Low Carbon Logistics Location Problem Under Multi-Vehicle Route

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Abstract. In order to solve the decision-making problem of distribution center location and multi-vehicle routing optimization combination under the background of low carbon emission, a planning model aiming at the minimum logistics comprehensive cost considering carbon emission was proposed, and a two-stage heuristic algorithm was designed to solve the problem. In the first stage, the improved k-means clustering method is designed to partition and cluster the customer nodes, and then the spatial single journey partitioning algorithm is used to determine the customers served by each distribution center with the full load condition as the limit. In the second stage, the lowest comprehensive logistics cost is taken as the optimization objective, and the quantum genetic algorithm is established to solve the problem. Combined with the data of a logistics company, it is shown that compared with other existing algorithms, the algorithm proposed in this paper can effectively reduce the comprehensive cost of logistics under the premise of low carbon emissions, and provides a new way to solve the problem of site-multi-vehicle routing.

Keywords: Site-path problem · Improved K-means clustering · Quantum genetic algorithm

1 Introduction

At present, reducing carbon emissions has become the legal obligation of developed countries, and China has played a huge role in the work of controlling carbon emissions. In 2019, the pollution prevention and control action of diesel trucks was officially launched. The logistics industry mainly uses diesel trucks and faces great pressure to reduce emissions. Therefore, reducing carbon emissions has become an urgent Problem to be solved in the Location Routing Problem (LRP). For example, Xu Maozeng et al. established a low-carbon site-routing algorithm with fuel consumption cost and tire wear factors as optimization objectives. Wang et al. [1] considered the carbon footprint and designed a hybrid genetic algorithm based on heuristic rules to deal with the path problem with low carbonization. Jiang Haiqing set up an open distribution process to solve the low-carbon site-routing problem.

Further, the study of traditional logistics management problems, the location of the car plant or material center and the optimization of distance transportation are often

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studied separately. Perny [2] solved the path problem precisely based on the preference spanning tree method. Valeria et al. [3] proposed an accurate algorithm to solve vehicle routing problem by using mixed integer linear formula and reduction process. Ismail et al. [4] proposed an exact solution method based on simulated annealing heuristic to solve the green vehicle routing problem. Osman et al. [5] solved the routing problem by using simulated annealing and tabu search algorithm to exchange vertices of different routes. Tang Huiling et al. solved the green path problem based on the improved ant colony algorithm and proposed corresponding improvement measures. Fang Wenting et al. studied route optimization through mixed ant colony algorithm and optimized the cold chain logistics system. Ge Xianlong et al. established quantum genetic algorithm aiming at on-board rate and fuel consumption to solve the routing problem of multi-vehicle types. At the same time, the research of distribution center location also gradually tends to mature. Wang Yong et al. [6] solved the shortcomings of method fusion in the location selection process of urban logistics multi-distribution centers. Qu Bin et al. solved the continuous location problem of distribution center by establishing the adaptive particle swarm optimization algorithm.

Site-routing problem is a joint decision problem based on vehicle path planning, which is a NP-Hard problem. Fazayeli et al. [7] proposed a two-stage genetic algorithm to solve the LRP problem with time window and fuzzy requirements. Lopes et al. [8] established a hybrid genetic algorithm to solve the site-routing problem. Wang Daoping et al. constructed a two-stage heuristic algorithm by introducing customer importance degree and aggregation degree to solve the site-routing problem of logistics distribution. Li Zhenping et al. established a three-stage algorithm to solve the optimization problem of different types of products in the common network. Shen et al. [9] solved the problem of location selection and route optimization of emergency logistics system through two-stage heuristic algorithm.

At present, the main research direction of LRP problem is the transportation of single car models after general clustering, and less consideration is given to the problems of multi-car models considering carbon emission. At the same time, there is less research on the situations where extreme points may lead to the local optimal solution of clustering. Therefore, a two - stage heuristic algorithm is designed in this paper. Firstly, the improved K-means algorithm is used to cluster the customer nodes and select the location of the distribution center. Secondly, the model with the lowest carbon emission and comprehensive cost as the objective function is designed. Finally, the quantum genetic algorithm is used to solve the problem.

2 Problem Analysis and Model Building

2.1 Problem Description

On the premise that the location of several customer nodes, information of various vehicle types, vehicle load, carbon emission conversion coefficient, fuel consumption cost, demand of customer nodes and distance between nodes are known, the distribution center site selection is carried out and the service customers of the distribution center are determined. The vehicle starts from the distribution center, and each customer is only served once, which minimizes the comprehensive cost under the limitation of meeting customer demand.

2.2 Determination of Objective Function

Objective function is the core to solve the LRP problem. According to the analysis in this paper, there are two ways to choose the objective function: (1) the shortest total distance; (2) The total cost is the lowest. In real life, enterprises tend to focus on profit, which is bound to lead to higher attention on cost. Therefore, if the objective function is the shortest total mileage, the model will have limitations. Logistics cost is not only closely related to transportation distance, but also directly related to on-board rate and fuel consumption rate. Logistics costs can be summarized into two aspects; Fixed cost and variable cost. Fixed cost refers to the consumption of fixed resources in the logistics process, such as wages of drivers and employees, fixed costs of distribution center operation, etc. Variable costs refer to the dynamic costs in the process of distribution and transportation, such as fuel, vehicle depreciation, etc. The existing studies that take the lowest total cost as the objective function usually only consider the fixed cost of distribution center, vehicle and vehicle wear cost, which is inconsistent with the low-carbon concept advocated by green logistics and cannot truly reflect the actual cost under the current environment of green and low-carbon logistics. Therefore, on the basis of existing research results, this paper takes the comprehensive cost of distribution center fixed cost, vehicle transportation cost and vehicle wear cost into consideration of carbon emissions as the optimization objective to explore the LRP problem in a low-carbon environment.

A vehicle carbon emission calculation system during transportation is established by combining the Greenhouse Gas Emission Assessment Code for the Life Cycle of Goods and Services and the Greenhouse Gas Inventory Agreement. The transportation mode in this paper is set as integral transportation, and carbon emissions in the process are allocated according to the physical relationship between vehicle service volume and carbon emissions. Among them, the collection of carbon emissions adopts the final carbon emissions obtained by multiplying the dynamic data (fuel consumption) in the service process with carbon emission factors. This paper mainly uses data from three aspects: fuel consumption, loading capacity and transportation distance.

Although the application of electric vehicles is a research hotspot of green logistics, the technical constraints of short driving range and long charging time lead to the current use of vehicles are still dominated by fuel vehicles whose fuel is diesel. In this paper, the conversion coefficient of diesel oil in the Greenhouse Gas Inventory Protocol is adopted: 2.676 kg CO2/L. At the same time, the carbon emission formula in the transportation process is given: Carbon emission = diesel consumption × diesel conversion coefficient.

2.3 Mathematical Modeling

Before establishing the LRP model, the following assumptions should be made according to the actual situation:

(1) A number of distribution centers and customer nodes are known, the distance between distribution centers and customers and customers is fixed, and the demand of customers is known;
(2) Customer demand cannot be split and each customer can only be served by one vehicle;
(3) The vehicle can be unloaded when it reaches the customer node without stopping;
(4) Carbon emissions in the distribution center location process are not considered, but carbon emissions generated in the transportation process:
(5) The cargo demand of each customer node shall not exceed the maximum loading capacity of the model;
(6) Each customer can only be served by a single distribution center and a single vehicle;
(7) Distribution models are classified according to the load capacity, which starts from the distribution center and eventually returns to the distribution center, and overload is not allowed;
(8) The supply of the distribution center is enough to distribute each customer node.

Decision variable.

$$Z_{\mathrm{m}} = \begin{cases} 1, & \text{set up distribution center m} \\ 0, & \text{otherwise} \end{cases}$$

$$W_{\mathrm{m}} = \begin{cases} 1, & \text{distribution center m is selected} \\ 0, & \text{otherwise} \end{cases}$$

$$x_m^{nk} = \begin{cases} 1, & \begin{array}{l}\text{the task of distribution center m is carried} \\ \text{out by vehicle k of model n}\end{array} \\ 0, & \text{otherwise} \end{cases}$$

$$x_{ij}^{nk} = \begin{cases} 1, & \begin{array}{l}\text{vehicle k of model n runs from} \\ \text{customer i to customer j}\end{array} \\ 0, & \text{otherwise} \end{cases}$$

$$x_{mi}^{nk} = \begin{cases} 1, & \begin{array}{l}\text{vehicle k of model n runs from} \\ \text{distribution center m to customer i}\end{array} \\ 0, & \text{otherwise} \end{cases}$$

$$x_{mj}^{nk} = \begin{cases} 1, & \begin{array}{l}\text{vehicle k of model n runs from} \\ \text{distribution center m to customer j}\end{array} \\ 0, & \text{otherwise} \end{cases}$$

$$y_m^{\alpha} = \begin{cases} 1, & \text{route } \alpha \text{ from distribution center m is selected} \\ 0, & \text{otherwise} \end{cases}$$

Symbol specification.

M said distribution center set {m | m = 1, 2,…, I}; I said client node set {i| i = 1, 2,…, J}; N said vehicle type set {n | n = 1, 2,…, M}; K said vehicles set {k | k = 1, 2,…, N}; $\mathbf{Q_n^k}$ represents the maximum load capacity of type n vehicle k; $\mathbf{F_n^k}$ represents the depreciation cost of type n vehicle k; $\mathbf{H_m}$ represents the fixed operating costs of the distribution center; $\mathbf{c_{ij}}$ is the distance between i and j, $\mathbf{c_{ij}} = \mathbf{c_{ji}}$; cer represents the carbon emission rate, which is defined in the Protocol on the Inventory of Greenhouse

Gases: 2.676 kgC $\mathbf{O}_2$/L; $\mathbf{s0_n^k}$ represents the diesel emission rate of type n vehicle k when unloaded; $\mathbf{sf_n^k}$ represents the diesel emission rate of type n vehicle when k is fully loaded; $\mathbf{F_{ce}}$ represents the cost of carbon emission; $\mathbf{q_i}$ represents the demand of the ith customer; $\mathbf{u_{ij}^{nk}}$ represents the real-time load of type n vehicle k from i to j.

Model building.

$$
\begin{aligned}
MinZ = & \sum_{m=1}^{M} H_m W_m \\
& + \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{n=1}^{N} \sum_{m=1}^{M} cer \left(s0_n^k + \frac{sf_n^k - s0_n^k}{Q_n^k} u_{mi}^{nk} \right) c_{mi} x_{mi}^{nk} \right) F_{ce} x_m^{nk} \\
& + \left(\sum_{j=1}^{J} \sum_{j=1}^{J} \sum_{n=1}^{N} \sum_{m=1}^{M} cer \left(s0_n^k + \frac{sf_n^k - s0_n^k}{Q_n^k} u_{ij}^{nk} \right) c_{ij} x_{ij}^{nk} \right) F_{ce} x_{ij}^{nk} \\
& + \sum_{n=1}^{N} \sum_{m=1}^{M} \sum_{i=1}^{I} \sum_{j=1}^{J} F_n^k x_{mi}^{nk} F_k^d + \sum_{n=1}^{N} \sum_{m=1}^{M} \sum_{i=1}^{I} \sum_{j=1}^{J} F_n^k x_{ij}^{nk} F_k^d
\end{aligned} \tag{1}
$$

s.t.

$$\sum_{m=1}^{I} \sum_{n=1}^{M} \sum_{k=1}^{N} x_{mi}^{nk} = 1 \quad \text{i} \in \{\text{ 1,2,} \cdots \text{J}\} \tag{2}$$

$$\sum_{n=1}^{M} \sum_{k=1}^{N} x_i^{nk} = 1 \quad \text{i} \in \{1,\, 2, \cdots ,\, \text{J}\} \tag{3}$$

$$\sum_{j=1}^{J} \sum_{n=1}^{M} \sum_{k=1}^{N} x_{ij}^{nk} = 1 \quad \text{i} \in \{\text{ 1,2,} \ldots \text{,J}\} \tag{4}$$

$$\sum_{i=1}^{J} \sum_{n=1}^{M} \sum_{k=1}^{N} x_{ij}^{nk} = 1 \quad \text{j} \in \{\text{ 1,2,} \ldots \text{,J}\} \tag{5}$$

$$\sum_{i=1}^{J} \sum_{m=1}^{I} \sum_{n=1}^{M} \sum_{k=1}^{N} q_i x_{mi}^{nk} \le Q_n^k \tag{6}$$

$$y_m^{\alpha} \sum_{i=1}^{J} q_i \le Q_n^k \tag{7}$$

$$\sum_{j=1}^{J} \sum_{n=1}^{M} \sum_{k=1}^{N} u_{ji}^{nk} - \sum_{j=1}^{J} \sum_{n=1}^{M} \sum_{k=1}^{N} u_{ij}^{nk} = q_i \quad i, j \in \{1,\, 2, \cdots ,\, \text{J}\} \tag{8}$$

$$\sum_{m=1}^{J} \sum_{n=1}^{M} \sum_{k=1}^{N} x_{ij}^{nk} = 1 \quad i \in \{1,\, 2, \cdots ,\, \text{J}\} \tag{9}$$

$$x_{ij}^{nk}(x_{ij}^{nk} - 1) = 0 \tag{10}$$

$$x_{m}^{nk}(x_{m}^{nk} - 1) = 0 \tag{11}$$

$$X = (x_{ij}^{nk}) \in S \tag{12}$$

Formula (1) represents the objective function, including distribution center fixed cost, vehicle transportation cost, carbon emission cost and vehicle wear cost. Formula (2) indicates that each customer can only be served once; Formula (3) means that customer i can only be served by one vehicle; Formulae (4) and (5) mean to ensure that each customer is only served once and at most once by a distribution center vehicle; Formula (6) represents the constraints of vehicle carrying capacity; Formula (7) represents that the total demand of all customer nodes on any distribution path starting from the distribution center m does not exceed the maximum load capacity of N-type k vehicle; Formula (8) represents the limitation of customer demand; Formula (9) means to ensure that the vehicle starts from the distribution center and returns to the distribution center; Eqs. (10) and (11) represent 0–1 variable constraints; Formula (12) represents the elimination of the running routes that constitute the incomplete lines.

3 Algorithm Design

Distribution site-multi-vehicle model problem is a NP-hard problem. For this kind of problem, a two-stage heuristic algorithm is designed in this paper. In the first stage, site selection and cluster classification are carried out, and in the second stage, intelligent algorithm is used to optimize transportation routes.

3.1 Site Selection and Cluster Classification

Firstly, the improved k-means clustering algorithm is used for distribution center location selection and customer node clustering, and each cluster class is divided and distribution center of each cluster class is determined. The spatial single journey partitioning algorithm is used to series the cluster center and customer based on vehicle load as the standard.

Step 1.1 n inner cluster centers are selected as initial clustering centers, and the number of cluster centers is:

$$n = \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N} qi/Q_n^k \tag{13}$$

Step 1.2 Assign customers to clusters and calculate the distance from each customer to all clusters based on the coordinates of each customer. Under the condition that the load limit of the delivery vehicle is satisfied, the customer node is assigned to the nearest cluster class. If the remaining capacity of the vehicle cannot accommodate the customer node, the customer node is assigned to the next nearest cluster class;

Step 1.3 Update the clustering center according to the location and demand of each type of customer node to determine whether the customer node is stable;

Step 1.4 Repeat steps 1.2 and 1.3 until the clustering center no longer changes;

Step 1.5 Output cluster class, through the spatial journey partitioning algorithm to each cluster customer nodes and distribution center series.

In order to prevent the traditional k-means algorithm from relying too much on the initial clustering center and falling into the local optimal solution due to premature convergence, n central points within the cluster were selected in advance as the initial clustering center to solve the customer point clustering problem.

3.2 Quantum Genetic Algorithm

(1) Qubit chromosome structure

Based on the analysis of the structure of the universal chromosome for vehicle routing problem, this paper designs a qubit matrix as the chromosome structure, in which a quantum individual is:

$$q_k^t = \begin{bmatrix} \alpha_{11}^t & \alpha_{12}^t & \cdots & \inf \\ \beta_{11}^t & \beta_{12}^t & \cdots & \inf \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{n-11}^t & \alpha_{n-12}^t & \cdots & \alpha_{n-1n}^t \\ \beta_{n-11}^t & \beta_{n-12}^t & \cdots & \beta_{n-1n}^t \end{bmatrix} \tag{14}$$

where, n is the number of customer nodes and q_k^t is the kth quantum individual of the t generation.

(2) Rotational quantum gate renewal mechanism

In quantum genetic algorithm, the conversion of population state is realized through quantum gate rotation. The quantum gate rotation operation designed in this paper is as follows:

$$U(\delta\theta) = \begin{bmatrix} \cos(\delta\theta) & -\sin(\delta\theta) \\ \sin(\delta\theta) & -\cos(\delta\theta) \end{bmatrix} \tag{15}$$

Its updating process is as follows:

$$\begin{bmatrix} \alpha_{i'} \\ \beta_{i'} \end{bmatrix} = U(\delta\theta) = \begin{bmatrix} \cos(\delta\theta) & -\sin(\delta\theta) \\ \sin(\delta\theta) & \cos(\delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \tag{16}$$

And after the transformation $|\alpha\prime|^2 + |\beta\prime|^2 = 1$, the rotating door rotation selection strategy is shown in Table 1:

Where, xi is the I-th position of the current staining site, besti is the current optimal chromosome, f(x) is the fitness function, S(αi, βi) is the rotation direction, $\Delta\theta i$ is the rotation angle, the rotation gate adjustment strategy designed in this paper is to compare xi and besti, if f(x) $>$ f(best),adjusts the probability amplitude to evolve in a direction favorable to the emergence of xi. Conversely, if f(x) $<$ f(best),adjusts the probability amplitude to S(αi, βi) changes in the direction favorable for occurrence.

Table 1. Revolving door rotation policy table.

xi	$besti$	$f(x) > f(best)$	$\Delta\theta i$	$S(\alpha i, \beta i)$			
				$\alpha i\beta i > 0$	$\alpha i\beta i < 0$	$\alpha i = 0$	$\beta i = 0$
0	0	*FALSE*	0	0	0	0	0
0	0	*TRUE*	0	0	0	0	0
0	1	*FALSE*	0.001π	$+1$	-1	0	± 1
0	1	*TRUE*	0.001π	-1	$+1$	$+1$	0
1	0	*FALSE*	0.001π	-1	$+1$	$+1$	0
1	0	*TRUE*	0.001π	$+1$	-1	0	± 1
1	1	*FALSE*	0	0	0	0	0

(3) Design the fitness function

The fitness function designed in this paper is consistent with the objective function. The qubit chromosome is decoded and converted into a natural number chromosome, which is put into Formula (1), and the objective function minz is calculated.

(4) cross operator

According to the characteristics of TSP problem chromosome, this paper uses the full interference crossover operator. If the number of TSP customer nodes is 7, namely A1, A2, A3, A4, A5, A6, A7, and the distribution center is X1, the sequence of a chromosome can be assumed to be:

X1	A1	A2	A3	A4	A5	A6	A7	X1

The chromosome sequence is:

The solution represented by the sequence is: X1->A1->A2->A3->A4->A5->A7->X1, that is, it starts from the distribution center X1 and returns to the distribution center X1 from A1, A2, A3, A4, A5, A6, A7. If seven populations C1, C2, C3, C4, C5, C6 and C7 contain the above eight chromosomes, the operation process of the total interference crossover operator is as follows: the second customer node in C1 population is selected as the second place of the new chromosome, and the third customer in C2 population is selected as the third place of the new chromosome. And so on, until a new chromosome with all the elements of the previous chromosome is formed, forming a new viable solution. In the process of crossover, if a duplicate customer node appears, the next customer node is selected.

(5) mutation operator

A chromosome is randomly selected and two genes on the chromosome are switched to become new genes, which can ensure the feasibility of the mutant chromosome.

4 Analysis of Examples

The example of this paper uses matlab software to write improved K-means algorithm and quantum genetic algorithm. In order to verify the effectiveness of the algorithm designed in this paper, an example of a logistics enterprise will be taken as the background. The cost parameters of multiple models are shown in Table 2, and the longitude and latitude coefficients of 30 customer nodes and customer demand are shown in Table 3.

(1) The first phase of distribution center site selection

Firstly, based on the known information, the first-stage algorithm is used to select the distribution center location and the optimal scheme of clustering service for 30 customer nodes. Finally, the distribution center is constructed at D1, D2 and D3, and the results are shown in Table 4. The service customers of each distribution center are connected through the spatial single-journey algorithm, as shown in Fig. 1:

(2) Quantum genetic algorithm for path optimization

While the service scope of customer nodes is determined by the first-stage algorithm, the path of distribution center and each customer node is optimized by quantum genetic algorithm, which minimizes carbon emission and total distribution cost. The application

Table 2. Multiple model fee schedule.

Vehicle type	Full load fuel consumption	Dead weight	Fixed charge
1	1.295	6t	70
2	1.809	8t	100
3	2.554	12t	150

Table 3. Customer demand table.

number	Geographical location	demand	number	Geographical location	demand
C1	[116.6393,39.7658]	1.31	C16	[116.7646,39.7611]	4.16
C2	[116.5811,39.7460]	0.69	C17	[116.5961,39.7611]	0.64
C3	[116.5637,39.7647]	1.14	C18	[116.8021,39.7809]	0.24
C4	[116.5435,39.7490]	3.20	C19	[116.7716,39.9351]	1.45
C5	[116.6258,39.9345]	3.70	C20	[116.7071,39.9478]	2.90
C6	[116.6416,39.7468]	2.46	C21	[116.7465,39.9135]	1.90
C7	[116.6413,39.7479]	2.63	C22	[116.8002,39.7638]	2.48
C8	[116.5656,39.7320]	3.13	C23	[116.7489,39.9673]	1.52
C9	[116.7312,39.7639]	2.08	C24	[116.7598,39.9550]	2.06
C10	[116.9041,39.7469]	1.04	C25	[116.7692,39.9225]	1.05
C11	[116.8345,39.7690]	0.66	C26	[116.6943,39.9414]	1.37
C12	[116.8073,39.7736]	2.88	C27	[116.1461,39.7793]	7.59
C13	[116.8075,39.7737]	3.34	C28	[116.8107,39.6446]	2.00
C14	[116.8184,39.7695]	2.47	C29	[116.7925,39.6757]	1.61
C15	[116.8757,39.9247]	2.27	C30	[116.7821,39.6643]	1.36

Table 4. Customer node service owning table.

Distribution center	Geographical location	Customer point
D1	[116.7346,39.9475]	C5, C26, C21, C25, C19, C23, C28, C15, C20, C24
D2	[116.5531,39.7548]	C9, C16, C22, C13, C18, C12, C14, C11, C10, C30, C29
D3	[116.8403,39,7430]	C1, C6, C7, C17, C2, C4, C8, C3, C7

of the algorithm to solve the distribution center D1 uses one type 3 car, one type 2 car, the shortest mileage of 250.29km. The distribution center D2 uses two Type 3 cars and one Type 1 car, with a minimum driving range of 315.18km. The distribution center D3 uses two Type 3 cars. The minimum driving range is 157.59km. The minimum total driving range is 723.06km. See Fig. 2 for the specific optimized route diagram, and see Table 5 for model selection and vehicle service table:

In order to demonstrate the superiority of the two-stage heuristic algorithm proposed in this paper, the data in the above example and the genetic algorithm, and the method adopted in this paper is combined for comparative analysis. The carbon emission comparison and comprehensive cost comparison table are as follows:

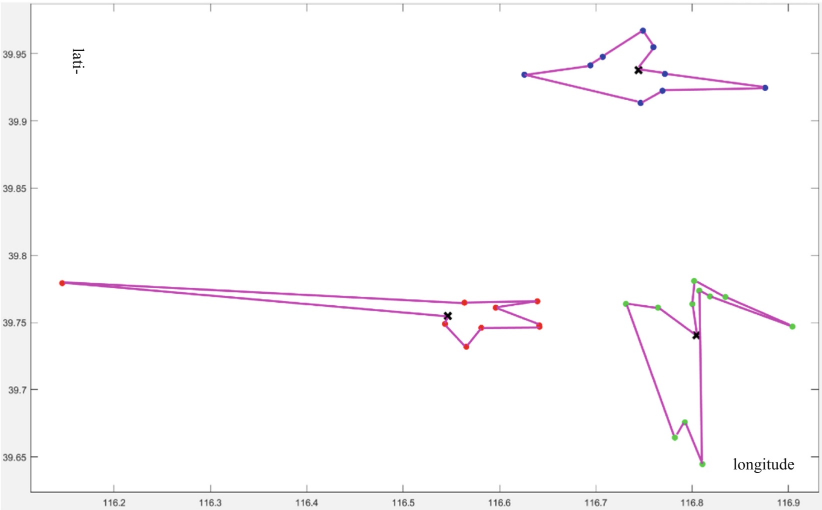

Fig. 1. Distribution center location and customer service map

Table 5. Model selection and vehicle service list

distribution center	Vehicle Service Type Code	Service customer path
D_1	3	D_1-C_{23}-C_{24}-$C_{19} - C_{15}$-C_{25}-C_{21}
	2	C_5-$C_{26} - C_{20}$
D_2	3	D_2-$C_3 - C_{17} - C_1$-$C_7 - C_6 - C_2$
	3	C_8-C_{27}
	1	C_4
D_3	3	D_3-$C_{10} - C_{28} - C_{30}$-$C_{29} - C_9$
	3	C_{22}-$C_{18} - C_{12}$-C_{13}-$C_{14} - C_{11}$

It can be seen from Table 6 and Table 7 that compared with the traditional method, the two-stage heuristic model established in this paper can reduce carbon emissions by 388.56 and optimize them by 7.8%. In the aspect of comprehensive cost saving 1397.6, the relative optimization 7.77%. The solution of higher quality can be obtained, which meets the requirements of enterprises in the decision-making problem of location selection and multi-vehicle routing under low carbon conditions.

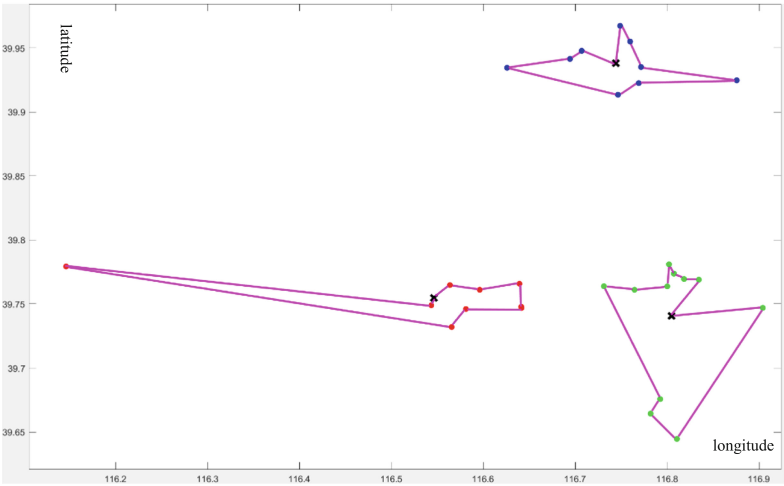

Fig. 2. Quantum genetic path optimization diagram

Table 6. Carbon emission comparison table

method of application	Diesel conversion rate	The distribution center corresponds to the service area	oil consumption	carbon emission	total carbon emission
quantum genetic algorithm	2.676kg CO_2/L	D_1	575.26	1539.39	4541.54
		D_2	719.39	1925.09	
		D_3	384.49	1077.06	
genetic algorithm		D_1'	633.65	1695.64	4930.1
		D_2'	774.63	2072.91	
		D_3'	434.06	1161.58	

Table 7. Comparative statement of comprehensive costs

cost service area	oil wear	Fixed cost of distribution center	Fixed service cost of vehicle	cost of depreciation	Carbon emission charge	total
D_1	575.26	1039	250	984	53.9	16580.45
D_2	719.39		370	1409	67.55	
D_3	402.49		300	791	37.70	
$D_1{\prime}$	633.65		250	1137	59.50	17978.35
$D_2{\prime}$	774.63		370	1731	72.8	
$D_3{\prime}$	434.06		300	903	40.6	

5 Conclusion

In this paper, the problem of location selection and multi-vehicle routing is studied, and the carbon emission minimization scheme is considered. A two-stage heuristic algorithm is established with the comprehensive cost of logistics process as the optimization objective. Firstly, the improved K-means clustering method was used to divide the customer nodes into clusters and select the best distribution center location. Then, the spatial single journey partitioning method was used to connect the customer nodes and distribution center in series. Finally, the quantum genetic algorithm was used to ensure that the algorithm would not fall into the local optimal solution through the complexity of the designed qubit chromosome. The feasibility and superiority of the proposed two-stage heuristic algorithm over other methods are proved by the example verification and comparison, which provides a new idea for solving the logistics site-multi-vehicle routing problem under the condition of low carbon emission.

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