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Green Cold Chain Logistics Vehicle Routing Problem with Resource Sharing

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Abstract

The cold chain logistics industry is faced with high costs and high carbon emissions. Integrating resource sharing (RS) into the optimization of multi-depot vehicle routing problem can greatly reduce logistics operation costs and carbon emissions by reconfiguring logistics networks. In this paper, a Green Cold Chain Logistics Vehicle Routing Problem with Resource Sharing (GCCLVRP-RS) model is developed, in which cold chain logistics companies cooperate with each other through a resource sharing strategy to jointly provide cold chain goods to customers. In order to construct a more comprehensive cost function, the carbon tax policy is considered and the carbon emission cost is calculated with the carbon tax price. In this paper, a two-stage hybrid algorithm consisting of k-means clustering algorithm and simulated annealing improved genetic algorithm (SAIGA) is designed. The first stage uses the k-means algorithm to reassign customers to distribution centers based on the spatial-temporal distance between customers, thus reducing the computational complexity of solving GCCLVRP-RS. In the second stage, SAIGA is used to optimize the distribution path. The comparison experiments show that resource sharing is an effective way to reduce the total cost and carbon emission compared with single distribution and joint distribution. Finally, numerical experiments are conducted using actual data in order to discuss the changes of distribution routes with different carbon emissions under different carbon taxes and their effects on the total distribution costs. Through the experimental analysis, the critical carbon tax values of carbon emission and distribution cost are obtained. The results of this paper provide effective suggestions for the government and enterprises, and cold chain logistics companies can improve delivery efficiency, reduce business costs and improve competitiveness through corporate cooperation. In addition, the government should advocate corporate cooperation and formulate an effective carbon tax policy to achieve a balance of economic and environmental benefits.

Keywords

Joint Distribution; Vehicle Routing Problem; Improved Genetic Algorithm; Carbon Tax.

1. Introduction

Global warming is becoming more and more serious, and the hot issue of reducing carbon emissions has attracted global attention [1]. At the United Nations Climate Change Conference in Copenhagen, China pledged to reduce CO2 emissions by 40% by 2020. Logistics, especially transportation, is considered one of the major contributors to these emissions, accounting for about 25% of global carbon emissions[2,3,4]. Cold chain logistics is an extremely important branch of transportation. Due to the perishable nature of cold chain products, transportation vehicles need to use refrigeration equipment to maintain a proper temperature during transportation, which will consume more fuel [5].Since 2013, the market size of cold chain logistics in China has been expanding rapidly, growing at 15% per year, with an estimated revenue of USD 80 billion in 2024 [6]. Although the cold chain logistics market is booming, cold

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chain logistics companies are usually small in size and numerous in number. Cooperation among them is quite limited, which leads to high costs and high carbon emissions during transportation [7]. Therefore, reducing total transportation costs and reducing carbon emissions is a priority for the entire cold chain logistics industry.

The vehicle routing problem (VRP) is the most widely used model in route planning [8]. The goal of VRP is to reduce transportation costs and transportation distances by optimizing routes. Cold chain logistics is a special logistics model in which distribution vehicles equipped with refrigeration equipment keep products at low temperatures and deliver them to customers on time [9,10]. During transportation, cold chain logistics consumes more fuel to keep goods fresh due to the perishable nature of cold chain products, damage costs and refrigeration costs are incurred in cold chain logistics [11]. Under the requirement of green development, carbon emission becomes another important factor affecting the delivery path in the vehicle routing issue [12]. The fuel consumption and carbon emissions of vehicles in cold chain logistics are higher than in normal logistics, causing more damage to the environment [13]. Hence, for cold chain logistics, it is not only necessary to reduce the total distribution cost, but also to reduce fuel consumption, refrigeration energy consumption, and carbon emission in distribution to achieve green distribution. This study provides comprehensive coverage of all relevant costs in the cold chain logistics delivery path, including fixed costs, transportation costs, damage costs, refrigeration costs, time penalty costs, and carbon costs.

Previous research on cold chain path optimization has focused on single distribution for large companies, ignoring the synchronization between similar businesses. With the rapid development of third-party logistics, the independent distribution mode of single distribution center of cold chain logistics gradually highlights the problems of high transportation cost, insufficient capacity and low service level, and the integration and sharing of distribution resources is the main trend of current cold chain logistics distribution. Distribution model with resource sharing supports the sharing of customer information and transportation resources, improves resource allocation among logistics facilities, and optimizes logistics networks [14]. Through the sharing of transportation resources and transportation equipment, distribution costs and carbon emissions can be effectively reduced [15]. The neglect of resource sharing makes the distribution path optimization of the whole cold chain logistics industry imperfect.

The main contribution of this paper is a comprehensive consideration of the costs associated with cold chain logistics and a Green Cold Chain Logistics Vehicle Routing Problem with Resource Sharing (GCCLVRP-RS) model has been proposed. Most previous scholars have studied the single distribution of cold chain companies, and fewer scholars have conducted research on the integration of cold chain logistics resources. Another contribution of this paper is the design of a two-stage algorithm based on customer clustering and vehicle routing optimization to solve the GCCLVRP-RS problem. The first stage uses a k-means clustering algorithm to integrate customers and resources. The second stage uses a simulated annealing improved genetic algorithm to optimize vehicle routes, which is one of the most efficient algorithms for solving large NP-Hard problems.

The rest of this article is structured as follows. Section 2 introduces a literature review of related work. Section 3 introduces the model of this study. Section 4 describes the two-stage algorithm, and Section 5 introduces the algorithm and case experiments. Section 6 emphasizes the impact of discussion and management. Finally, Section 7 concludes the article.

2. Review of the Literature

Solving the vehicle routing problem can achieve rational distribution and thus reduce distribution costs and carbon emissions costs. In this paper, we will review the literature from three aspects: cold chain logistics research, green vehicle routing problem research and resource sharing.

2.1. Research on Cold Chain Logistics

With the rapid development of cold chain logistics, scholars have been researching on cold chain logistics distribution. At present, the optimization of cold chain logistics distribution network is mainly based on the modeling and solution of practical problems. In terms of algorithms, the main methods are particle swarm algorithm, genetic algorithm, neighborhood search algorithm, and so on [16,17,18,19]. Combinatorial algorithms are also innovative ideas [20].

In terms of costing, products in cold chain logistics are perishable and require the use of refrigeration equipment, which incurs loss costs and refrigeration costs. Zhang and Chen developed a VRP model to find the most economical delivery path for frozen products [21]. However, the proposed model does not take into account the cost of damage to the goods. Osvald et al. developed a vehicle path planning model for perishable fresh food logistics delivery that considers the loss cost but ignores the refrigeration cost [22].Solomon was the first to study VRP with time window constraints [23]. Considering the randomness of perishable fresh food, Hsu et al. first proposed a fresh food logistics VRP model with a time window [24]. Later, in the research of scholars, cold chain logistics VRP problems with time windows were divided into two categories: hard time windows and soft time windows [25,26]. In addition, Ren improved and proposed a hybrid time window setting with a hard time window to meet the customer's time constraints and a soft time window to reflect different customer satisfaction [27]. If the service occurs before or after the ideal time, customer satisfaction will decrease and penalties will be applied to reflect the level of customer dissatisfaction. Previous studies were not comprehensive in terms of cost components. In this study, cargo damage cost, refrigeration cost and time penalty cost will be considered.

2.2. Research on Green Vehicle Routing Problem

Due to the growing concern about climate change, low-carbon and green economies have also been gradually introduced into vehicle path planning. The GVRP model was introduced by Erdoğan and Miller-Hooks [28], and GVRP usually considers the emissions of carbon dioxide. In order to reduce fuel consumption and carbon emissions, numerous scholars have conducted studies. Kuo et al. proposed a model to optimize VRP for green transportation with the goal of minimizing fuel consumption [29]. Koç et al. achieved reduction in fuel consumption and distribution carbon emissions by using multiple types of vehicles for distribution planning [30]. Liao's study demonstrated that by considering carbon emission factors in the GVRP model, CO2 emissions can be significantly reduced [31]. Niu et al. proposed a green VRP with a time window that includes carbon emissions to reduce the negative impact on the environment [32]. Kwon et al. focused on carbon emissions in vehicle distribution and demonstrated that carbon emissions can be reduced without increasing the total cost [33]. Although previous GVRP studies have examined carbon emissions to some extent, no literature has fully explored the impact of carbon tax mechanisms in cold chain logistics. When optimizing distribution routes, the cost of distribution cannot be ignored by only considering carbon emissions. Therefore, this paper will consider the carbon tax mechanism and consider the cost of carbon emissions as one of the costs.

2.3. Research on Resource Sharing

Currently, most of the cold chain logistics companies have been distributing independently, and a large number of studies have focused on the single distribution model [34,35]. Single distribution ignores the cooperation between similar companies, resulting in low vehicle fill rates, large number of rented vehicles, and high distribution costs. These disadvantages severely limit the development of the cold chain logistics industry. Resource sharing (RS) is a strategy that can be used to reconfigure logistics networks, which can significantly reduce logistics operating costs and required transportation resources [36]. Therefore, resource sharing is a new option for current cold chain logistics companies to consider.

Neghabadi, PD applied the resource sharing strategy in urban logistics and the results showed that the resource sharing improved the efficiency of logistics [37]. Quintero-Araujo studied the impact of resource sharing on logistics site selection, and the results showed that cost optimization and environmental protection have significant advantages under resource sharing [38]. Xu et al. studied the task resource allocation problem in shared logistics networks, constructed a task resource allocation model considering multi-stage resource sharing, and designed a multi-objective intelligent bee colony algorithm to solve the model [39]. Fan proposed a multi-center joint distribution model, which can effectively reduce distribution costs compared with individual distribution [40]. However, carbon emissions during vehicle operation were ignored during model construction. Wang integrates resource sharing into the optimization of multi-location pickup and delivery problems to significantly reduce logistics operating costs and required transportation resources by reconfiguring the logistics network [36]. Although previous studies have demonstrated the advantages of resource sharing strategies, less research has been conducted on resource sharing in cold chain logistics. Therefore, this question investigates the total cost and carbon emission in the cold chain logistics vehicle path problem based on resource sharing.

The Green Cold Chain Logistics Vehicle Routing Problem based on Resource Sharing (GCCLVRP-RS) model in this study takes into account cargo damage cost, refrigeration cost and carbon emission cost, which is more comprehensive and can better cope with cold chain logistics. The comparison between the factors considered in the RS model and the factors considered in the relevant literature is shown in Table 1, indicating that the GCCLVRP-RS model is comprehensive and close to practical applications.

Table 1. Comparison of the factors considered in the models of this paper and relevant literature

Studies	Product Damage	Refrigeration cost	Time penalty	Carbon Emission	Resource Sharing
Hsu[24]			√		
Osvald[22]	√		√		
Zhang and Chen[21]	√	√	√		
Ren[27]	√	√	√	√	
Niu[32]				√	
Wang[34]		√	√	√	
Fan[40]	√		√		√
This Study	√	√	√	√	√

3. Model Formulation

3.1. Problem Description

The cold chain logistics distribution model studied in this paper is to distribute goods after integrating the cold chain logistics distribution center and related equipment resources of several enterprises, the demand point only accepts the service operation of the vehicle, the demand point has a time window limit, and the service beyond the customer's time window will incur penalty costs. The vehicle returns to the nearest distribution center after completing the distribution task. The vehicle distribution process will generate fixed cost, transportation cost and time penalty cost. Due to the perishability of cold chain products, damage cost, refrigeration cost and carbon emission cost will be generated in the distribution process. According to the number of distribution centers and different information of demand points, there may be various distribution schemes. Figure 1 shows the distribution path of the single distribution mode of the cold chain logistics enterprise vehicles. Figure 2 shows the possible distribution paths of vehicles in the resource sharing mode of cold chain logistics enterprises.

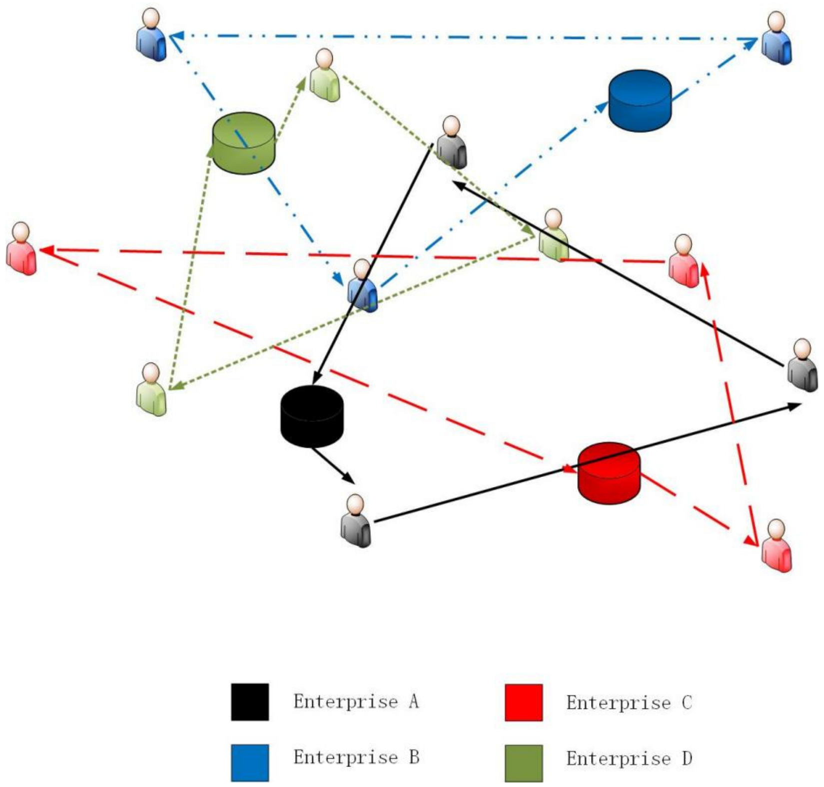

Figure 1. Cold chain logistics single distribution mode

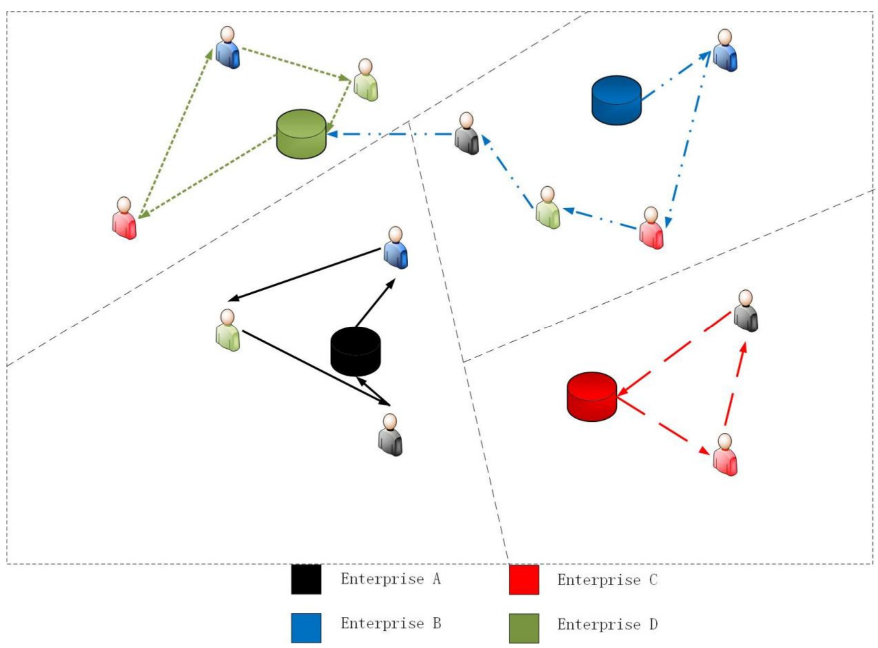

Figure 2. Cold chain logistics resources sharing distribution model

The Green Cold Chain Logistics Vehicle Routing Problem with Resource Sharing (GCCLVRP-RS) studied in this paper can be described as follows: M distribution centers and N demand points exist. The distance between each distribution center and demand point and the distance between each demand point are known. A refrigerated truck starts its service from one distribution center and can return to the nearest distribution center after completing its distribution service. The loading capacity of the refrigerated truck does not exceed the maximum load capacity of the vehicle type. In addition, there is a time limit for cold chain products to keep fresh, and the transportation process will lead to quality degradation. The demand point has a time window constraint in accepting the delivery service, and failure to reach or exceed the service range of the delivery time window will directly affect customer satisfaction. Refrigerated trucks will incur carbon emissions and carbon tax costs during vehicle driving, loading and unloading. Based on the above analysis, this paper constructs an optimization model targeting the sum of fixed cost, transportation cost, time penalty cost, cargo damage cost, refrigeration cost and carbon emissions cost. Minimize the number of refrigerated vehicles and the total driving distance of vehicles required for delivery services, thereby increasing the utilization rate of refrigerated vehicles, reducing the damage of fresh goods and carbon emissions.

3.2. Model Assumptions

The model assumes as follows:

1. The enterprise has the relevant information of all customer points, and each customer point can only receive the service once.

2. Multiple distribution centers exist at the same time from cold chain logistics enterprises participating in resource sharing, and the service capacity of the distribution centers meets customer demand without shortage. The vehicles used by the distribution centers are of the same type.

3. During the loading and unloading process, the doors of the cold chain vehicles are opened, the refrigeration equipment consumes more energy, and the damage rate of the cold chain products during the loading and unloading process is the same as during the transportation process.

4. All vehicles leave the distribution center at the same time and finally return to the nearest distribution center, without returning to the distribution center for replenishment in the middle.

5. All vehicles travel at a uniform speed and are not allowed to be overloaded.

3.3. Symbols and Parameters

See Table 2.

3.4. Model Development

3.4.1. Objective Function Analysis of Model

(1) Fixed cost

The fixed cost of vehicles refers to the depreciation, and rent of the vehicles involved in the distribution tasks, which will not change because of the change in the number of customers and distribution distance. The fixed costs are calculated as follows.

$$C_1 = K.C_f \tag{1}$$

Where C_f denotes the fixed cost of vehicles and K denotes the quantity of vehicles used.

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Table 2. Description of symbols

Symbols	Description
m	Number of distribution centers $(1,2,\ldots,m)$
n	Number of customers $(m+1, m+2, \ldots, m+n)$
K	Vehicle quantity
i, j	Index of nodes $(i, j = 1,2,\ldots,m, m+1, m+2, \ldots, m+n)$
k	Index of vehicles $(k = 1,2,\ldots,K)$
d_{ij}	Distance between nodes i and j
t_{ij}	Time of vehicle from node i to j
g_i	Demand for customer point i
S_j	Service time of customer j
C_f	Fixed cost of each vehicle
C_t	Transportation cost of per unit distance
C_p	Cold chain products'price per unit
C_r	Refrigeration consumption cost per unit
C_e	Punishment cost due to the early arrival
C_l	Punishment cost due to the late arrival
C_c	Carbon price
ε	The deterioration rate of the product freshness during transportation
θ	Sensitivity factor for cold chain products
α_1	The fuel consumption of refrigeration equipment per unit time during transportation
α_2	The fuel consumption of refrigeration equipment per unit time during unloading
v	Vehicle speed
Q	The maximum load capacity of a vehicle
Q_{ij}	Products quantity from customer i to customer j
T_e	Time window's starting time
T_{ee}	The earliest time the customer can accept
T_l	Time window's ending time
T_{ll}	The latest time the customer can accept
T_s	Departure time of all vehicles
W_i	Time point from vehicle departure to customer i
T_{jk}	Time point when vehicle k arrives at customer j
ρ_{max}	The fuel consumption per unit distance (full load)
ρ_0	The fuel consumption per unit distance (empty load)
η	The coefficient values of the carbon emissions
x_{ijk}	0–1 value, when vehicle k delivers cargo from node i to node j,$x_{ijk} = 1$; otherwise, $x_{ijk} = 0$.

(2) Transportation cost

Vehicle transportation cost is the cost incurred by the vehicle when it normally travels for distribution and mainly refers to the labour cost and the fuel consumption cost during the distribution process, which is positively related to the distance traveled by the vehicle. The transportation cost is given by:

$$C_2 = C_t \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} d_{ij} \quad (2)$$

Where C_t indicates the transportation cost per unit distance, d_{ij} indicates the distance from point i to point j, x_{ijk} is a 0–1 variable. When vehicle k travels from point i to point j, the value is 1; otherwise, the value is 0.

Damage cost

In the distribution process, the quality of fresh food is degraded to a certain extent over time, which results in damage cost. Quality loss is shown as an exponential change with the advance of time, and the damage cost is calculated as:

$$C_3 = C_p \sum_{i=1}^{n} g_i . \varepsilon (1 - e^{-\theta W_i}) \tag{3}$$

Where C_p is the price per unit of product, g_i is the customer demand at point i, ε is the deterioration rate of the product during transportation and handling, θ is the product sensitivity coefficient, and W_i is the time from the departure of the vehicle to point i.

Refrigeration cost

In the distribution process, fresh food should be kept at a low temperature to ensure quality. To maintain a low temperature, the vehicle battery-powered freezer refrigerator consumes electrical energy, and the vehicle does the same in the transportation process. When the vehicle arrives early at the customer's point to wait, the door of the vehicle freezer remains closed, resulting in a certain amount of energy consumption. When the vehicle begins to unload, the freezer's door stays open, which can lead to higher energy consumption to keep the product from deteriorating [41]. The refrigeration energy consumption is given by:

$$C_{41} = C_r \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \alpha_1 t_{ij} \tag{4}$$

$$C_{42} = C_r \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \alpha_2 S_j \tag{5}$$

Where C_r denotes the unit refrigeration consumption cost, α_1 and α_2 denote the fuel consumption per unit time of the refrigeration equipment during transportation and during loading and unloading. The latter is greater because the doors are kept open during loading and unloading. t_{ij} denotes the time the vehicle takes to travel from i to j, and S_j denotes the service time of the vehicle at the customer's point j.

$$C_4 = C_r \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \left(\alpha_1 t_{ij} + \alpha_2 S_j\right) \tag{6}$$

(3) Time penalty cost

In cold chain logistics, the conditions under which the customer receives the product are critical because they directly affect the customer revenue, inventory control, and quality management. Cold chain logistics companies should deliver products according to the customer's specific time requirements. If the vehicle arrives too early, they must wait until the customer begins receiving the product and cannot meet customer satisfaction requirements. If the vehicle arrives too late, the customer may experience restocking and sales problems. The relationship between customer satisfaction and customer time window is shown in Equation 7 and Figure 3. If the vehicle does not arrive within the customer's time window, penalty costs are incurred [40].

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$$u(t_i) = \begin{cases} 0, & T_{ik} < T_{ee} \\ \frac{T_{ik}-T_{ee}}{T_e-T_{ee}}, & T_{ee} \le T_{ik} \le T_e \\ 1, & T_{ee} \le T_{ik} \le T_l \\ \frac{T_{ll}-T_{ik}}{T_{ll}-T_l}, & T_l \le T_{ik} \le T_{ll} \\ 0, & T_{ik} > T_{ll} \end{cases} \tag{7}$$

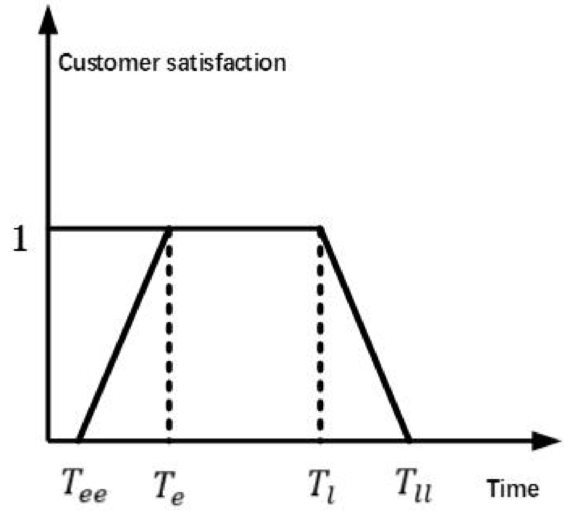

Figure 3. Customer satisfaction based on hybrid time window

Where $[T_e, T_l]$ denotes the time window required by the customer. $[T_{ee}, T_{ll}]$ denotes themaximum delivery time range acceptable to the customer. Exceeding the time range, customer satisfaction is 0 and the goods will be rejected. The penalty cost is calculated as follows:

$$C_5 = \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} \left[C_e \, max\left(T_e - T_{jk}, 0\right) + C_l max\left(T_{jk} - T_l, 0\right) \right] \tag{8}$$

Where C_e and C_l denote the penalty cost due to early arrival and late arrival, respectively, and T_{jk} denotes the time for vehicle k to arrive at customer point j.

(4) Carbon emission cost

During the transportation process, the fuel consumption of vehicles generates a large amount of carbon dioxide, which causes the greenhouse effect. By reducing the carbon emission cost, it not only reduces the total distribution cost to some extent but also reduces greenhouse gas emissions and harm to the environment [42]. The carbon emission costs are as follows:

The fuel consumption of vehicle travel is related to the distance traveled and influenced by the vehicle's loading conditions. The fuel consumption per unit distance can be expressed as follows:

$$\rho(X) = \rho_0 + \frac{\rho_{max} - \rho_0}{Q} X \tag{9}$$

Where ρ_0 and ρ_{max} denote the fuel consumption per unit distance when empty and fully loaded, Q is the maximum loading capacity of the vehicle, and X is the current loading weight.

Therefore, the fuel consumption of vehicle driving is given as:

$$FC_1 = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \rho\left(Q_{ij}\right) d_{ij} \tag{10}$$

Where Q_{ij} denotes the loading capacity of the vehicle from point i to point j.
The cost of fuel consumption in the refrigeration process is calculated by:

$$FC_2 = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} (\alpha_1 t_{ij} + \alpha_2 S_j) \tag{11}$$

Carbon emission is the product of fuel consumption and CO2 emission factor.
Therefore, the carbon emission can be expressed as follows:

$$EM = \eta (FC_1 + FC_2) \tag{12}$$

Where η denotes the carbon emission factor.

$$C_6 = C_c \eta \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} [\rho(Q_{ij}) d_{ij} + \alpha_1 t_{ij} + \alpha_2 S_j] \tag{13}$$

Where C_c denotes carbon tax price.

3.4.2. Model Setting

The total cost of cold chain transportation includes fixed cost (C_1), transportation cost (C_2), damage cost (C_3), refrigeration cost (C_4), time penalty cost (C_5), and carbon emission cost (C_6). Thus, the mathematical model is expressed as follows.

$$\mathbf{minC = C_1 + C_2 + C_3 + C_4 + C_5 + C_6} \tag{14}$$

$$\mathbf{W_j = W_i + S_i + t_{ij}\,, i \neq j\,, i \in V\,, j \in V\,, W_0 = T_s} \tag{15}$$

S.T.

$$\mathbf{\sum_{i=1}^{m+n} \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} g_j \cdot x_{ijk} \leq Q, \forall k \in \{1, 2, \dots, K\}} \tag{16}$$

$$\mathbf{\sum_{i=1}^{m} x_{ijk} = 0, \forall k \in \{1, 2, \dots, K\}, j \in \{1, 2, \dots, m\}} \tag{17}$$

$$\mathbf{\sum_{i=1}^{m+n} \sum_{j=1}^{m} x_{ijk} = 1, \forall k \in \{1, 2, \dots, K\}} \tag{18}$$

$$\mathbf{\sum_{i=m+1}^{m+n} \sum_{j=m+1}^{m+n} x_{ijk} = 1, \forall k \in \{1, 2, \dots, K\}} \tag{19}$$

$$\mathbf{\sum_{i=1}^{m+n} \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} x_{ijk} = 1, \forall k \in \{1, 2, \dots, K\}} \tag{20}$$

$$\mathbf{\sum_{j=m+1}^{m+n} \sum_{i=1}^{m} \sum_{k=1}^{K} x_{ijk} = \sum_{i=m+1}^{m+n} \sum_{j=1}^{m} \sum_{k=1}^{K} x_{jik} \leq 1} \tag{21}$$

Where Equation (14) indicates the composition of the total cost of the objective function; Equation (15) indicates that the whole cold chain logistics distribution process is continuous; Equation (16) indicates that the vehicle cannot be overloaded in the transportation process; Equations (17)–(19) indicate that the vehicle can only depart from the distribution center and cannot enter other distribution centers in the distribution process; Equation (20) indicates that each customer can only be served by one vehicle once; Equation (21) states that the distribution vehicle can start from the distribution center and can return to any distribution center after serving all customers.

4. Solution Methodology

The classical VRP belongs to the NP-hard problem, so the GCCLVRP-RS to be solved in this paper also has the NP-hard property. When the actual distribution chain contains more demand points, the solution process is more complicated, and it is more difficult to solve the problem with the exact algorithm. In this paper, a two-stage algorithm based on customer clustering and vehicle routing optimization is designed to solve the GCCLVRP-RS problem. This paper presents a two-stage hybrid algorithm consisting of k-means and simulated annealing improved genetic algorithm. In the first stage, the k-means clustering algorithm is used to reconstruct customers and resources. The main objective of the second stage is to optimize the vehicle routes and find the optimal solution. In Figure 4, we clearly show the two-stage algorithm.

4.1. K-Means Clustering Algorithm

Customer clustering is an important measure to reduce the complexity of solving multi-depot VRP problems. K-means algorithm is widely used to solve multi-depot VRP due to its simplicity and efficiency [43]. The model studied in this paper has multiple distribution centers, so it can also be considered as a multi-depot VRP. In the existing research on multi-network VRP distribution path optimization, most of the customer points are clustered using Euclidean distance. For the characteristics of time-sensitive cold chain logistics distribution, time is also added to the Euclidean distance to portray the similarity among customers in this paper. Customers A, B are geographically located in distribution areas (x_a, y_a) and (x_b, y_b). Distribution time windows are $[T_{a1}, T_{a2}]$ and $[T_{b1}, T_{b2}]$. The distribution time window arithmetic averages are $t_a = (T_{a1} + T_{a2})/2$ and $t_b = (T_{b1} + T_{b2})/2$. Define the spatial-temporal distance between any two customers A and B as:

$S_{ab} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2 + \beta^2(t_a - t_b)^2}$. Where β is the time cost conversion coefficient, which is the ratio of time loss cost to transportation cost. The k-means clustering pseudo-code based on spatial-temporal distance is listed in Algorithm 1.

Input: Nodes information, including distribution centers and customers information, such as the coordination, demands, and time windows
Output: The clustering results
Step 1: Select k objects as the initial clustering centers
Step 2: Calculate the spatial-temporal distance between each customer and each clustering center
Step 3: Assign each customer to their closest clustering center
Step 4: If some customers need to be adjusted among the clustering results, then enter Step 3; otherwise, go to Step 5
Step 5: Update the clustering centers
Step 6: Output the clustering results

ALGORITHM 1. Procedure of k-means algorithm

4.2. Simulated Annealing Improved Genetic Algorithm

The traditional genetic algorithm has premature convergence and is easy to fall into a local optimal solution. Hence, this paper designs and proposes a Simulated Annealing Improved Genetic Algorithm (SAIGA), which combines the global search performance of the simulated annealing algorithm with the fast convergence performance of the genetic algorithm, thereby improving the local search capability of the genetic algorithm. Avoid falling into the local optimum, and use the rule of probability change to guide the search direction, so that the algorithm has self-learning and self-adaptability.

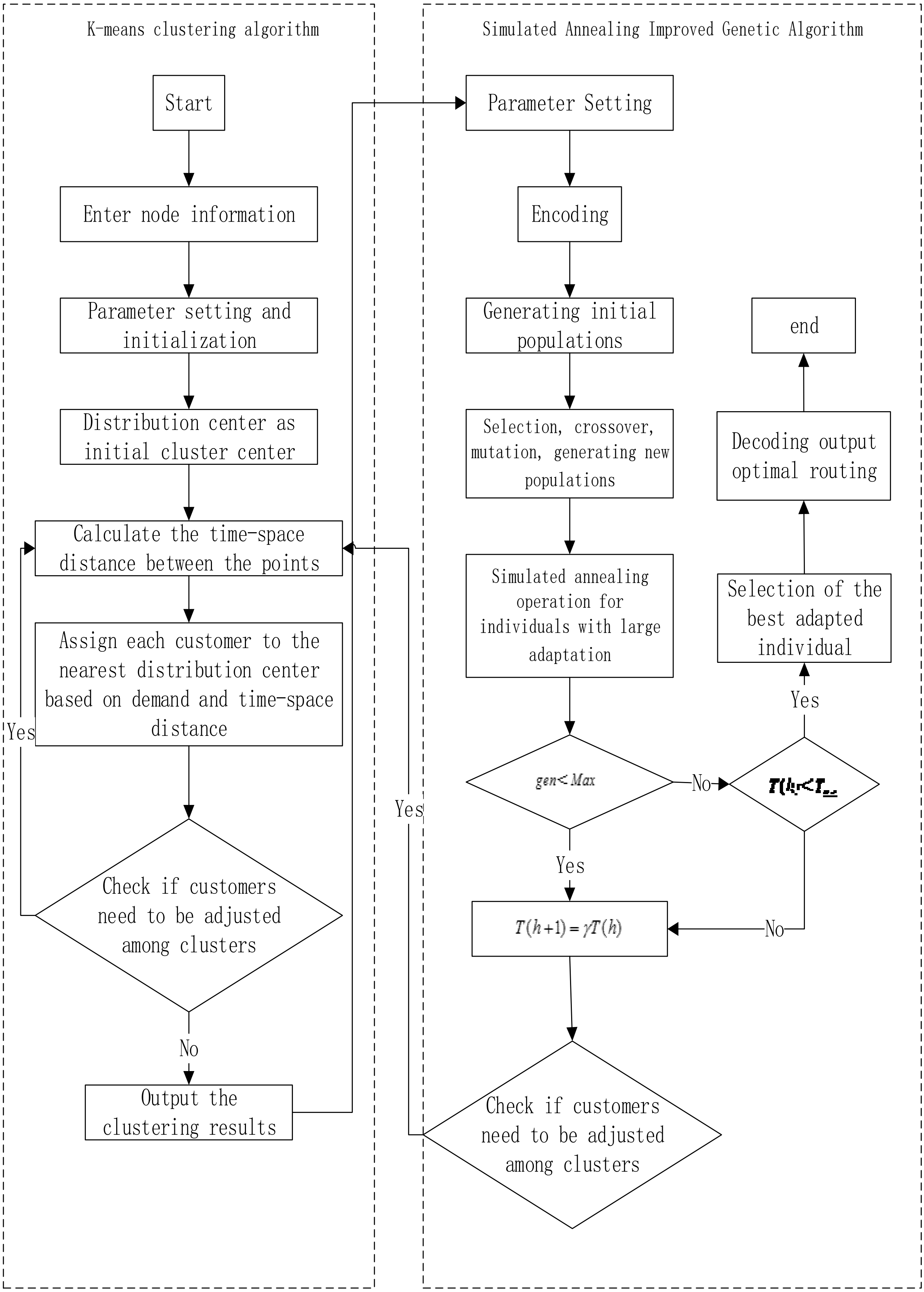

Figure 4. Flow chart of the two-stage algorithm

4.2.1. Chromosome Coding and the Generation of Initial Population

(1) Chromosome coding

Integer encoding is used in this study, Negative numbers $\{-m, -m+1, \dots, -1\}$ are used to represent the distribution center, and real numbers $\{1,2, \dots, n\}$ are used to represent customer points. The chromosome is composed of n customer points arrangements. The decoding process of the chromosome is shown in Figure 5. Taking 10 customer points and 4 distribution centers as an example, first insert the virtual distribution center 0 at the beginning and end of the chromosome, and then accumulate the demand for customer points from the first customer point of the chromosome Assuming that at the time of customer 3, the total demand is greater than the maximum load of the vehicle, insert two zeros in front of customer 3, and start from customer 3 and re-accumulate. After traversing all chromosomes, according to the customer point to the left or right of 0, replace 0 with the distribution center closest to the customer point.

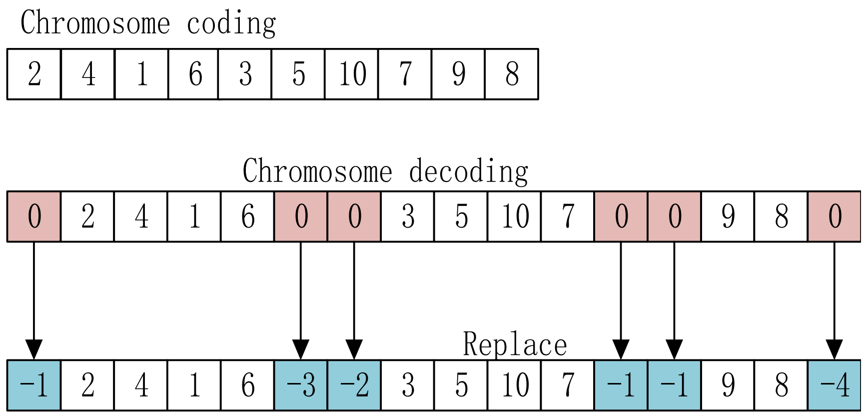

Figure 5. Schematic diagram of chromosome encoding and decoding

(2) Population initialization

Using the method of random generation, popsize individuals are generated to form the initial population pop(h) , the number of initialization iterations $gen = 0$, $T(0)$ is the initial temperature, and Max is the maximum number of initialization iterations. If the initial temperature $T(0)$ is too large, the algorithm iteration time is longer, and it is not easy to converge; if it is too small, it is easy to fall into a local optimum. In this paper, the initial temperature of the simulated annealing algorithm is set to 5000, the cooling coefficient γ is 0.95, and the termination temperature $T_{min} = 300$.

(3) Fitness function

The fitness of each chromosome in the population can be constructed by the model objective function equation (14). In this paper, the objective function value is the total delivery cost, so the smaller the delivery cost, the greater the chromosome fitness value. Therefore, the reciprocal of the objective function is selected as the fitness.

$$f_i = \frac{1}{C} \tag{22}$$

4.2.2. Algorithm Operator

(1) Elite retention strategy

According to the calculated fitness value, the individuals of the population are arranged in descending order, and the individual with the largest objective function value is marked as F_{max}, and the individual does not perform crossover and mutation operations.

(2) Select operation

Through the roulette selection method, chromosomes are selected in the population. The higher the chromosome fitness, the greater the probability of roulette selection, as shown in equation (23). p_i is the probability that i individual is selected, f_i and f_j are the fitness values of i and j individuals, and popsize is the population size. $p_0 = 0$, R_1 is a random number in the interval [0,1], when $\sum_{j=0}^{i-1} p_j \le R_1 \le \sum_{j=0}^{i} p_j$, choose Individual i. Through the selection operation cycle selection, a new population Newpop(h) is formed.

$$p_i = \frac{f_i}{\sum_{j=1}^{popsize} f_j} \tag{23}$$

(3) Crossover and mutation operation

According to the sequential crossover method, Newpop(h) is crossed with the crossover probability P_c to obtain the new population Cpop(h). This means that individuals participating in the crossover operation will have the probability that P_c crosses their gene sequences through the partially mapped crossover operator to generate new individuals with new gene sequences. The first step of the sequential crossover method is to first insert two crossovers on one individual of the paired chromosomes, copy the gene segment between the crossovers to the same position in the offspring, as shown in the operation in Figure 6 below, and finally find the position of the same gene on the other parent chromosome and insert the remaining genes into the offspring individuals in sequence.

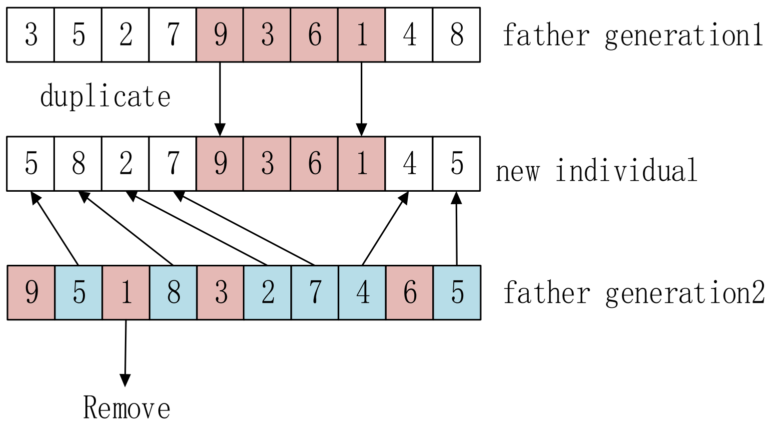

Figure 6. Crossover operations

The population Cpop(h) is subjected to swap mutation operation with the mutation probability P_m, and a new population Mpop(h) is obtained. Swap mutation is a relatively simple way of mutation, the mutation is achieved by randomly selecting two gene sites on a certain chromosome to swap positions. By this operation, the local search ability of the algorithm can be improved. The specific mutation method is shown in Figure 7. This paper sets the adaptive crossover and mutation probability, as shown in equations (24) and (25).

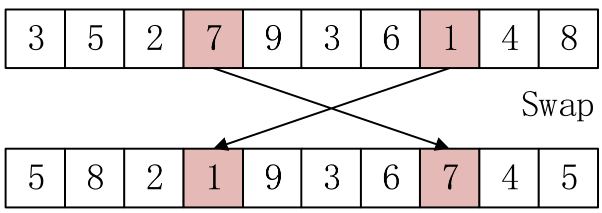

Figure 7. Mutation operation

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$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1}-P_{c2})(f'-F_{ave})}{F_{max}-F_{ave}}, f' \geq F_{ave} \\ P_{c1}, f' < F_{ave} \end{cases} \tag{24}$$

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1}-P_{m2})(F_{max}-f)}{F_{max}-F_{ave}}, f \geq F_{ave} \\ P_{m1}, f < F_{ave} \end{cases} \tag{25}$$

Where P_{c1} and P_{c2} are the maximum and minimum crossover probability, P_{m1} and P_{m2} are the maximum and minimum mutation probability, f' is the larger fitness value among the individuals to be crossed, and f is the fitness value to be mutated , The fitness of the individual to be mutated is greater, and the probability of mutation is lower. When the fitness value is lower, the population variation and crossover probability values are larger, and the population diversity can be increased, avoiding the algorithm from falling into the local optimal solution, and improving the global search ability. This article sets up simulated annealing improvement steps after the cross-mutation operation to further strengthen the global search capability.

(4) Improved simulated annealing operation

In view of the poor local search ability of genetic algorithm, a large number of iterations are required to obtain the optimal solution. After the simulated annealing algorithm is introduced into the cross-mutation operation, the simulated annealing algorithm is tolerant to some poor solutions and can jump out of the local optimal solution. Strong search ability. Calculate the temperature T(h) iterated to the current generation by formula (26), and then perform the following operations on the individuals in Mpop(h) to form a new population Spop(h).

1) Sort the population Mpop(h) according to the fitness value, and select individuals with greater fitness after the genetic link. Calculate the fitness value f_i of the current individual i.

2) Perform genetic manipulation and generate a new individual a. Calculate the fitness value of the individual and record it as f_a.

3) If the fitness value f_a of the individual is greater than the fitness value f_i of the current individual i in the corresponding population, replace the individual i in the population with individual a; otherwise, calculate the fitness difference $\Delta E = f_i - f_a$ of the two bodies, according to formula (27) Calculate the probability P_s, and then generate a random number R_2 in the interval [0,1]. If $P_s > R_2$, still use the randomly generated chromosome to replace the chromosome in the population. Otherwise, no replacement will be performed, and the original individual in the population will remain unchanged.

$$T(h+1) = \gamma T(h) \tag{26}$$

$$P_s = e^{[-\Delta E/T(h)]} \tag{27}$$

Replace the individual with the lowest fitness value in Spop(h) with F_{max}, and then determine whether gen is less than the maximum number of iterations Max, if gen < Max, update the annealing temperature, let $h = h + 1$, $pop(h+1) = Spop(h)$, $gen = gen + 1$, proceed to the next iteration; if $gen \geq Max$, judge whether the current temperature T(h) is less than the termination temperature T_{min}, if yes, terminate the iteration and output the optimal solution, if not, update The annealing temperature proceeds to the next iteration.

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5. Computational Experiments

5.1. Case Study 1

Table 3. Customer locations, demands, and time windows

Customers	X(km)	Y(km)	Demands(t)	Time windows		Service time(h)
				$[T_e, T_l]$	$[T_{ee}, T_{ll}]$	
1	-29.73	64.136	1.2	8:30-14:30	7:30-15:30	0.4
2	-30.664	5.463	0.8	8:30-15:30	7:30-16:30	0.27
3	51.642	5.469	1.6	7:30-11:00	6:30-12:00	0.53
4	-13.171	69.336	0.5	8:30-15:30	7:30-16:30	0.17
5	-67.413	68.323	1.2	8:30-15:30	7:30-16:30	0.40
6	48.907	6.274	0.5	8:30-10:30	7:30-11:30	0.17
7	5.243	22.26	1.3	8:30-15:30	7:30-16:30	0.43
8	-65.002	77.234	2.0	8:30-15:30	7:30-16:30	0.67
9	-4.175	-1.569	1.3	8:30-10:30	7:30-11:30	0.43
10	23.029	11.639	1.8	7:30-12:30	6:30-13:30	0.60
11	25.482	6.287	0.7	8:30-11:00	7:30-12:00	0.23
12	-42.615	-26.392	0.6	8:30-15:30	7:30-16:30	0.20
13	-76.672	99.341	0.9	7:30-15:30	6:30-16:30	0.30
14	-20.673	57.892	0.9	6:30-10:30	6:30-11:30	0.30
15	-52.039	6.567	0.4	6:30-9:30	6:30-10:30	0.13
16	-41.376	50.824	2.5	7:30-16:30	6:30-17:30	0.83
17	-91.943	27.588	0.5	7:30-15:30	6:30-16:30	0.17
18	-65.118	30.212	1.7	6:30-9:30	6:30-10:30	0.57
19	18.597	96.716	0.3	7:30-15:30	6:30-16:30	0.10
20	-40.942	83.209	1.6	6:30-12:00	6:30-13:00	0.53
21	-37.756	-33.325	2.5	7:30-12:00	6:30-13:00	0.83
22	29.083	29.083	2.1	7:30-16:30	6:30-17:30	0.70
23	43.03	20.453	1.4	7:30-16:30	6:30-17:30	0.47
24	-35.297	-24.896	1.9	6:30-16:30	6:30-17:30	0.63
25	-54.755	140368	1.4	8:30-15:30	7:30-16:30	0.47
26	-49.329	33.374	0.6	6:30-12:00	6:30-13:00	0.20
27	57.404	23.822	1.6	7:30-14:30	6:30-17:30	0.53
28	-22.754	55.408	0.9	8:30-13:30	7:30-14:30	0.30
29	-56.622	73.34	2.0	7:30-16:30	6:30-17:30	0.67
30	-38.562	-3.705	1.3	6:30-12:00	6:30-13:00	0.43
31	-16.779	19.537	1.0	7:30-15:30	6:30-16:30	0.33
32	-11.53	11.615	1.6	6:30-10:30	6:30-11:30	0.53
33	-46.545	97.974	1.9	6:30-9:30	6:30-10:30	0.63
34	16.229	9.32	2.2	7:30-12:00	6:30-13:00	0.73
35	1.294	7.349	1.4	7:30-16:30	6:30-17:30	0.47
36	-26.404	29.529	1.0	8:30-14:00	7:30-15:00	0.33
37	4.352	14.685	1.1	7:30-15:30	6:30-16:30	0.37
38	-50.665	-23.126	1.5	7:30-16:30	6:30-17:30	0.50
39	-22.833	-9.814	1.3	6:30-12:00	6:30-13:00	0.43
40	-71.1	-18.616	1.5	7:30-16:30	6:30-17:30	0.50
41	-7.849	32.074	0.8	7:30-16:30	6:30-17:30	0.27
42	11.877	-24.933	2.2	7:30-11:30	6:30-12:30	0.73
43	-18.927	-23.73	2.4	7:30-16:30	6:30-17:30	0.80
44	-11.92	11.755	0.3	7:30-16:30	6:30-17:30	0.10
45	29.84	11.633	2.5	7:30-11:30	6:30-12:30	0.83
46	12.268	-55.811	1.9	6:30-13:30	6:30-14:30	0.63
47	-37.933	-21.613	2.1	7:30-12:00	6:30-13:00	0.70
48	42.883	-2.966	1.0	7:30-16:30	6:30-15:30	0.33

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The empirical data for Case Study 1 were obtained from Fan [40]. The empirical data consisted of four distribution centers and 48 customer locations. Each distribution center is responsible for the distribution of 12 customer points. These characteristics of the empirical data used in this study are consistent with the actual situation in the cold chain logistics industry. Table 3 shows the customer locations, customer demand, and customer preferred time windows. Table 4 shows the detailed settings of the parameters. Fan proposes a joint distribution method to optimize the distribution path and compares it with single distribution. However, it ignores the environmental impact during the transportation process, nor does it consider the spatial-temporal distance between customers. In this paper, we consider the carbon tax mechanism and compare the above two distribution models with the distribution model under the resource sharing strategy.

Table 4. Parameter settings in the case study

Symbols	Description	value	Unit
m	Number of distribution centers	4	none
n	Number of customers	28	none
C_f	Fixed cost of each vehicle	200	RMB/car
C_t	Transportation cost of per unit distance	3	RMB/km
C_p	Cold chain products price per unit	5000	RMB/t
C_r	Refrigeration consumption cost per unit	6.68	RMB/L
C_e	Punishment cost due to the early arrival	30	RMB/h
C_l	Punishment cost due to the late arrival	50	RMB/h
C_c	Carbon price	0.25	RMB/kg
ε	The deterioration rate of the product freshness during transportation	1	none
θ	Cold chain products′ sensitivity factor	0.002	none
α_1	The fuel consumption of refrigeration equipment per unit time during transportation	2	L/h
α_2	The fuel consumption of refrigeration equipment per unit time during unloading	2.5	L/h
v	Vehicle speed	60	km/h
Q	The maximum load capacity of a vehicle	10	t
ρ_{max}	The fuel consumption per unit distance (full load)	0.677	L/km
ρ_0	The fuel consumption per unit distance (empty load)	0.253	L/km
η	The coefficient values of the carbon emissions	2.63	kg/L
β	Time-cost conversion factor	0.443	none

Table 5 and Figure 8 give the optimal vehicle routes for the single distribution mode of the logistics network, including specific information for each service route. In Figure 8, an obvious feature is that the customer locations of each distribution center are scattered, and distribution through the single distribution mode results in a long distance from the distribution vehicle to the customer point and a long distribution and delivery time, leading to high logistics costs.

Table 5. Specific costs for the single distribution model scheme

Number	Route	Total Costs (RMB)	Travel distance (km)	Carbon emissions costs(kg)	Cargo load(t)
1	C1-->7-->1-->5-->8-->4-->3-->6-->C1	1569.02	302.08	358.684	8.3
2	C1-->10-->11-->9-->12-->2-->C1	940.31	171.07	170.568	5.2
3	C2-->23-->15-->18-->17-->16-->22-->C2	1535.72	271.57	375.196	8.6
4	C2-->24-->21-->14-->20-->13-->19-->C2	2006.31	418.73	456.12	8.1
5	C3-->32-->35-->34-->27-->31-->28-->C3	1346.78	242.51	298.024	8.7
6	C3-->33-->29-->26-->25-->30-->36-->C3	1254.01	218.48	281.092	8.2
7	C4-->39-->42-->46-->48-->45-->C4	1273.29	224.56	277.58	8.9
8	C4-->40-->38-->47-->43-->44-->37-->41-->C4	1269.18	210.43	276.036	9.7
Total		11194.62	2059.44	2493.3	65.7

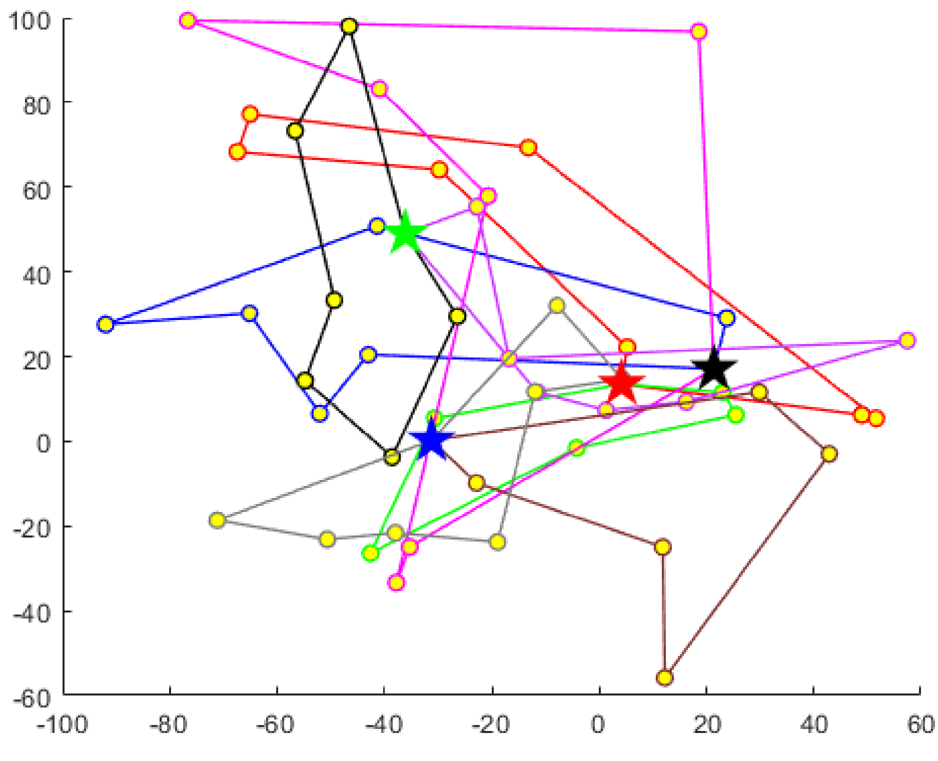

Figure 8. Optimal distribution routes for single distribution model

Table 6 and Figure 9 give the optimal vehicle routes for joint distribution model, including specific information of each service route. The joint distribution considers the distribution problem as a vehicle path problem of multiple distribution centers, but when planning the vehicle routes, the temporal and spatial distances of customer points are not considered, and the advantages of resource sharing are not fully exploited. Therefore, although there is some reduction in total cost and carbon emission compared with the individual distribution model, there is still room for optimization.

Table 6. Specific costs for the joint distribution model scheme

Number	Route	Total Costs (RMB)	Travel distance (km)	Carbon emissions costs(kg)	Cargo load(t)
1	C1-->41—>31-->44-->32-->9-->35-->37-->7-->C1	820.00	96.95	151.39	8.80
2	C2-->22-->45-->11-->10-->34-->C2	658.56	60.00	101.00	9.30
3	C2-->48-->3-->6-->27-->19-->4-->16-->C3	1314.30	227.70	290.89	8.00
4	C3-->18-->17-->5-->8-->13-->29-->C3	1234.80	207.92	279.52	8.30
5	C3-->33-->20-->1-->14-->28-->36-->26-->C3	1064.10	172.05	225.95	8.10
6	C4-->30-->21-->43-->39-->2-->C4	746.23	95.99	136.81	8.30
7	C4-->24-->47-->12-->46-->42-->C1	1045.40	168.77	213.54	8.70
8	C4-->38-->40-->15-->25-->23-->C4	821.71	127.81	157.76	6.20
Total		7705.10	1157.19	1556.86	65.7

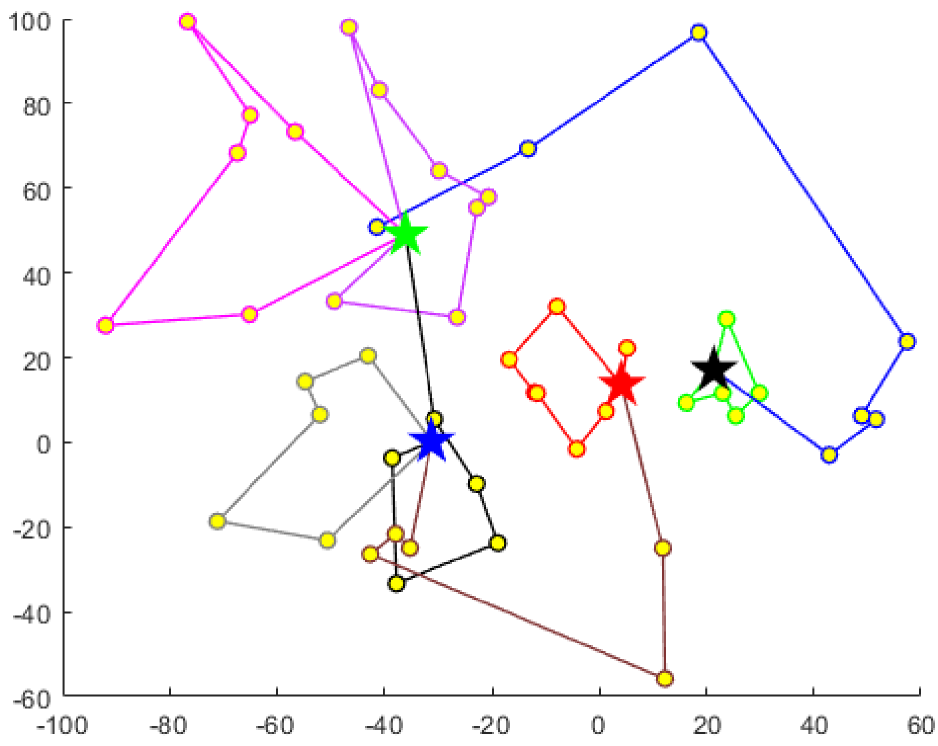

Figure 9. Optimal distribution routes for joint distribution model

Resources are integrated and distribution tasks are planned through a resource sharing strategy. Customer points are first clustered by spatial-temporal distance using K-means

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clustering method. The results of the customer point clustering are shown in Table 7 and Figure 10. In which, the customer points 39 and 43 are relatively close to the distribution center 4 in terms of spatial distance. If the vehicle departs from the distribution center 1 and the customer points 39 and 43 are the last customers to deliver, it will return to the distribution center 4. In the same way, although customer points 17,18,26,36 are served by distribution center 4, they are closer to distribution center 3. If the last service point of the vehicle distribution route is 17,18,26,36, it will return to distribution center 3.After completing the customer clustering, the optimal path of the distribution center is solved by the improved genetic algorithm, which is run 10 times to obtain the optimal solution as shown in Table 8. Figure 11 shows the distribution paths after resource sharing optimization.

Table 7. Distribution centers and customer points of service

Depots	X(km)	Y(km)	Customers
C1	4.163	13.559	7,9,31,32,35,37,39,41,42,43,44,46
C2	21.387	17.105	3,6,10,11,22,27,34,45,48
C3	-36.118	49.097	1,4,5,8,13,14,16,19,20,28,29,33
C4	-31.201	0.235	2,12,15,17,18,21,23,24,25,26,30,36,38,40,47

Table 8. Specific costs of resource sharing distribution scheme

Number	Route	Total Costs (RMB)	Travel distance (km)	Carbon emissions costs(kg)	Cargo load(t)
1	C1-->37-->7-->35-->9-->32-->44-->31-->41-->C1	745.67	96.80	122.36	8.80
2	C1-->39-->43-->46-->42-->C1	996.71	165.04	207.48	7.80
3	C2-->10-->45-->11-->48-->6-->3-->27-->C2	821.15	108.87	134.58	9.70
4	C2-->34-->22-->C2	417.18	42.70	49.11	4.30
5	C3-->20-->33-->13-->8-->5-->29-->C3	1072.48	158.28	227.96	9.60
6	C3-->16-->1-->28-->14-->4-->19-->C3	888.62	165.79	153.76	6.30
7	C4-->15-->25-->23-->36-->26-->18-->17-->40-->2-->C4	1448.36	231.49	292.32	9.30
8	C4-->30-->38-->12-->21-->24-->47-->C4	755.79	84.24	129.82	9.90
Total		7145.94	1053.21	1317.39	65.7

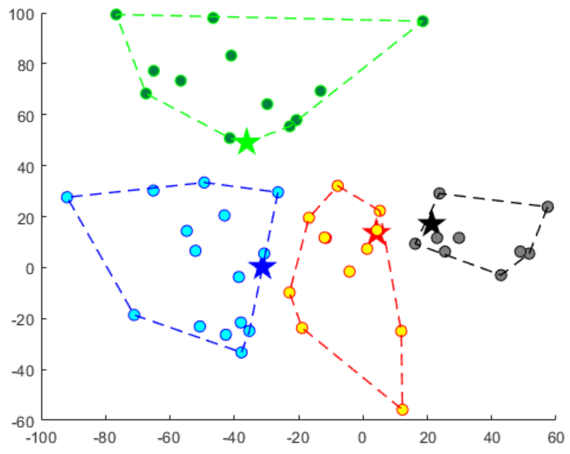

Figure 10. Clustering Result

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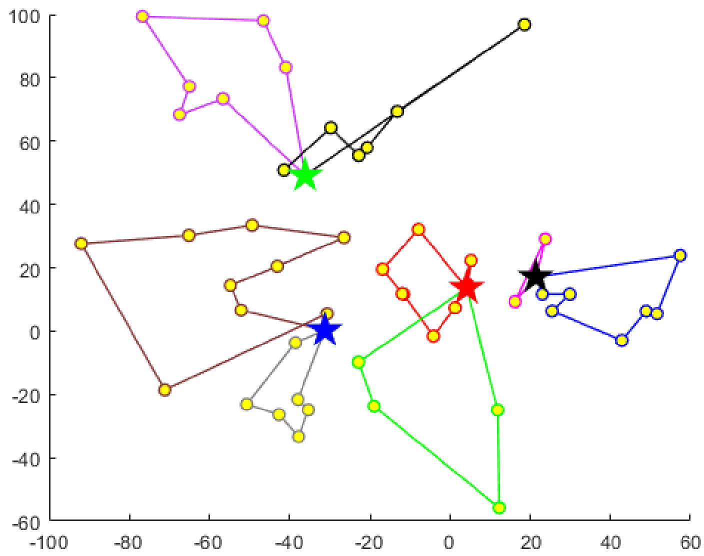

Figure 11. Optimal distribution routes for resource sharing distribution model

Table 9. Comparison of different models

Distribution mode	Total costs	Carbon emissions(kg)	Distance (km)	Damage costs(RMB)
Single distribution	11194.62	2493.3	2059.44	1965.94
Joint distribution	7705.10	1556.86	1157.19	1531.47
Resource sharing	7145.94	1317.39	1053.21	1370.27

Comparison of different modes is shown in Table 9. The total cost was reduced by 33.17% through the joint distribution model. Under the distribution model based on the resource sharing strategy, the cumulative total cost was 7,145.95 RMB, which was significantly lower than the cumulative total cost of 4048.68 RMB for single distribution and 559.16 RMB for joint distribution. In addition, the carbon emission of the product was reduced to 1317.39 kg, which was optimized by 47.16% compared to the single distribution mode and 15.38% compared to the joint distribution. Moreover, when the distribution mode with resource sharing strategy is adopted, the distribution distance can be reduced to 1053.21 km, and the joint distribution mode is 1157.19km. In terms of damage costs, 434.47 RMB can be saved through joint distribution, while the resource sharing model is 595.73 RMB. Since the two previous distribution models did not consider the spatial-temporal distances between distribution centers, longer travel times with larger vehicle loading rates resulted in higher costs and carbon emissions. The GCCLVRP-RS proposed in this paper shares the resources of enterprises, clusters them by the spatial-temporal distance of customers, and then plans distribution paths by simulated annealing improved genetic algorithm. The GCCLVRP-RS fully improves inter-enterprise cooperation, rational planning of resources, and reduction of driving distance, while achieving economic and environmental benefits.

5.2. Case Study 2

In the previous section, we demonstrated the superiority of GCCLVRP-RS. In reality, carbon prices are likely to increase or decrease over time. Therefore, 17 different carbon prices are considered in this section to analyze the trends in carbon emissions, carbon costs and total costs.

Empirical data are from four cold chain logistics companies in Chengdu, China. They distributed the same frozen food to customers in the center of Chengdu. Each cold chain logistics company operates independently and has a warehouse serving 7 customers, which is relatively small.

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Cold chain logistics companies need to sell very few cold chain products every day. The empirical data used in this study are representative of the cold chain logistics industry in China and reflect its characteristics. Table 10 shows the customer locations, customer demand, and customer preferred time windows. The maximum loading capacity of the transport vehicle is 2t, and the fuel consumption per unit distance is 0.165L/km and 0.377L/km when empty and fully loaded. After several trials set β to 0.064. Other parameters are set as shown in the previous section. When the unit carbon emission cost is 0.25 kg/yuan. The results of customer clustering are shown in Table 11. The optimal path is shown in Table 12 and Figure 12.

Table 10. Customer locations, demands, and time windows for case study 2

Customers	X(km)	Y(km)	Demands(t)	Time windows		Service time
				$[T_e, T_l]$	$[T_{ee}, T_{ll}]$	
1	14.1	14.4	0.6	10:30–11:00	9:30–12:00	0.17
2	25	15	0.4	10:00–10:30	9:00–11:30	0.11
3	17.2	15.8	0.9	10:30–11:00	9:30–12:00	0.25
4	12.6	11.8	0.9	10:00–10:30	9:00–11:30	0.25
5	11.6	16.1	1.3	10:30–11:00	9:30–12:00	0.36
6	13.3	18.9	0.6	11:00–11:30	10:00–12:30	0.17
7	14.45	11.1	0.4	10:30–11:00	9:30–12:00	0.11
8	7.1	21.4	1.2	10:00–10:30	9:00–11:30	0.33
9	1.2	25.7	0.6	11:00–11:30	10:00–12:30	0.17
10	18.7	12.5	1.2	10:00–10:30	9:00–11:30	0.33
11	15.47	13.5	1.2	10:00–10:30	9:00–11:30	0.33
12	17.8	16	1	10:00–10:30	9:00–11:30	0.28
13	14.64	15.56	0.2	10:00–10:30	9:00–11:30	0.06
14	10.8	14.05	1	11:00–11:30	10:00–12:30	0.28
15	11.5	11.3	0.5	11:00–11:30	10:00–12:30	0.14
16	18.2	16	0.9	11:00–11:30	10:00–12:30	0.25
17	6.2	12.8	1.3	10:00–10:30	9:00–11:30	0.36
18	14.03	9.5	1.2	10:00–10:30	9:00–11:30	0.33
19	16	9.1	0.5	11:00–11:30	10:00–12:30	0.14
20	10.2	18.2	0.7	10:00–10:30	9:00–11:30	0.19
21	16.3	15.3	0.3	11:30–12:00	10:30–13:00	0.08
22	22.1	6.9	0.8	10:30–11:00	9:30–12:00	0.22
23	5.8	8.6	0.3	10:00–10:30	9:00–11:30	0.08
24	17.6	14.14	1.2	11:00–11:30	10:00–12:30	0.33
25	11	10.2	0.2	10:00–10:30	9:00–11:30	0.06
26	13.1	15.8	0.8	11:00–11:30	10:00–12:30	0.22
27	17.1	17	0.6	10:30–11:00	9:30–12:00	0.17
28	21.9	6.6	0.6	10:00–10:30	9:00–11:30	0.17

Table 11. Distribution center and customer service point of case study 2

Depots	X(km)	Y(km)	Customers
C1	12.2	23.6	5,6,8,9,13,14,20,26
C2	25	17.7	2,3,12,16,27
C3	2	2.1	17,23
C4	18	7.5	1,4,7,10,11,15,18,19,21,22,24,25,28

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Table 12. The optimal distribution paths when carbon tax is 0.25

Number	Route	Total Costs	Carbon emissions costs
1	C1-->13-->5-->C1	299.67	17.29
2	C1-->8-->20-->C1	268.16	15.51
3	C1-->26-->14-->C1	283.85	18.67
4	C1-->6-->9-->C1	310.78	21.73
5	C2-->2-->12-->27-->C2	281.99	18.58
6	C2-->3-->16-->C2	282.92	15.95
7	C3-->23-->17-->C3	291.36	19.93
8	C4-->25-->11-->1-->C4	295.24	22.70
9	C4-->28-->4-->15-->C4	320.97	22.42
10	C4-->18-->22-->C4	275.36	16.92
11	C4-->10-->21-->7-->C4	343.65	16.96
12	C4-->19-->24-->C4	261.52	13.65
Total		3515.47	220.31

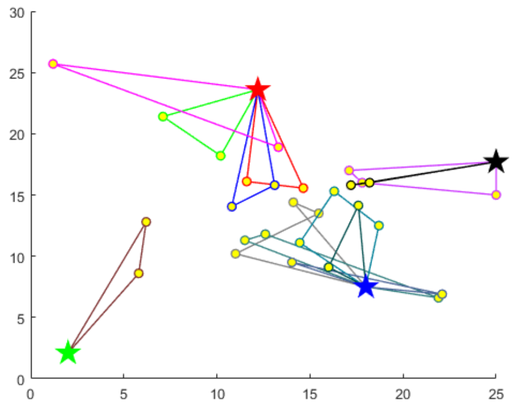

Figure 12. The optimal distribution paths when carbon tax is 0.25

Table 13. The results of a comparative test in which the carbon price changes

Carbon price (RMB/kg)	Carbon emissions (kg)	Total costs (RMB)	Carbon costs(RMB)	Carbon cost/Total costs(%)
0.25	220.31	3515.47	55.08	1.57
0.5	208.26	3555.25	104.13	2.93
0.75	207.73	3617.50	155.80	4.31
1	207.73	3668.46	207.73	5.66
2	207.73	3895.04	415.46	10.67
3	207.72	4084.89	623.16	15.26
4	208.00	4315.27	832.00	19.28
5	205.46	4490.54	1027.30	22.88
6	205.27	4695.63	1231.62	26.23
7	204.68	4900.73	1432.76	29.24
8	204.68	5105.42	1637.44	32.07
9	205.45	5336.06	1849.05	34.65
10	205.45	5517.84	2054.50	37.23
20	201.16	7556.12	4023.20	53.24
30	192.45	9582.77	5773.50	60.25
40	192.45	11507.32	7698.00	66.90
50	192.45	13431.88	9622.50	71.64

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Based on the data analysis, we get the curve of carbon emissions, carbon emission costs and total cost under different carbon tax. Table 13 shows the results of a comparative test in which the carbon price changes.

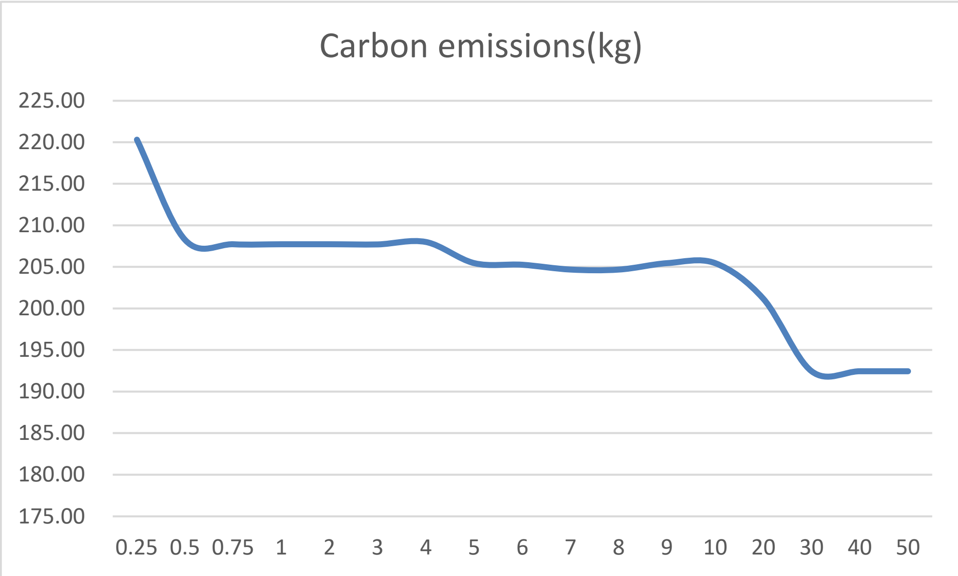

Figure 13. The change of carbon emissions under different carbon tax

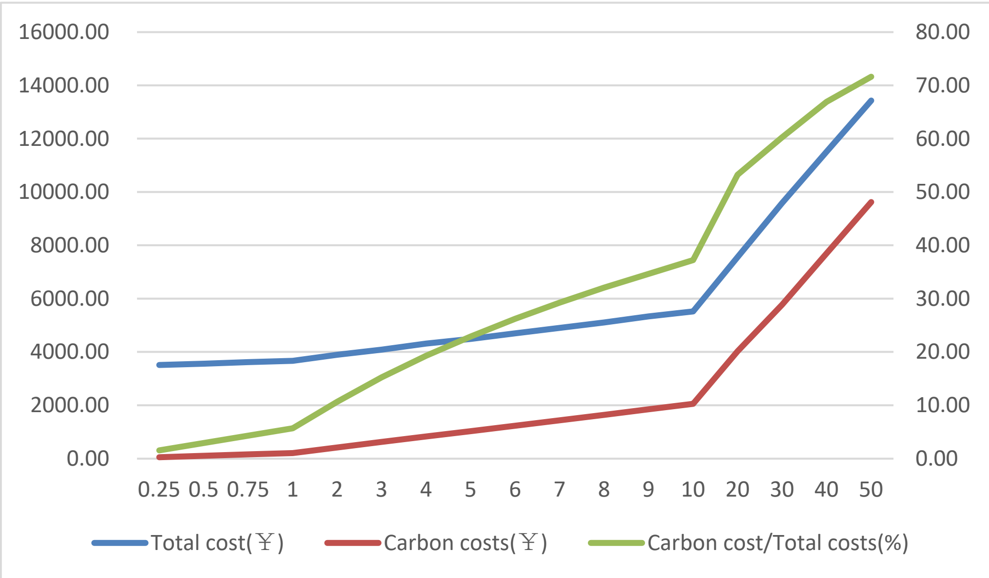

Figure 14. The change of carbon emission costs and total cost under different carbon tax

According to Table 13 ,Figure 13 and Figure 14, the carbon emissions were reduced faster in the interval of [0.25,0.75] with a total reduction of 12.58 kg, more slowly in the interval of [0.75,4], 2.54 kg in the interval of [4,5], and basically remained the same in the interval of [5,10]. When the carbon price jumps to the [30,50] range, the carbon emissions remain more or less the same. We can draw the following inference.

Inference I: The cost of carbon emissions and the total cost of distribution increase as the price of the carbon tax increases.

Inference II: When the carbon tax exceeds the critical point, the change of the carbon tax has no impact on the distribution route planning, nor does it have any impact on carbon emissions.

Inference III: As the carbon tax increases, carbon emissions gradually decrease.

In the case of this article, when C_c increases in [0.25,50], the carbon emission cost and total cost also change with the increase of C_c. Obviously, as shown in the Table 13 and Figure 14, Inference I is correct.

According to Figure 13, we can conclude that in this example, the critical point is 30. When $C_c \geq 30$, carbon emissions will not decrease with the increase of carbon tax. We set C_c for six groups of experiments to 35, 40, 45, ..., and 60. Each group of data is brought into the model and solved ten times, and then the optimal solution with the optimal fitness value and the optimal distribution path in each group can be selected. The distribution paths of the ten sets of data are the same, and the optimal distribution path is proved to be constant. The distribution paths are shown in the Table 14 and Figure 15. As the carbon tax price increases, the cost of carbon emissions becomes a progressively larger share of the total cost. When the carbon tax price is 30, the carbon emission cost accounts for 60.25% of the total cost, which is the largest proportion of all costs. Hence, when the carbon tax price is 30, the distribution path has the lowest carbon emission and can no longer be optimized. Inference II is correct.

Table 14. The optimal distribution paths when carbon tax is greater than 30

Number	Route
1	C1-->8-->9-->C1
2	C1-->20-->5-->C1
3	C1-->26-->13-->14-->C1
4	C1-->6-->C1
5	C2-->2-->12-->27-->C2
6	C2-->16-->3-->C2
7	C3-->23-->17-->C3
8	C4-->7-->4-->15-->25-->C4
9	C4-->11-->>1-->C4
10	C4-->28-->22-->C4
11	C4-->18-->19-->C4
12	C4-->24-->21-->C4
13	C4-->10-->C4

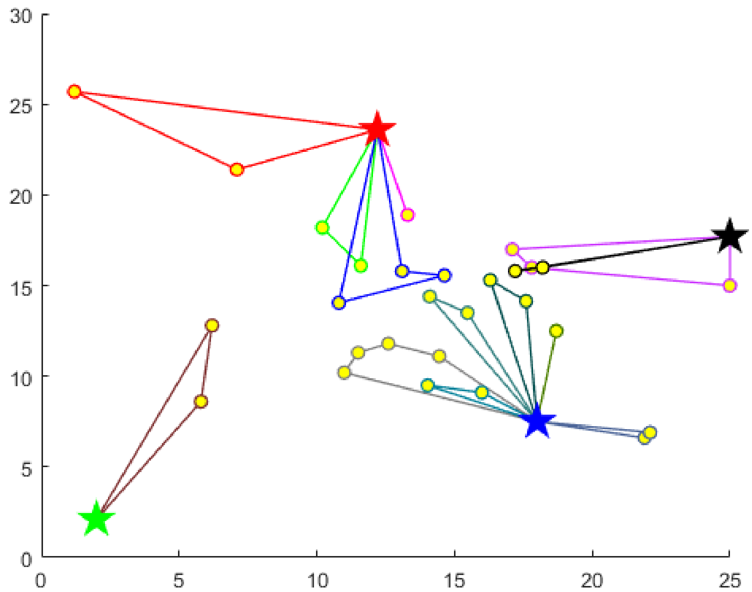

Figure 15. The optimal distribution paths when carbon tax is greater than 30

According to Figure 13 and Inference II, carbon emissions decrease when the carbon price is in the range of [0.25,30], and at the carbon tax price of 30, carbon emissions reach the minimum value and will not decrease further. We set C_c for six groups of experiments to 0.05, 0.1, 0.15, 0.2, 0.3 and 0.4. Each set of data is brought into the model and solved 10 times to select the optimal solution and the optimal allocation path with the optimal fitness value in each set. The carbon emissions and total costs under different carbon taxes are shown in Table 15. When the carbon price is in the range of [0.05,0.1] and [0.15,0.25], the carbon emissions increase, especially in the range of [0.15,0.25] with a faster growth. Carbon emissions continue to decrease when the carbon price is in the [0.1,0.15] and [0.25,0.4] intervals. Inference III is not correct. From this, we can conclude that when the carbon tax price is below 0.25, the carbon tax cost has less impact on the total cost of distribution and cannot reduce carbon emissions. When the carbon tax price is greater than 0.25, the carbon emissions gradually decrease as the carbon tax price increases. When the carbon tax price is 0.05, 0.1, 0.2 and 0.4, the distribution path is shown in Table 16-Table 19 and Figure 16-Figure 19.

Table 15. Results of comparative tests of carbon prices from 0.05 to 0.4

Carbon price (RMB/kg)	Carbon emissions (kg)	Total costs (RMB)	Carbon costs(RMB)	Carbon cost/Total costs(%)
0.05	213.33	3466.68	10.67	0.31
0.1	215.63	3472.64	21.56	0.62
0.15	213.33	3488.01	32.00	0.92
0.2	217.81	3491.20	43.56	1.25
0.25	220.31	3515.47	55.08	1.57
0.3	217.81	3516.98	65.34	1.85
0.4	208.26	3544.80	83.30	2.35

Table 16. The optimal distribution paths when carbon tax is 0.05

Number	Route
1	C1-->8-->20-->C1
2	C1-->13-->5-->C1
3	C1-->26-->14-->C1
4	C1-->6-->9-->C1
5	C2-->2-->12-->27-->C2
6	C2-->3-->16-->C2
7	C3-->23-->17-->C3
8	C4-->11>22-->C4
9	C4-->7-->4-->15-->C4
10	C4-->10-->28-->C4
11	C4-->18-->25-->1-->C4
12	C4-->19-->21-->24-->C4

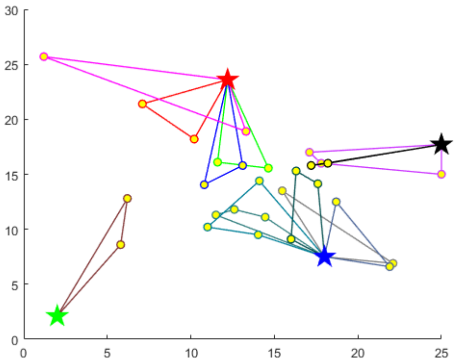

Figure 16. The optimal distribution paths when carbon tax is 0.05

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Table 17. The optimal distribution paths when carbon tax is 0.1

Number	Route
1	C1-->8-->20-->C1
2	C1-->13-->5-->C1
3	C1-->26-->14-->C1
4	C1-->6-->9-->C1
5	C2-->2-->12-->27-->C2
6	C2-->3-->16-->C2
7	C3-->23-->17-->C3
8	C4-->19-->24-->C4
9	C4-->10-->22-->C4
10	C4-->18-->25-->1-->C4
11	C4-->28-->4-->15-->C4
12	C4-->11-->21-->7-->C4

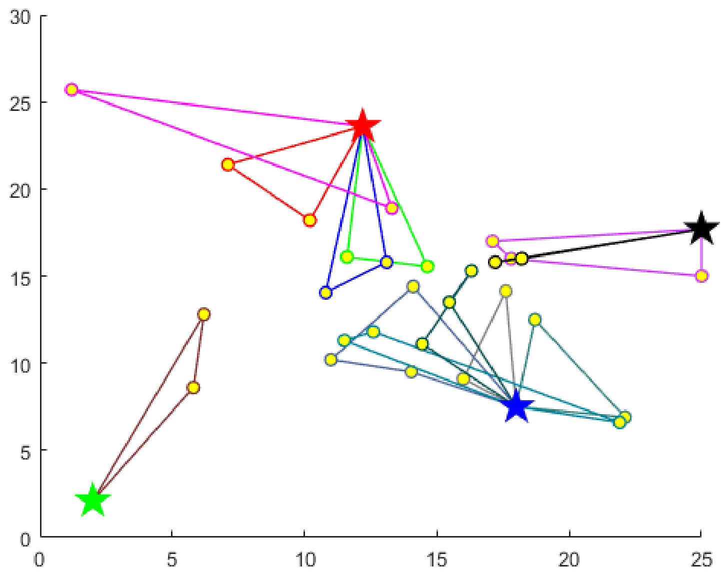

Figure 17. The optimal distribution paths when carbon tax is 0.1

Table 18. The optimal distribution paths when carbon tax is 0.2

Number	Route
1	C1-->26-->14-->C1
2	C1-->8-->20-->C1
3	C1-->13-->5-->C1
4	C1-->6-->9-->C1
5	C2-->2-->12-->27-->C2
6	C2-->3-->16-->C2
7	C3-->23-->17-->C3
8	C4-->28-->25-->18-->C4
9	C4-->11-->21-->7-->C4
10	C4-->1-->4-->15-->C4
11	C4-->19-->24-->C4
12	C4-->10-->22-->C4

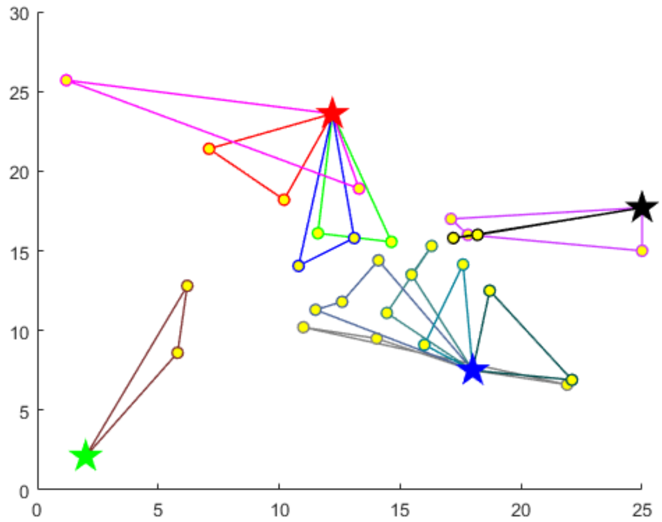

Figure 18. The optimal distribution paths when carbon tax is 0.2

Table 19. The optimal distribution paths when carbon tax is 0.4

Number	Route
1	C1-->20-->13-->C1
2	C1-->8-->9-->C1
3	C1-->26-->14-->C1
4	C1-->5-->6-->C1
5	C2-->2-->12-->27-->C2
6	C2-->3-->16-->C2
7	C3-->23-->17-->C3
8	C4-->10-->28-->C4
9	C4-->11-->21-->19-->C4
10	C4-->7-->4-->15-->C4
11	C4-->22-->24-->C4
12	C4-->18-->25-->1-->C4

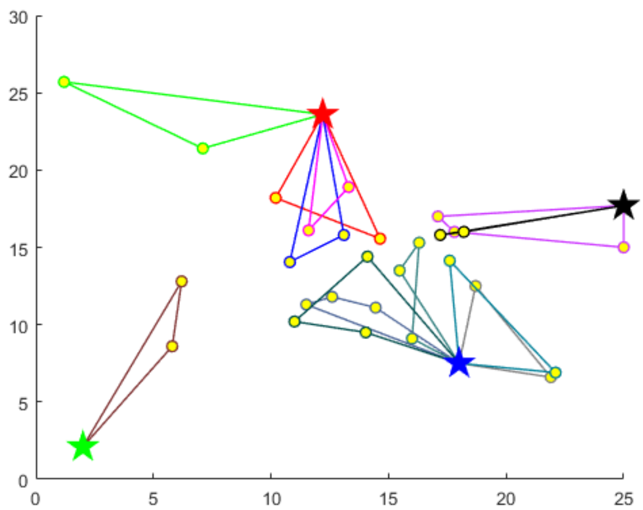

Figure 19. The optimal distribution paths when carbon tax is 0.4

The results show that when the carbon tax price is too low ($C_c < 0.25$), the proportion of carbon emission cost is too low, and carbon emission may increase as the carbon tax price increases. When the carbon tax price is too high ($C_c > 30$), carbon emissions are already the lowest and cannot be further optimized because the proportion of carbon emission cost is too high. When the carbon tax price gradually increases in the interval [0.25,30], the cold chain logistics enterprises can reduce the total cost of distribution by optimizing the path, and then reduce the cost pressure due to the rising carbon tax. Objectively, it is also able to reduce carbon emissions and has better environmental benefits.

6. Discussion and Managerial Implications

In this study, the redistribution of customers through a resource sharing strategy significantly optimized the cold chain logistics network and reduced logistics operation costs and carbon emissions. The impact of different carbon tax prices on distribution paths is also investigated. As a result, the following management insights were obtained from this study.

(1) For cold chain logistics companies, they must place greater emphasis on reducing total distribution costs and carbon emissions. By introducing resource sharing strategies and enhancing inter-firm cooperation to share customer information, facility capacity and transportation resources, resource utilization can be amplified to significantly reduce delivery distances, carbon emissions and total costs, and improve logistics operational efficiency.

(2) Cold chain logistics companies need to choose quality refrigeration equipment to reduce quality losses and ensure their carbon footprint is in line with government policies. On the one hand, the cost of quality loss represents a portion of the total cost of logistics, so maintaining constant temperature, quality and freshness has naturally become a top priority to reduce the cost of product damage. However, some refrigerated truck equipment is relatively outdated, which can lead to rapid deterioration of fresh produce during transportation. On the other hand, the refrigerated truck refrigeration process will produce a large amount of carbon dioxide, and with the introduction of the national carbon tax policy, cold chain logistics companies should seriously consider the carbon tax policy, improve environmental awareness, and implement new technologies to replace the current more backward refrigeration equipment and transportation equipment.

(3) For the government, first, it can guide the development of cold chain logistics through good program policies, such as the implementation of resource sharing policies to promote cold chain logistics enterprises to integrate resources and common distribution. Second, the government can invest in the development of cold chain logistics equipment, such as the development and production of new energy refrigerated vehicles instead of traditional diesel vehicles. Third, the government can set an appropriate carbon tax price to reduce carbon emissions, for example, in this case, the carbon tax price is set at 0.75, which can effectively reduce carbon emissions.

7. Conclusions and Future Work

At present, the environmental pollution problem is becoming more and more serious, and optimizing the cold chain logistics distribution path can realize both environmental and economic benefits. This study proposes the GCCLVRP-RS model to minimize the total cost and reduce carbon emissions. It has three contributions to theory and industry. First, this study contributes to the VRP model. In previous VRP models for cold chain logistics, the construction of total costs is not comprehensive. the GCCLVRP-RS model considers six different costs (fixed costs, transportation costs, damage costs, refrigeration costs, penalty costs, and carbon costs) to extend the VRP model to reflect the characteristics of the cold chain logistics industry. Secondly, the cold chain logistics and distribution enterprises are united through the resource sharing strategy, and the spatial-temporal distance is proposed to cluster the customers, enterprises work together to complete the distribution tasks. The research results prove that the resource sharing model can effectively reduce the total cost and carbon emission. GCCLVRP-RS not only fills the gap of insufficient research on resource sharing, but also fits into the sharing economy and provides reasonable suggestions for the government. Third, the carbon tax mechanism is introduced into the cold chain logistics industry. The trends of carbon emission and total cost of distribution under different carbon taxes are analyzed. The experimental results of this paper provide management suggestions for the government and logistics enterprises to effectively balance the economic and environmental costs in distribution.

The research in this paper has important practical significance for the shared distribution mode of cold chain logistics resources under the carbon tax mechanism. The research results have important reference value for the formulation of energy-saving and emission reduction policies in China's cold chain logistics and transportation industry. There are several limitations that guide the future research direction. This paper assumes that all customer point information is known, and does not consider changes in customer point information during transportation, such as new orders or canceled orders. In addition, this paper assumes that the speed of vehicle transportation is fixed and does not consider situations such as traffic congestion. Therefore, the dynamics in the distribution process is a further research direction.

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