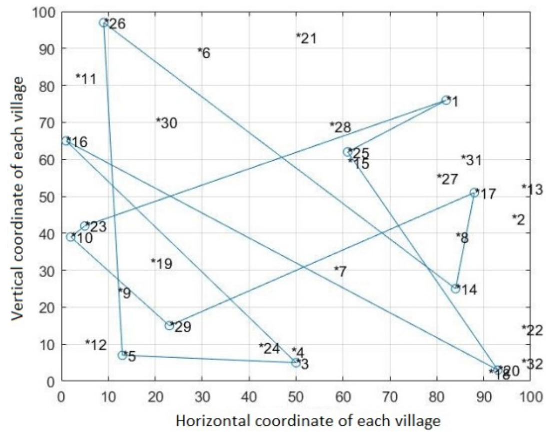
Multiple Matlab tests were carried out on a laptop (CPU: Intel Core i7; memory: 16GB). Table 3 records the mean profit of each test dataset in the ten tests under each parameter combination. For node set with 32-56 nodes and $\rho = 0.2$ for node set with 68-80 nodes, the three default parameters were set as follows: the weight of pheromone factor $\alpha = 1$; the weight of heuristic factor $\beta = 1$; the pheromone volatility $\rho = 0.3$.

TABLE 3. Mean profits of 10 tests.

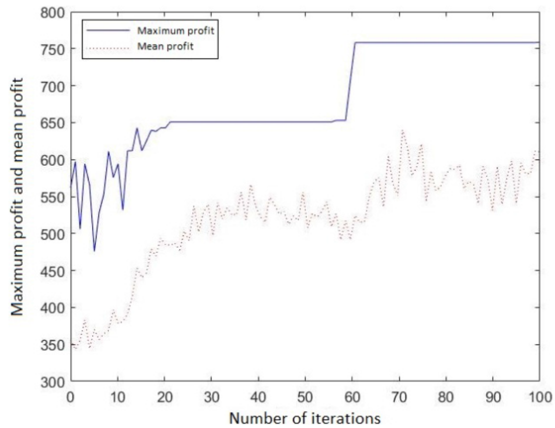
Parameter values		n32	n45	n56	n68	n80
α	1	908.512	872.731	857.185	886.689	781.917
	2	780.786	727.456	754.266	801.099	649.624
	3	765.090	711.927	717.268	764.269	683.039
β	0.5	875.844	858.998	835.609	863.757	742.790
	1	908.512	872.731	857.185	886.689	781.917
	2	865.319	826.939	826.017	861.909	734.124
	3	854.606	828.638	791.928	857.340	724.707
ρ	0.1	890.113	841.694	842.117	871.211	794.254
	0.2	905.043	832.480	857.185	886.689	781.917
	0.3	908.512	872.731	863.732	——	——
	0.4	885.117	857.553	——	——	——
	0.5	852.780	848.291	——	——	——
	0.6	875.762	835.828	——	——	——
	0.7	867.676	821.782	——	——	——

For example, the value "780.786" in row 2 is the mean result after the model ran 10 times at $\alpha = 2$, $\beta = 1$, and $\rho = 0.3$; the value "861.909" in row 6 is the mean result after the model ran 10 times at $\alpha = 1$, $\beta = 2$ and $\rho = 0.2$. The blank cells in Table 3 mean that the improved ICO did not converge under the corresponding parameter combinations.

As shown in Table 3, parameters α and β had far greater impacts than parameter ρ on the solution quality. When β and ρ remained constant, the solution at $\alpha = 1$ was much better than those at the other values of α. With the growing value of α, the solution quality declined continuously. Hence, α value of the improved ACO should be set to 1 in the example analysis and actual application. When α and ρ remained constant, the optimal and suboptimal solutions were obtained respectively at $\beta = 1$ and $\beta = 0.5$. As the value of β increased from 1 to 3, the solution quality steadily declined. Hence, $\beta = 1$ was selected for our algorithm.



(a). Optimal route (m=1).



(b). Convergence results (m=1).

FIGURE 2. (a) Optimal route (m = 1). (b) Convergence results (m = 1).

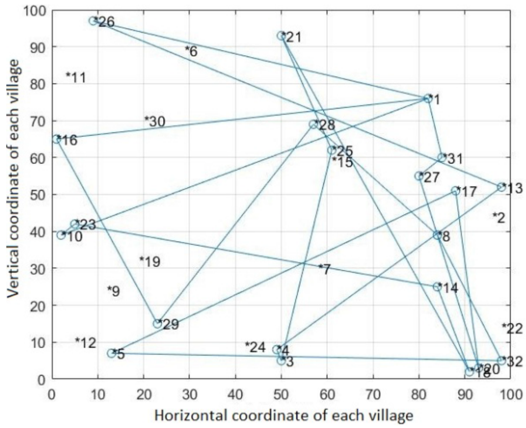
Compared with α and β, parameter ρ exhibited a consistently weak influence on the solution quality. With the growth in the number of nodes, the value range of ρ become increasingly small, and the ρ value began to affect the convergence to the optimal solution. Our tests show that, when there were fewer than 45 nodes, the ρ value had no impact on convergence; in this case, the optimal value of ρ is 0.3. When there were 56 nodes, the algorithm did not converge after ρ surpassed 0.3; in this case, the optimal value of ρ is also 0.3. When there were 68 $\sim$ 80 nodes, the algorithm did not converge after ρ surpassed 0.2; in this case, the optimal value of ρ is 0.2 for the node set with 68 nodes and 0.1 for the node set with 80 nodes. The relevant results are listed in Table 4 below.

2) RESULTS AND DISCUSSION

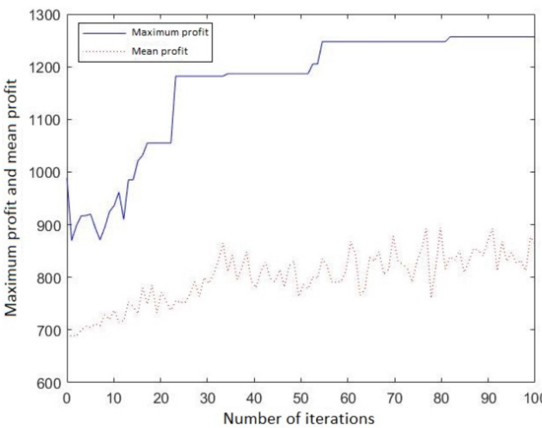
Because the rural logistics distribution area is much smaller than the conventional urban logistics, the route optimization of the RECL is a small-scale problem. The small-scale problem here mainly refers to the rural logistics distribution point

TABLE 4. **Optimal parameter combinations of the improved ACO.**

Parameter values	Fewer than 56 nodes	57-79 nodes	More than 80 nodes
α	1	1	1
β	1	1	1
ρ	0.3	0.2	0.1



(a) Optimal route (m=2).



(b). Convergence results (m=2).

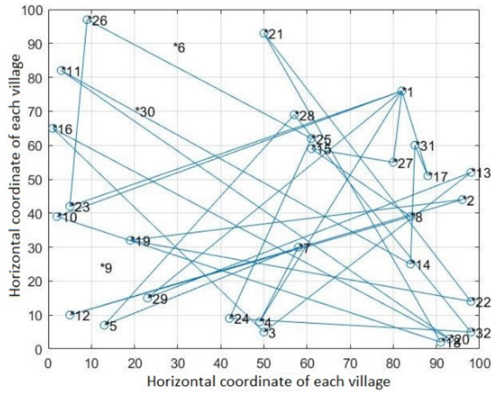
FIGURE 3. **(a) Optimal route (m = 2). (b) Convergence results (m = 2).**

is less. Therefore, the 32-node test dataset was selected to verify the effects of the number of vehicles on the model parameters. According to the optimal parameter combinations of the improved ACO for node sets of different sizes, the maximum number of iterations was set to 100, the colony size to 60, the weight of pheromone factor α to 1, the weight of heuristic factor β to 1, and the pheromone volatility to 0.3.

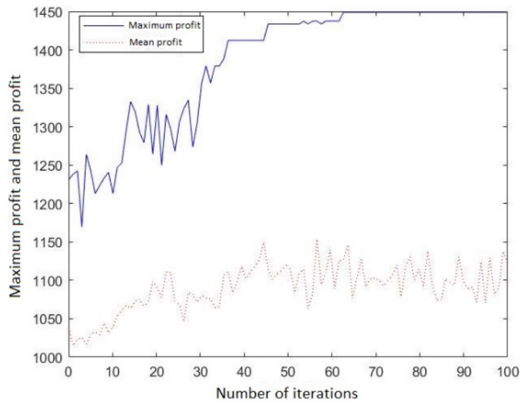
In the last-mile distribution network for the RECL, each vehicle leaves from node 1 and returns to node 1. The location, pickup quantity and delivery quantity are known at each node to be visited. The 32-node test dataset is shown in Table 5. The parameter values in the model are listed in Table 6. On this basis, the established model was solved by the improved ACO.

When only one vehicle left from the LSC-T to serve the area (m = 1), the maximum profit of 758.721 was obtained at the 60th iteration, and the optimal route is 1 → 25 → 20 → 16 → 3 → 5 → 26 → 14 → 17 → 29 → 10 → 23 → 1 (Figure 2). It took 2.157s for the improved ACO to converge to the optimal solution.

When two vehicles left from the LSC-T to serve the area (m = 2), the maximum profit of 1,257.3921 was obtained at the 81st iteration, and the two optimal routes are 1 → 26 → 13 → 4 → 3 → 25 → 21 → 18 → 14 → 23 → 10 → 1,



(a). Optimal route (m=3).



(b). Convergence results (m=3).

FIGURE 4. **(a) Optimal route (m = 3). (b) Convergence results (m = 3).**

TABLE 5. **The 32-node test dataset.**

Node	x	y	q	p	Node	x	y	q	p
1	82	76	0	0	17	88	51	18	16
2	96	44	19	2	18	91	2	19	10
3	50	5	21	16	19	19	32	1	16
4	49	8	6	2	20	93	3	24	6
5	13	7	19	8	21	50	93	8	8
6	29	89	7	4	22	98	14	12	12
7	58	30	12	11	23	5	42	4	20
8	84	39	16	5	24	42	9	8	11
9	12	24	6	7	25	61	62	24	12
10	2	39	16	14	26	9	97	24	11
11	3	82	8	17	27	80	55	2	14
12	5	10	14	7	28	57	69	20	11
13	98	52	21	4	29	23	15	15	17
14	84	25	16	5	30	20	70	2	4
15	61	59	3	12	31	85	60	14	16
16	1	65	22	6	32	98	5	9	17

TABLE 6. Parameter settings.

Description	Unit	Symbol	Value
Unit delivery income	RMB yuan	s_1	2
Unit pickup income	RMB yuan	s_2	3
Vehicle cost	RMB yuan	c	60
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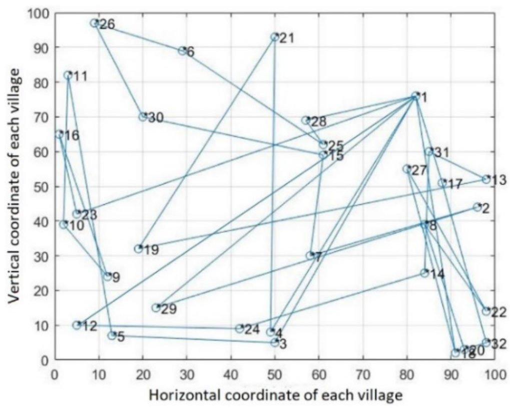
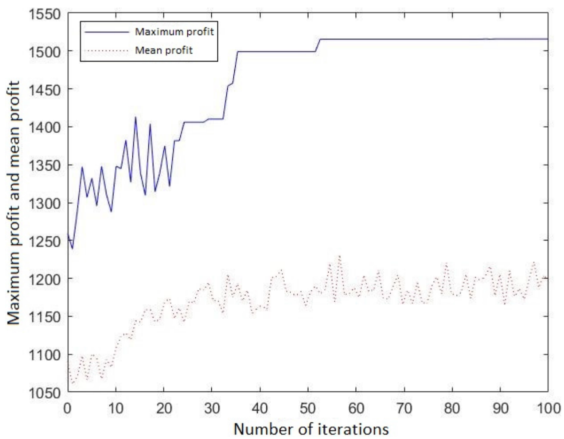
Number of vehicles	each	Q_{max}	500
Maximum capacity of each vehicle	each	T_{max}	10
Maximum working hours of the driver	h	v	70
Travel speed	km/h	t	0.5



(a). Optimal route (m=4).



(b). Convergence results (m=4).

FIGURE 5. (a) Optimal route (m = 4). (b) Convergence results (m = 4).

and 1 → 16 → 29 → 28 → 8 → 32 → 5 → 17 → 20 → 27 → 31 → 1 (Figure 3). It took 3.117s for the improved ACO to converge to the optimal solution.

When three vehicles left from the LSC-T to serve the area (m = 3), the maximum profit of 1,447.2334 was obtained at the 62nd iteration, and the three optimal routes are 1 → 29 → 13 → 3 → 16 → 20 → 11 → 14 → 31 → 17 → 1, 1 → 23 → 26 → 25 → 24 → 32 → 28 → 5 → 7 → 4 → 1, and 1 → 10 → 18 → 21 → 22 → 19 → 2 → 12 → 8 → 15 → 27 → 1 (Figure 4). It took 4.593s for the improved ACO to converge to the optimal solution.

When four vehicles left from the LSC-T to serve the area (m = 4), the maximum profit of 1,447.2334 was obtained at the 58th iteration, and the four optimal routes are 1 → 29 → 2 → 7 → 15 → 30 → 26 → 6 → 25 → 28 → 1, 1 → 23 → 16 → 9 → 10 → 11 → 5 → 3 → 1, 1 → 18 → 27 → 22 → 8 → 20 → 32 → 17 → 1, and 1 → 4 → 21 → 19 → 13 → 31 → 14 → 24 → 12 → 1 (Figure 5). It took 6.039s for the improved ACO to converge to the optimal solution. The demand of all nodes could be satisfied with four vehicles.

IV. CONCLUSION

Considering the cost and benefit of the RECL, this paper puts forward the VRP of the last-mile distribution in the RECL, and designs a route optimization model for the RECL's last-mile distribution to maximize the profit of the logistics enterprise. The model was constructed based on the modelling practices for route optimization and vehicle orientation problems. To solve the established model, the ACO was improved to suit the RECL's last-mile distribution by modifying the heuristic information, the update rules of pheromone, solution construction and local search strategy. Besides, the optimal combination of the weight of heuristic factor α, the weight of pheromone factor β and pheromone volatility ρ was determined through repeated tests on five test datasets. Meanwhile, the improved ACO was also verified on these test datasets. The results show that the improved ACO could provide a feasible routing plan for the RECL's last mile distribution. The research findings lay a solid basis for solving the last-mile distribution in the RECL.

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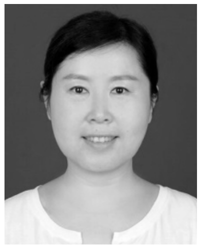

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