Hindawi
Wireless Communications and Mobile Computing
Volume 2021, Article ID 2930366, 10 pages
https://doi.org/10.1155/2021/2930366

Research Article

Optimization of VRR for Cold Chain with Minimum Loss Based on Actual Traffic Conditions

Lishuan Hu[1], **Caihong Xiang**[2] **and Chengming Qi**[1]

[1]College of Urban Rail Transit and Logistics, Beijing Union University, Beijing, China
[2]TAIJI Computer Corporation Limited, Beijing, China

Correspondence should be addressed to Lishuan Hu; hulishuan@buu.edu.cn

Received 13 August 2021; Accepted 21 October 2021; Published 10 December 2021

Academic Editor: Rajesh Kaluri

Recently, fresh agricultural cold-chain logistics have been greatly developed with the increasing needs of people's life. Reducing costs of cold-chain distribution has become the main object of loss control in logistics enterprises. The objective of this research is to find a set of optimal routes that minimize the total loss, including fuel cost, refrigeration cost, soft time window penalty cost, and cargo damage cost over transit time. In this paper, the definition and model construction of vehicle routing problem (VRP) with multiobjective minimum lost are introduced first. Then, an ant colony optimization (ACO) algorithm combined with Pareto local search (PLS) is put forward to solve the minimum loss model. In order to avoid the influence of complex road conditions during distribution, the distance matrix and the transit time matrix are both derived from the recommended navigation road based on E-map API. At last, a compare experiment between the traditional method and our proposed method is performed. The results indicate that our method has strong applicability and potential advantages in cold-chain logistic and has important practical significance and application value.

1. Introduction

According to relevant media reports, rotting fruit, vegetables, and other foods transported by truck alone are worth about 70 billion yuan each year, causing a huge economic waste. Agricultural products especially for fruit, vegetables, fish, meat, etc. require strictly limited temperature, humidity, and time in the process of transportation and storage. As a branch of the logistics industry, cold-chain logistics provides a guarantee for the safe transportation of fresh agricultural products. In the process of transportation from cold storage to customers, a complete cold-chain logistics realizes the temperature control of the whole process of refrigerated and frozen food, as well as the closed environment, storage, and transportation during loading and unloading of goods. By selecting the optimal path in the process of cold-chain logistics transmission, the circulating rate of fruits and vegetables, meat, and aquatic products is reduced; the waste of resources and the cost of logistics costs are reduced too. The vehicle routing problem (VRP) introduced by Dantzig and Ramser [1] plays a central role in the optimization of distribution networks.

Recently, the loss problem of cold-chain distribution has attracted the attention of many scholars and experts. For distribution problem of fresh agricultural products, fuel cost, refrigeration cost, cargo damage cost, and soft time window penalty cost have become the important components of loss control in distribution companies [2]. Li et al. [3] proposed a low-carbon model for fresh food and a genetic simulated annealing algorithm to solve the model in the cold-chain distribution. Yao et al. [4] proposed a minimizing fuel consumption solution to time-dependent VRP with time window. Kim et al. [5] proposed a Markov decision process method to solve a dynamic VRP (DVRP) model with nonstationary transit times under actual traffic congestion. Chen et al. [6] developed a hybrid heuristic algorithm including harmony search and neighborhood descent to solve DVRP with time window. Abidi et al. [7] proposed a GA with a simple heuristic to solve a variant of RVPR (Rich VPR) with time widows and dynamically changing orders. Dongdong and Yinzhen [8] proposed a green multitype VRP with time windows to reduce the wastes of fuel consumption and carbon emission and use an improved tabu search algorithm to solve the G-MVRPTW. Fan et al. [9] pointed out that in fresh agricultural product cold-chain logistics, the total costs are composed of five kinds: fixed, transportation, damage, penalty, and energy consumption. Fang and Ai [10] proposed a mathematical model with soft time window penalty cost, refrigeration cost, cargo damage cost, and a hybrid ant colony algorithm to minimize the total costs. The DVRP mainly deal with the time-variation information of customer demands and road conditions. To share the traffic information and classify traffic conditions, Big Data and classification techniques are used in logistics and transportation. If the drivers receive the information of the traffic congestion or poor weather, they can change their way to reduce the costs and save time. Dimensionality reduction must be performed first in Big Data transmitted and stored process. Thippa et al. [11] proposed a machine learning (ML) algorithm with PCA to reduce the dimension of Big Data when the data sets are high. Gadekallu et al. [12] have studied the hybrid PCA-whale optimization algorithm to extract features and used a deep neural network to classify the diseases of tomato. Guha et al. [13] proposed an ANN-based content classification in combination with n-grame TF-IDF feature descriptor to classify the documents with accurate, sensitive information. The ant colony optimization (ACO) proposed by Colorni et al. [14] has been widely used in solving NP-hard vehicle routing problems. Many scholars used ACO algorithms to solve multiobjective combinatorial optimization problems [15–19]. These papers considered the costs of fuel, refrigeration, cargo damage, and delay simultaneously. However, their studies are not comprehensive enough in factors affecting the loss, such as the cost of energy consumption and rotting consumption when the door of compartment is opening.

We construct a total cost model, including soft time window penalty cost, fuel cost, refrigeration cost in transit and during unloading, and cargo damage cost in transit and during unloading. In our model, to take into account the actual traffic condition, the distance matrix and the transit time matrix are both archived from the navigation functions based on E-Map API. The traditional heuristic algorithm ACO has some limitations, such as easy stagnation in the initial stage and slow search speed. We perform an ACO algorithm with Pareto local search (PLS) on ants to obtain the uniform Pareto-optimal frontier and keep the diversity of Pareto solution set.

The paper is organized as follows. Section 1 introduces the definition and structure of VRP for cold-chain logistics. Section 2 constructs a minimum cost model based on actual traffic conditions. Then, an improved ACO algorithm with PLS is presented in Section 3. In Section 4, a compare experiment is performed to indicate our proposed model and the improved method. At last, we make a conclusion of our contributions in Section 5.

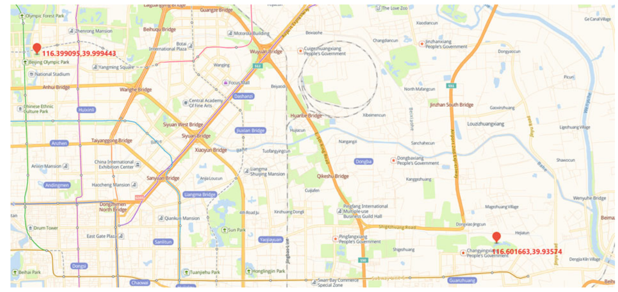

Figure 1: Two points on the E-map.

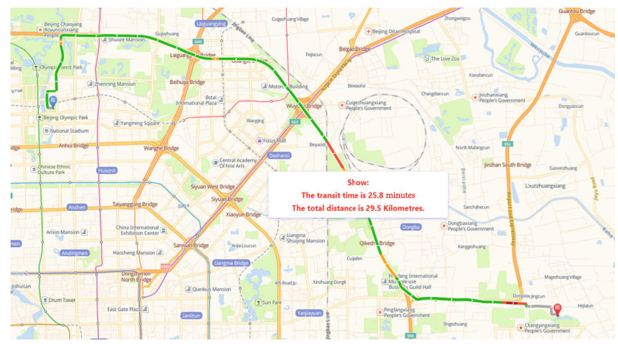

Figure 2: The output of navigation result.

2. Problem Description

A cold-chain supplier has a warehouse with a certain number of transportation vehicles that delivers a variety of fresh products to a certain number of customers. The capacity of the transportation vehicles is limited, and the vehicles are all the same type with a total capacity at the starting point. The object of vehicle routing problem is to distribute goods to each customer with correct goods, limited time, minimum cost, and so on. VRP with time window means that a vehicle has to visit a customer within a certain time window. So, the service time, the transit time, and the total time must be calculated when dealing with the VRP. The mathematical model of VRPTW in cold-chain distribution is defined as follows [20].

There are K transportation trucks in this distribution center. The maximum load and the maximum transit time of per vehicle are Q and T. The kth distribution vehicle is responsible for path k. N is the total customers. The needs and the service time of customer point i are q_i and u_i; t_{ij} means the delivery time from customer points i to j. x_i^k is a 0-1 variable, and $x_i^k = 1$ means the point i in the path k. x_{ij}^k is a 0-1 variable, and $x_{ij}^k = 1$ means that the kth distribution vehicle travels from i to j.

3. Model

Minimizing the loss cost is the target of this paper. Therefore, the following paper introduces the structure of the loss cost of cold chain.

Table 1: Parameter setting.

Parameter of the symbol	Meaning	Value	Parameter of the symbol	Meaning	Value
K	The total vehicles	4	p	Unit price of goods	5
N	The total customer points	20	m	Number of ants	50
Q	Full load of one vehicle	2000	n	Number of iterations	60
C_{11}	Penalty coefficients earlier than TW	2.0	Alpha	The pheromone important factor	1
C_{12}	Penalty coefficients later than TW	3.0	Beta	Heuristic function important factor	3
C_{21}	Unit fuel cost of no load	2.5	Rho	The pheromone factor	0.85
C_{22}	Unit fuel cost of full load	3.0	k_1	Positive constant	0.75
C_{31}	Unit refrigeration cost in transit	2.0			
C_{32}	Unit refrigeration cost in unloading	2.5			
C_{41}	Coefficient of damage in transit	0.01			
C_{42}	Coefficient of damage in unloading	0.015			

Table 2: The data of the distribution center and customers.

Number of customers	Latitude and longitude on E-map Latitude (easting)	Longitude (northing)	The demand of customer (kg)	Starting time (min)	Ending time (min)	Server time (min)
0	116.4843	39.8768	0	0	0	0
1	116.486081	39.801535	300	912	967	15
2	116.43287	39.851657	1100	825	870	30
3	116.571474	39.857011	125	65	146	10
4	116.51774	39.86957	100	727	782	10
5	116.258165	39.896287	200	15	67	10
6	116.598001	39.920533	150	621	702	10
7	116.475892	39.92811	150	170	225	10
8	116.659393	39.9282	450	255	324	20
9	116.110548	39.943414	300	534	605	20
10	116.50121	39.967727	100	357	410	10
11	116.450433	39.971126	950	448	505	30
12	116.408206	39.973734	125	652	721	10
13	116.339988	39.978354	150	30	90	10
14	116.468832	40.006183	150	567	620	10
15	116.584485	40.007985	550	384	429	20
16	116.601421	40.054617	150	475	528	10
17	116.439297	40.057803	100	99	148	10
18	116.670363	40.140651	150	179	254	10
19	116.226626	40.228101	400	278	345	20
20	116.653284	40.332406	300	10	73	20

3.1. Distance and Transit Time Analysis. In traditional methods, the distance between two points is achieved by Euclidean distance formula and the transit time is achieved by the distance divided by assumed average speed. But, the actual transit time is influenced greatly by road congestion, traffic accidents, traffic control, raining, snowing, etc. Collecting real-time traffic data will result in large amounts of data, and Big Data analysis technology should be considered.

In our literature, the navigation function of E-map is used to avoid the mentioned shortcomings. The distance matrix and the transit time matrix under actual traffic conditions among customer points (including the distribution center) are derived from the E-map public platform [21].

As Figure 1 shows, there are two points with their latitudes and longitudes on the E-map.

```
Initialize the coefficient variables and pheromone;
for iteration 1,…,M{
Initialize a taboo table and a start position for each ant.
for ant, 1,…,N{
Select the next node according to rules
The selected node is stored in the taboo table
If all nodes are stored in taboo tables, the iteration is completed, break;
The total cost is calculated
The local pheromone is updated
}
The global pheromone is updated
All ants' total costs are compared
The current optimal solution is stored
}
The process is stopped and the current path with the shortest cost is output.
```

Algorithm 1

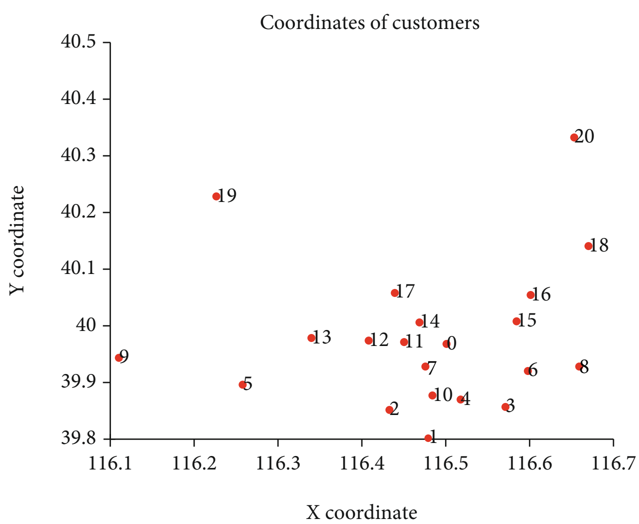

Figure 3: Distribution of warehouse and customers in the XY system.

As Figure 2 shows, the distance and the transit time between the two points are shown by the navigation function of the E-map platform.

In our study, t_{ij} represents transit time between customer i and customer j, and d_{ij} is the distance between customer i and customer j. As abovementioned, t_{ij} and d_{ij} are both achieved from the navigation result based on E-map API.

3.2. Loss Cost Target Construction

3.2.1. Soft Time Window Penalty Cost. Each customer has different numbers of good needs and a soft time window. Penalty cost will be incurred if the vehicle arrives beyond the time window boundary. The service time of each customer point is $u_i (i = 1, 2, \cdots, N)$, $[Et_i, Lt_i]$ is the range of the time window of customer point i, C_{11} is the penalty coefficient when vehicle k_i arrives at customer i earlier than Et_i, and C_{12} is the penalty coefficient when vehicle k_i leaves from customer i later than Lt_i. The arrival time of vehicle k at customer i is T_{ki}. According to the analysis above, the penalty cost of cold chain can be defined as the following:

$$
\begin{aligned}
C_1 = C_{11} \sum_{k=1}^{K} \left[\sum_{i=1}^{N} x_i^k \max\left(Et_i - T_{ki}, 0\right) \right] \\
+ C_{12} \sum_{k=1}^{K} \left[\sum_{i=1}^{N} x_i^k \max\left(T_{ki} + u_i - Lt_i, 0\right) \right], \\
\text{s.t.} \quad T_{ki} \geq T_{k0} + t_{0i}, \\
T_{k(i+1)} \geq T_{ki} + t_{i(i+1)} + u_i.
\end{aligned} \tag{1}
$$

3.2.2. Fuel Cost. The fuel consumption of the distribution vehicle is inevitable for completing the distribution task. We assume that the fuel cost is proportional to the load of the vehicle pert unit distance. Let Q_k be the load of the k vehicle and P_k be the load rate of the kth vehicle.

$$
\begin{aligned}
Q_k = \sum_{i=1}^{n} x_i^k q_i, \\
P_k = \frac{Q_k}{Q}.
\end{aligned} \tag{2}
$$

Sets C_{21} and C_{22} represent no load and full load fuel consumption costs per unit distance of the distribution vehicle. C_2^k means the fuel consumption cost per unit distance of the kth vehicle.

$$
C_2^k = C_{21} + p_k (C_{22} - C_{21}). \tag{3}
$$

The total cost of fuel consumption C_2 can be expressed as

$$
C_2 = \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij}^k d_{ij} \left(C_{21} + P_k (C_{22} - C_{21})\right). \tag{4}
$$

```
......
var output_t = “The transit time:”;
var output_d = “The traveling distance:”;
var distance_time_search = function (customerPoints){.
if (vehicle_transit.getStatus() != BMAP_STATUS_SUCCESS){.
return ;
}
var t_d_result = customerPoints.getPlan(0);
travel_time += t_d_result.getDuration(true) + “\n”; //get transit time of two points.
trave_distance+= t_d_result.getDistance(true)+”\n”; //get travel distance of two points.
}
var vehicle_transit = new BMapGL.DrivingRoute(map, {renderOptions: {map: map},
onSearchComplete: distance_time_search;
}});
for(var i=0;i<=NumberOfCustomers;i++)
for( var j=i+1;j<= NumberOfCustomers;j++)
{
var start=new BMapGL.Point(vertex[i][0], vertex[i][1]);
var end=new BMapGL.Point(vertex[j][0], vertex[j][1]);
vehicle_transit.search(start, end);
}
......
```

Algorithm 2

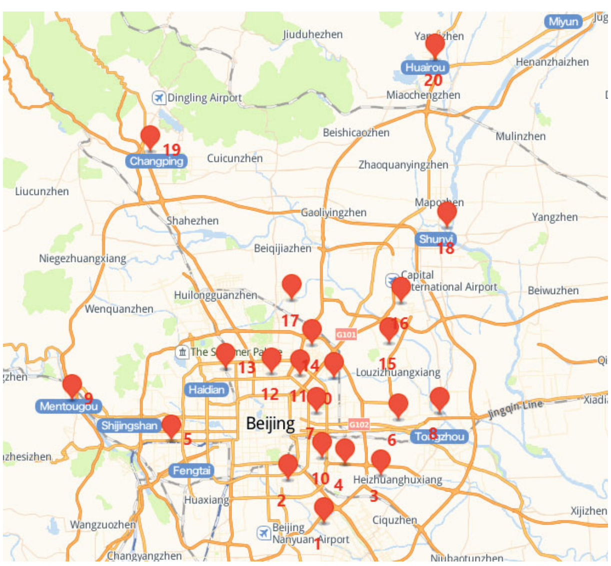

Figure 4: Geographic locations of warehouse and customers in E-map.

3.2.3. Refrigeration Cost. The temperature of the cold-chain logistic must be maintained at a certain low level to keep the freshness of goods. The refrigeration function of vehicles must be operated to achieve the required temperature, which causes the refrigeration cost immediately.

(1) Refrigeration cost in transit

The refrigeration cost generated by maintaining the required low temperature per unit time in transit is C_{31}; the total cooling cost C_3^1 in transit can be expressed as

$$C_3^1 = \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij}^k t_{ij} C_{31}. \tag{5}$$

(2) Refrigeration cost during unloading

Opening the door of the compartment will cause the cool air inside to flow out and the hot air from outside to flow in. To maintain the temperature inside, more energy will be consumed. C_{32} is set to be the cooling cost per unit time during opening the door, and the total refrigeration cost of unloading C_3^2 is

$$C_3^2 = \sum_{k=1}^{K} \sum_{i=1}^{N} x_i^k u_i C_{32}. \tag{6}$$

C_3 represents the total cooling cost, which consists of the total cooling cost in transit, and the total cooling cost of unloading can be expressed as

$$C_3 = \sum_{k=1}^{K} \sum_{i=1}^{N} \left(\sum_{j=1}^{N} x_{ij}^k t_{ij} C_{31} + x_i^k u_i C_{32} \right). \tag{7}$$

3.2.4. Cargo Damage Cost. The most cargo of the cold chain is fresh goods; with the increase of transit time even in low temperature, the growth of microorganisms will happen. When opening the door of compartment during unloading process, the temperature inside will be unstable which results in the damage of fresh goods more significantly. As mentioned above, p is the unit price of goods, and Q_{ki} is the load of the kth vehicle when it leaves from point i.

Table 3: Transit time matrix under actual traffic conditions (minutes).

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	0	22	25	25	26	35	13	16	24	43	25	13	18	23	25	21	24	15	43	46	40
1	22	0	17	19	28	27	21	26	38	17	28	34	51	34	37	32	43	40	59	58	55
2	25	17	0	25	20	26	32	30	18	43	33	28	35	34	38	37	45	63	42	61	61
3	25	19	25	0	16	24	24	14	26	36	34	28	43	57	34	27	51	55	53	41	32
4	26	28	20	16	0	9	23	24	21	22	28	38	52	35	29	39	36	29	57	51	53
5	35	27	26	24	9	0	26	28	35	27	50	42	33	51	36	50	65	49	54	49	71
6	13	21	32	24	23	26	0	13	27	20	26	25	33	31	38	41	19	59	53	35	50
7	16	26	30	14	24	28	13	0	9	23	17	14	24	25	20	27	28	48	47	42	49
8	24	38	18	26	21	35	27	9	0	24	27	32	42	35	24	63	32	37	41	58	57
9	43	17	43	36	22	27	20	23	24	0	39	40	46	46	51	60	63	42	48	69	78
10	25	28	33	34	28	50	26	17	27	39	0	18	29	23	25	34	26	33	51	48	49
11	13	34	28	28	38	42	25	14	32	40	18	0	8	16	10	23	40	20	26	34	38
12	18	51	35	43	52	33	33	24	42	46	29	8	0	16	13	22	34	26	43	24	40
13	23	34	34	57	35	51	31	25	35	46	23	16	16	0	22	34	36	36	32	52	50
14	25	37	38	34	29	36	38	20	24	51	25	10	13	22	0	18	24	35	39	26	37
15	21	32	37	27	39	50	41	27	63	60	34	23	22	34	18	0	19	32	49	36	49
16	24	43	45	51	36	65	19	28	32	63	26	40	34	36	24	19	0	25	31	45	46
17	15	40	63	55	29	49	59	48	37	42	33	20	26	36	35	32	25	0	43	38	41
18	43	59	42	53	57	54	53	47	41	48	51	26	43	32	39	49	31	43	0	33	45
19	46	58	61	41	51	49	35	42	58	69	48	34	24	52	26	36	45	38	33	0	42
20	40	55	61	32	53	71	50	49	57	78	49	38	40	50	37	49	46	41	45	42	0

Table 4: The distance matrix derived from the E-map navigation function (KM).

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	0	22	13.6	20.7	17.6	6.5	19.2	5.6	11.3	21.2	31.6	16.8	11.4	7.2	17.4	41.6	22	14.2	53.4	41.6	35.1
1	22	0	9.1	12.7	11.3	21	19.5	26.6	13.1	29.5	45.4	23.5	27.8	32.7	37.9	27.3	39.5	35.4	62.2	86.4	64.7
2	13.6	9.1	0	12.3	19.1	11.7	22.4	22.9	6.5	29.3	16.2	40	36.3	27	27	15.4	37.2	55.6	67.3	34	69.1
3	20.7	12.7	12.3	0	9.8	8.8	15.2	18.2	10.3	24.6	39.6	27.4	21.5	24.6	29.8	31.5	55.6	34.1	52.5	74.2	59.1
4	17.6	11.3	19.1	9.8	0	3.8	16.9	10.5	17.9	19	28.9	18.7	33.6	26.1	49.6	21.9	25.7	28.3	53.1	79.8	55.3
5	6.5	21	11.7	8.8	3.8	0	22.6	24.1	26.8	32.2	17.8	37.5	33.9	19	29.8	45	57.8	33	74.8	44.6	60.5
6	19.2	19.5	22.4	15.2	16.9	22.6	0	6	17.1	11.5	21.9	32.3	24.4	20.6	12.3	17.6	64.4	55.6	30.4	31.3	64.1
7	5.6	26.6	22.9	18.2	10.5	24.1	6	0	18.3	8.2	11.9	16.9	6	13.5	21	21.4	57.2	40.9	18.5	44	38
8	11.3	13.1	6.5	10.3	17.9	26.8	17.1	18.3	0	21.4	26.2	28.7	14.9	36.6	26.5	18.7	25.4	59.8	34.4	52.4	65.2
9	21.2	29.5	29.3	24.6	19	32.2	11.5	8.2	21.4	0	29.4	32.6	55.4	42.1	36.9	40.2	85.5	44.6	41.9	86.9	75
10	31.6	45.4	16.2	39.6	28.9	17.8	21.9	11.9	26.2	29.4	0	17.7	12.5	27.8	26.9	17	24.6	81.2	27.2	52	59.4
11	16.8	23.5	40	27.4	18.7	37.5	32.3	16.9	28.7	32.6	17.7	0	5.8	6.1	11.6	24.2	13.2	26.7	36.8	51.1	38
12	11.4	27.8	36.3	21.5	33.6	33.9	24.4	6	14.9	55.4	12.5	5.8	0	11.7	22.1	9.3	7.7	26.6	38.4	35.7	52.7
13	7.2	32.7	27	24.6	26.1	19	20.6	13.5	36.6	42.1	27.8	6.1	11.7	0	14	28.4	37.1	59	44.7	21	32.9
14	17.4	37.9	27	29.8	49.6	29.8	12.3	21	26.5	36.9	26.9	11.6	22.1	14	0	8.7	21.2	16.6	37.6	48	33.7
15	41.6	27.3	15.4	31.5	21.9	45	17.6	21.4	18.7	40.2	17	24.2	9.3	28.4	8.7	0	8.5	16.4	23.3	57.3	50.5
16	22	39.5	37.2	55.6	25.7	57.8	64.4	57.2	25.4	85.5	24.6	13.2	7.7	37.1	21.2	8.5	0	18.8	51.9	17.6	50.3
17	14.2	35.4	55.6	34.1	28.3	33	55.6	40.9	59.8	44.6	81.2	26.7	26.6	59	16.6	16.4	18.8	0	36	44.1	29.7
18	53.4	62.2	67.3	52.5	53.1	74.8	30.4	18.5	34.4	41.9	27.2	36.8	38.4	44.7	37.6	23.3	51.9	36	0	25	47.5
19	41.6	86.4	34	74.2	79.8	44.6	31.3	44	52.4	86.9	52	51.1	35.7	21	48	57.3	17.6	44.1	25	0	56.3
20	35.1	64.7	69.1	59.1	55.3	60.5	64.1	38	65.2	75	59.4	38	52.7	32.9	33.7	50.5	50.3	29.7	47.5	56.3	0

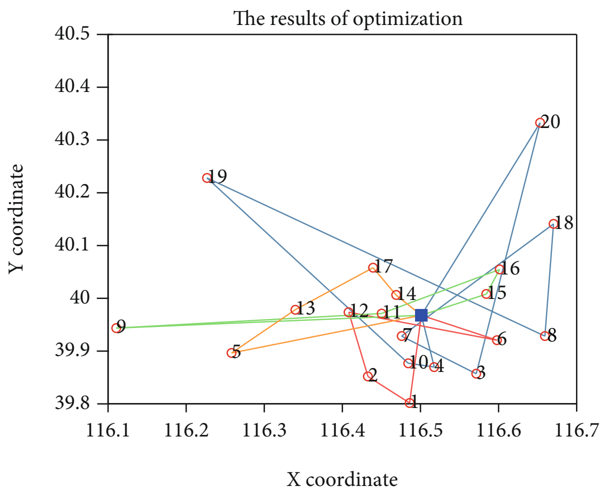

Figure 5: The optimal path plan based on the traditional method.

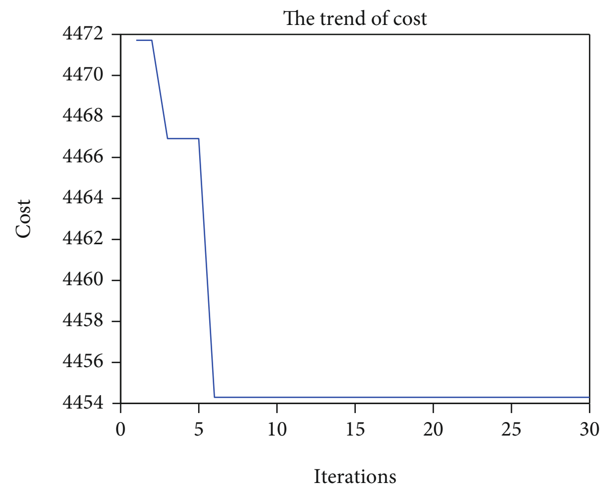

Figure 6: The trend of cost during the iteration.

(1) Cost of cargo damage in transit

C_{41} is given as the loss coefficient of goods per unit weight per unit time in transit; the total cost of cargo damage in transit is as follows:

$$C_4^1 = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij}^k t_{ij} p Q_{ki} C_{41}. \tag{8}$$

(2) Cost of cargo damage during unloading

During unloading at a customer point, the door of the compartment is open and the cost of cargo damage will increase obviously. Let the cargo damage coefficient of goods per unit weight per unit time when unloading be C_{42}; the cost of cargo damage during unloading can be expressed as

$$C_4^2 = \sum_{k=1}^{K}\sum_{i=1}^{N} x_i^k u_i p Q_{ki} C_{42}. \tag{9}$$

The total cost of damage is

$$C_4 = pQ_{ki}\sum_{k=1}^{K}\sum_{i=1}^{N}\left(\sum_{j=1}^{N} x_{ij}^k t_{ij} C_{41} + x_i^k u_i C_{42}\right). \tag{10}$$

In conclusion, the mathematical model of minimum loss target can be expressed as

$$\min Z = C_1 + C_2 + C_3 + C_4. \tag{11}$$

3.3. Mathematical Model of Minimum Loss Analysis. According to the above analysis, the minimum loss model of the cold-chain distribution problem is as follows:

$$\begin{aligned}\min\ Z = {} & C_{11}\sum_{k=1}^{K}\left[\sum_{i=1}^{N} x_i^k \max\left(Et_i - T_{ki}, 0\right)\right] \\ & + C_{12}\sum_{k=1}^{K}\left[\sum_{i=1}^{N} x_i^k \max\left(T_{ki} + u_i - Lt_i, 0\right)\right] \\ & + \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij}^k\left(C_{21} + P_k\left(C_{22} - C_{21}\right)\right) \\ & + \sum_{k=1}^{K}\sum_{i=1}^{N}\left(\sum_{j=1}^{N} x_{ij}^k t_{ij} C_{31} + x_i^k u_i C_{32}\right) \\ & \cdot pQ_{ki}\sum_{k=1}^{K}\sum_{i=1}^{N}\left(\sum_{j=1}^{N} x_{ij}^k t_{ij} C_{41} + x_i^k u_i C_{42}\right)\end{aligned} \tag{12}$$

$$\text{s.t.}\quad x_i^k = \begin{cases} 1, & \text{point } i \text{ is serviced by car } K, \\ 0, & \text{other,}\end{cases} \tag{13}$$

$$x_{ij}^k = \begin{cases} 1, & \text{vehicle } K \text{ travels from point } i \text{ to point } j, \\ 0, & \text{other,}\end{cases} \tag{14}$$

$$\sum_{k=1}^{K} x_i^k = 1, \quad \forall i \in N, \tag{15}$$

$$\sum_{i=1}^{N} x_i^k q_i \le Q, \quad \forall k \in K, \tag{16}$$

$$\sum_{j=1}^{N} x_{0j}^k = \sum_{i=1}^{N} x_{i0}^k \le 1, \quad \forall k \in K. \tag{17}$$

Equation (12) is the objective optimization function which is aimed at finding the minimum total cost during the whole distribution process. Equation (13)–Equation (17) are the constraint conditions, where Equation (13) is a 0-1 variable; the value 1 means the given customer is

Table 5: Distribution paths of 4 vehicles based on the traditional method.

Vehicles	The route of each vehicle	The realistic delivery on E-map (minutes)
Fist vehicle	0 – >20 – >3–>7–>18–>8–>19–>10–>4–>0	334
Second vehicle	0 – >6 – >12–>2–>1–>0	120
Third vehicle	0 – >15 – >16–>11–>9–>0	163
Fourth vehicle	0 – >5 – >13–>17–>14–>0	182
The total time		799
The total cost		4504.5

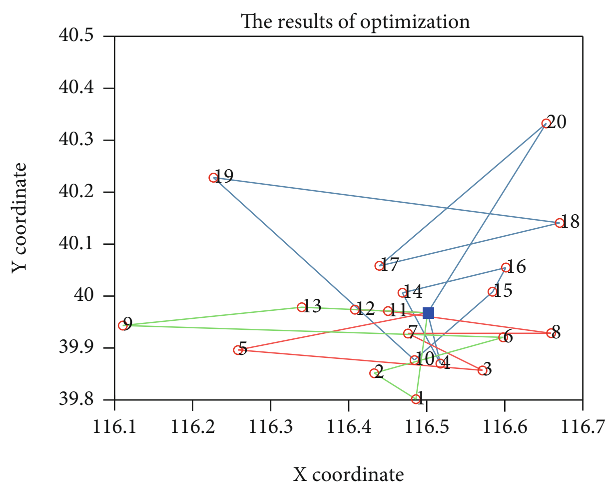

Figure 7: The optimal path plan based on the proposed method.

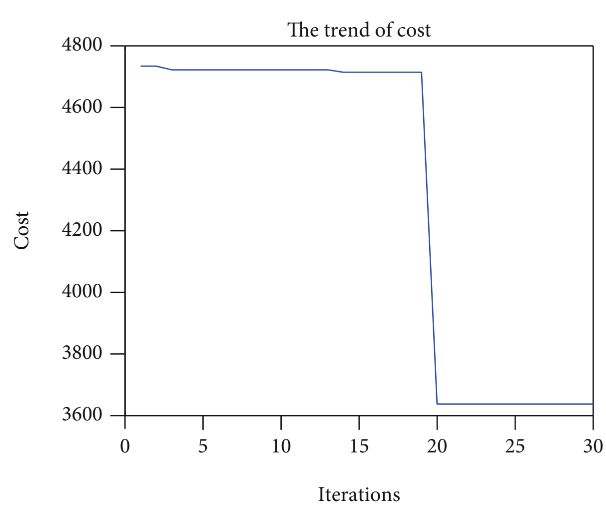

Figure 8: The trend of cost during the iteration.

serviced by the given vehicle. Equation (14) is a 0-1 variable too; the value 1 means the given route is travelled by the given vehicle. Equation (15) means each customer point is serviced by one and only one vehicle for distribution. Equation (16) means that the total demand served by the vehicle cannot exceed its maximum load. Equation (17) means that the vehicle can only start or end once.

4. Ant Colony Optimization Algorithm

4.1. Ant Colony Optimization Algorithm. The ant colony optimization (ACO) algorithm with parallelism, positive feedback, and strong robustness is used to solve the NP-hard and highly constrained problem. In the 1990s, Italian scholars Dorigo and Maniezzo found that ants will release a certain amount of substance called pheromone in the path when they are searching for food. When they need to choose a path, they prefer to choose the path with high concentration of pheromone. At last, the route with the highest concentration will be selected as an optimist route between their home and the food source.

The ACO algorithm is defined as follows:

$$p_{ij}^{k}\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}(t)}{\sum_{s\in\text{allowed}_k}\tau_{is}^{\alpha}(t)\cdot\eta_{is}^{\beta}(t)}, & \text{if } j\in\text{allowed}_k,\\ 0, & \text{otherwise,}\end{cases}$$
$$\tau_{ij}(t+n)=\rho\cdot\tau_{ij}(t)+\Delta\tau_{ij},$$
$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}, \tag{18}$$

where p_{ij}^{k} is probability of ant k transferring from point i to point j at time t; $\eta_{ij}(t)$ is the heuristic function, and β is the heuristic function important factor; $\tau_{ij}(t)$ means the pheromone concentration on the path at time t, and α is the pheromone important factor. $allowed_k$ represents points that ant k is allowed to select in the next step; $\tau_{ij}(t+n)$ is the pheromone update over time; ρ is the pheromone factor; and $\Delta\tau_{ij}^{k}$ represents the pheromone enhancer.

The rough process of the algorithm is as follows:

4.2. Combining ACO Algorithm with PLS. We applied Pareto local search (PLS) in our paper. After finding a path, PLS is used to further optimize the path. PLS proposed by Paquete et al. is a heuristic algorithm for tackling NP-hard multiobjective combinatorial optimization problems in the Pareto sense [22]. Pareto dominance defines a partial order on the set of feasible solutions. The goal when tackling the multiobjective problems in the Pareto sense is to find the set of Pareto-optimal solutions. The weak component-wise ordering is used as a mutually nondominated criterion in PLS. Let a solution $s\in A$ and its neighborhood $s'\in N(s)$. If each s' in $N(s)$ is

Table 6: Distribution paths of 3 vehicles based on the proposed method.

Vehicles	The route of each vehicle	The realistic delivery on E-map (minutes)
Fist vehicle	0 – >20 – >17–>18–>19–>10–>15–>16–>14–>4–>0	331
Second vehicle	0 – >5 – >3–>7–>8–>11–>12–>0	113
Third vehicle	0 – >13 – >9–>6–>2–>1–>0	160
The total time		593
The total cost		3673

not dominated by any solution in A, s is marked visited and is added into A. When A contains only solutions that have been visited, a Pareto local optimum is achieved [23].

An improved ACO with PLS is proposed in our research to deal with the mode. In our approach, ants are used to optimize solutions and generate new Pareto solutions, and the new pheromone updating strategy is used to control the path selection. The procedure is described as follows:

Step 1. Compute p_{ij}^k of n customers and update the trail level τ_{ij}_new for each k.

Step 2. Run PLS, and update the current solution according to calculating results.

Step 3. Compare (Cost, CostBest), and record the costBest and BestSolution.

Step 4. For each move (i, j) in BestSolution to update the trail level τ_{ij}_new.

Step 5. Repeat step 1 until the maximum computation time reaches.

The proportion of the pheromone update model of the ACO algorithm with PLS is as follows:

$$\omega = 1 - k_1 \frac{S_{\max} - S(t)}{S_{\max}}, \tag{19}$$

$$S(t) = -K \sum_{j \in D} p_{ij}(t) \log p_{ij}(t), \tag{20}$$

where $S(t)$ means information entropy value and $p_{ij}(t)$ is transition probability. Equation (19) means that the proportion of the pheromone update will decreases with the increase of the pheromone value. k_1 is the positive constant, and its value range is [0,1]. The value 1 means the proportion of the pheromone update is high influenced by the information entropy value, and 0.75 is usually used as the value of k_1. This definition combined a sequence of arithmetic with information entropy to adjust the pheromone adaptively.

5. Experimental Results and Discussion

5.1. Data Set Description. In our experiments, the distribution situation of JingKeLong in Beijing City with one distribution center and 20 customer points is selected to verify our proposed mathematical model and algorithm. The distribution center has 4 vehicles of the same type with an average speed of 60 km/h, a maximum driving time of 1200 minutes, and a maximum load of 2000 kg. Table 1 shows the settings of parameters in our given minimum loss model and ACO+PLS algorithm.

The data of the distribution center and customers are shown in Table 2. The distribution center is defined as 0, and customer points are defined as 1 to 20. Figure 3 shows the latitude and longitude of each point in the XY system, and Figure 4 shows the actual locations of them in E-map.

Our proposed method needs an actual transit time matrix and distance matrix both derived from E-map API. We supposed that the coordinates of points are stored into vertex $[N]$ [2]; the core codes with E-map API to achieve the transit time matrix and distance matrix are described as follows.

Table 3 shows the transit time matrix among customer points and distribution center obtained by E-map API.

Table 4 shows the distance matrix among customer points and distribution center obtained by E-map API.

5.2. Experimental Result and Discussion. In the traditional method, the distance matrix is achieved by the Euclidean distance formula. The Euclidean distance formula of two points on earth is defined as the following:

$$\begin{aligned} D_{AB} = R * \arccos\,(&\cos\,(\mathrm{lon}A) * \cos\,(\mathrm{lon}B) \\ &* \cos\,(\mathrm{lat}A - \mathrm{lat}B) + \sin\,(\mathrm{lon}A) * \sin\,(\mathrm{lon}B)) * \frac{\pi}{180}, \end{aligned} \tag{21}$$

where A and B are two points on the surface of earth and R is the radius of the earth. Lat$A$ and lon$A$ represent the longitude and latitude of point A.

First, the traditional method ACO with the Euclidean distance matrix is performed to solve the VRP with minimum cost. Figures 5 and 6 are the optimal distribution routes and the trend of cost during iteration processed. The optimal distribution routing scheme, the total transit time, and the total cost based on the traditional method are shown in Table 5.

Second, our proposed method ACO+PLS with the actual transit time matrix and travel distance matrix is performed to solve the VRP with minimum cost. Figures 7 and 8 are the calculated distribution routes on map and the trend of cost during iteration processed. The optimal distribution routing scheme, the total transit time, and the total cost based on the proposed method are shown in Table 6.

From the above compare experimental results, we can see that ACO+PLS with actual traffic conditions can get smaller total cost and save more transit time. Our proposed method can be used to get the optimal solution effectively for VRP of cold-chain logistics.

6. Conclusion

This paper studies the model of VPR with minimum cost of cold-chain distribution. Minimizing the total cost of distribution can maximize the economic benefit of distribution enterprises. To consider the dynamic change of transit speed under actual traffic conditions, the transit time matrix and distance matrix are both derived from the navigation function based on E-map API. We proposed a heuristic approach ACO+PLS to solve the minimum loss model of cold-chain logistics. The experiments show that our proposed method has strong applicability and potential advantages in cold-chain distribution. In future studies, a combination of multiple spatial information technologies such as geographic information technology and remote sensing technology can be realized to make the problem more practical.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no competing interest.

Acknowledgments

This work was supported by Scientific Research Project of Beijing Municipal Education Commission (KM201911417006).

References

[1] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Management Science*, vol. 6, no. 1, pp. 80–91, 1959.

[2] Z. Rao, "Common distribution path of cold chain logistics of fresh agricultural products," *Agronomia*, vol. 36, no. 5, 2019.

[3] L. Li, Y. Yang, and G. Qin, "Optimization of integrated inventory routing problem for cold chain logistics considering carbon footprint and carbon regulations," *Sustainability*, vol. 11, no. 17, p. 4628, 2019.

[4] E. Yao, Z. Lang, Y. Yang, and Y. Zhang, "Vehicle routing problem solution considering minimising fuel consumption," *IET Intelligent Transport Systems*, vol. 9, no. 5, pp. 523–529, 2015.

[5] G. Kim, Y. S. Ong, T. Cheong, and P. S. Tan, "Solving the dynamic vehicle routing problem under traffic congestion," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 8, pp. 2367–2380, 2016.

[6] S. Chen, R. Chen, and J. Gao, "A modified harmony search algorithm for solving the dynamic vehicle routing problem with time windows," *Scientific Programming*, vol. 2017, Article ID 1021432, 13 pages, 2017.

[7] H. Abidi, K. Hassine, and F. Mguis, "Genetic algorithm for solving a dynamic vehicle routing problem with time windows," in *2018 International Conference on High Performance Computing & Simulation (HPCS)*, pp. 782–788, Orleans, France, 2018.

[8] H. E. Dongdong and L. I. Yinzhen, "Optimization model of green multi-type vehicles routing problem," *Journal of Computer Applications*, vol. 38, no. 12, pp. 3618–3624, 2018.

[9] S. Q. Fan, D. Lou, and Y. Sun, "Research on vehicle distribution path optimization of fresh agricultural products cold-chain logistics," *Storage Process*, vol. 17, no. 6, pp. 106–111, 2017.

[10] W. T. Fang and S. Z. Ai, "Research on cold chain logistics distribution path optimization based on hybrid ant colony algorithm," *Chinese Journal of Management Science*, vol. 27, no. 11, pp. 108–115, 2020.

[11] R. G. Thippa, M. P. K. Reddy, K. Lakshmanna et al., "Analysis of dimensionality reduction techniques on big data," *IEEE Access*, vol. 99, 2020.

[12] T. R. Gadekallu, D. S. Rajput, M. P. K. Reddy et al., "A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU," *Journal of Real-Time Image Processing*, vol. 18, no. 4, pp. 1383–1396, 2021.

[13] A. Guha, D. Samanta, A. Banerjee, and D. Agarwal, "A deep learning model for information loss prevention from multipage digital documents," *IEEE Access*, vol. 9, pp. 80451–80465, 2021.

[14] A. Colorni, M. Dorigo, and V. Mariiezzo, "Distributed optimization by ant colonies," in *Proceedings of the first European conference on artificial life*, pp. 134–142, Cambridge, MA, 1991.

[15] B. Chandra Mohan and R. Baskaran, "A survey: ant colony optimization based recent research and implementation on several engineering domain," *Expert Systems with Applications*, vol. 39, no. 4, pp. 4618–4627, 2012.

[16] D. Angus and C. Woodward, "Multiple objective ant colony optimisation," *Swarm Intelligence*, vol. 3, no. 1, pp. 69–85, 2009.

[17] M. López-Ibáñez and T. Stützle, *The impact of design choices of multiobjective antcolony optimization algorithms on performance: an experimental study on the biobjective TSP*, ACM, 2010.

[18] D. M. Chitty, "Applying ACO to large scale TSP instances," 2017, https://arxiv.org/abs/1709.03187.

[19] J. Li, P. Fu, X. Li, J. Zhang, and D. Zhu, "Study on vehicle routing problem and tabu search algorithm under low-carbon environment," *Chinese Journal of Management Science*, vol. 23, pp. 98–106, 2015.

[20] N. Labadie, C. Prins, and C. Prodhon, *Metaheuristics for Vehicle Routing Problems*, John Wiley & Sons, 2016.

[21] http://lbsyun.baidu.com/.

[22] L. L. Paquete, *Pareto Local Optimum Sets in the Biobjective Traveling Salesman Problem: An Experimental Study*, Springer, Berlin Heidelberg, 2004.

[23] A. Jaszkiewicz and T. Lust, "ND-tree: a fast online algorithm for updating a Pareto archive and its application in many-objective Pareto local search," 2016, https://arxiv.org/abs/1603.04798.