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Research on a Joint Distribution Vehicle Routing Problem Considering Simultaneous Pick-Up and Delivery under the Background of Carbon Trading

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Abstract: In order to explore the positive impact of the joint distribution model on the reduction in logistics costs in small-scale logistics enterprises, considering the demand on enterprises for simultaneous pick-up and delivery, as well as the cost of carbon emissions, this study considers the vehicle routing problem of simultaneous pick-up and delivery under a joint distribution model. First of all, an independent distribution model and a joint distribution model including fixed transportation, variable transportation, time penalty, and carbon emissions costs are established; second, by adding the self-adaption cross-mutation probability and the destruction and repair mechanism in the large-scale neighborhood search algorithm, the genetic algorithm is improved to adapt to the solution of the model in this paper, and the effectiveness of the improved algorithm is verified and analyzed. It is found that the improved genetic algorithm is more advantageous than the original algorithm for solving the problems of both models designed in this paper. Finally, the improved genetic algorithm is used to solve the two models, and the results are compared and analyzed. It is found that the joint distribution model can reduce the total cost by 6.61% and the carbon emissions cost by 5.73%. Additionally, the impact of the carbon trading mechanism on the simultaneous pick-up and delivery vehicle routing problem under the joint distribution model is further explored. The results of this study prove that enterprises can effectively reduce costs, improve profits, reduce carbon emissions, and promote the sustainable development of logistics enterprises under the condition of joint distribution.

Keywords: carbon trading; simultaneous delivery; joint distribution; vehicle routing problem; improving genetic algorithm; sustainable development

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1. Introduction

In recent years, with the vigorous development of e-commerce and the rapid growth of the logistics industry, people have gradually shifted their choice of shopping from offline to online, and the "last kilometer" service, especially the surge in demand for pick-up and delivery services, has led to increasing pressure on logistics enterprises, the ability of which to resist competitive pressure is often weak. A joint distribution model breaks the limitations of traditional independent distribution, and is based on the overall logistics distribution system, rationally allocating logistics resources to achieve joint scheduling of vehicles. Under the joint distribution model, a logistics enterprise can effectively reduce their total transportation costs and improve the competitiveness of the enterprise by joining other logistics enterprises in the region. With the intensification of global warming, people are facing a very severe carbon emissions reduction situation, especially in the transportation industry, whose carbon emissions present a rapid growth trend. During 2020 alone, China's transportation sector carbon emissions reached 930 million tons, accounting for 15% of the country's end-point carbon emissions. With China's two goals of "peak carbon dioxide emissions" and "carbon neutrality", as well as the official opening of China's carbon trading market, China's logistics enterprises must respond to the low-carbon era. The dual requirements of environmental protection and economic development make rational arrangements and control of carbon emissions in the operation process necessary, in order to realize the green and sustainable development of the logistics industry.

In recent years, although scholars have made a lot of achievements in the field of joint distribution and the routing problem of pick-up and delivery vehicles, there are still some problems that need to be solved. In the current research, there are few studies on joint distribution based on the routing problem of simultaneous pick-up and delivery. And under this problem, there are few studies on the carbon trading mechanism. Therefore, this article is to combine these problems, study a joint distribution model under the carbon trading mechanism and pick-up and delivery vehicle routing problem, explore the advantages of the joint distribution model compared to the independent distribution model for logistics enterprises to reduce carbon emissions and logistics costs, and explore the impact of the carbon trading mechanism on the total distribution cost of enterprises under this problem.

The research on the joint distribution model in this paper can find the following research significance:

(1) This paper applies the principle of joint distribution to the field of route optimization of pick-up and delivery vehicles, and explores the advantages of a joint distribution model over an independent distribution model in reducing carbon emissions and transportation costs. To a certain extent, it expands and enriches the application of pick-up and delivery vehicles. Research on route optimization provides a certain theoretical reference for promoting the rational allocation of resources in the logistics industry.
(2) Based on the background that the carbon trading market is just starting in China, this paper strengthens the research of carbon trading in the field of route optimization of pick-up and delivery vehicles. The carbon trading mechanism is introduced, so that carbon emissions are converted into carbon emission costs and added to the model, which is conducive to promoting the green, coordinated, and sustainable development of the logistics industry.

After studying the problems raised in this article, the results show that logistics enterprises can better reduce the distribution cost of logistics enterprises and reduce the carbon emissions of logistics enterprises by adopting a joint distribution model. And by analyzing the impact of the carbon trading mechanism on the cost of logistics enterprises under this problem, it is found that logistics enterprises should always pay attention to the changes in carbon prices and carbon quotas in the carbon trading market, and formulate appropriate strategies to avoid the increase in costs caused by the rise in carbon prices.

2. Literature Review

For the vehicle routing problem of simultaneous pick-up and delivery, scholars have conducted in-depth research. In terms of research on the multi-stage simultaneous pick-up and delivery vehicle routing problem, Liu et al. [1] have studied a two-stage vehicle routing problem (2E-VRPSPD) for simultaneous pick-up and delivery. Under the 2E-VRPSPD problem, the cargo transported from the warehouse to the customer is transferred through a transfer station, which is divided into two stages for route optimization. The 2E-VRPSPD problem is an extension of the two-echelon vehicle routing problem (2E-VRP) and the simultaneous pick-up and delivery vehicle routing problem. Zhou et al. [2] have also studied a two-stage vehicle routing problem for simultaneous pick-up and delivery, and used the tabu search algorithm of the variable neighborhood to solve a large-scale example problem under the 2E-VRPSPD problem. In order to effectively coordinate forward and reverse logistics, Meng and Guo [3] have proposed a truck–drone joint pick-up and delivery mode when the energy consumption of drone batteries changes with the load and takes and delivers goods at the same time, and constructed a two-stage solution method to solve the model. Che et al. [4] have studied a random customer's simultaneous pick-up and delivery problem, divided the problem into two stages, and used the Integer L-shaped algorithm to solve it. In view of research on the route problem of pick-up and delivery vehicles with time windows at the same time, Sun et al. [5] have studied the route problem of pick-up and delivery vehicles considering the order pick-up time and a flexible time window in intra-city distribution, considering the order start and end points in the intra-city distribution, the order pick-up time, flexible time window of order distribution, vehicle capacity constraints, and other factors, and constructed a mixed integer linear model with the goal of minimizing the sum of the distribution cost and the overtime penalty cost. Li et al. [6] have constructed the corresponding mixed integer non-linear programming (MINLP) model for the vehicle routing problem under a soft time window and the dual demand of customers for simultaneous pick-up and delivery. Gui [7] have studied a vehicle routing problem considering a time window and simultaneous pick-up and delivery under the background of the vigorous development of e-commerce, and designed a hybrid heuristic algorithm (h-LAHC) to solve the VRPSPDTW problem. In order to solve the routing problem of pick-up and delivery vehicles with time windows, Wu [8] have proposed an improved ant colony optimization algorithm with damage and repair strategies on the basis of the ant colony algorithm, in order to solve the problem and obtain better results. Takada et al. [9] have studied a selective pick-up and delivery problem with time window constraints. A local search method was designed for this problem, and a dynamic programming method was proposed to enable the model to obtain upper and lower bounds in linear time. The optimal solution was obtained in pseudo-polynomial time. For the study of the dynamic simultaneous pick-up and delivery vehicle routing problem, Cai et al. [10] have discussed a new dynamic pick-up and delivery problem, and established a dynamic pick-up and delivery model with constraints such as terminal quantity constraints, time window constraints, capacity constraints, and LIFO loading. For the route optimization problem of simultaneous pick-up and delivery vehicles, Praxedes et al. [11] have used a branch pricing algorithm to solve the problem by considering factors including heterogeneous fleets, time windows, route duration, multiple warehouses, and location decisions.

As for the joint distribution vehicle routing problem, Wang et al. [12] have proposed studying the multi-center joint distribution opening and closing hybrid vehicle routing optimization problem in view of the shortcomings of existing research on the combination of resource integration and sharing and the design of a cooperative revenue distribution mechanism. Zhang et al. [13] have studied a joint distribution problem between multi-product and multi-logistics enterprises, and used an improved branch-cutting algorithm to solve it. Finally, it was concluded that joint distribution between multi-logistics enterprises can more effectively reduce costs. Hou et al. [14] have studied the multi-yard joint distribution vehicle routing problem under a time-varying network considering energy consumption, established a multi-yard joint distribution vehicle routing optimization model, and verified the effectiveness of the designed algorithm through multiple sets of numerical examples at different scales. Zheng et al. [15] have discussed the cooperative vehicle routing problem in the urban logistics network during the COVID-19 pandemic, considering the order exchange distribution mode in the outer ring of the city, and established a multi-commodity mixed integer planning problem, which verified that this model can effectively improve transportation under traffic restrictions. Regarding in-city distribution efficiency, Fu et al. [16] have studied the vehicle path problem related to multi-logistics center joint distribution, considering a shared logistics mode of sharing customer demand, distribution vehicles, and logistics centers, and combined factors such as vehicle capacity, fuel consumption, carbon emissions, longest running time, customer demand, and service time, in order to construct a vehicle path planning model of multi-logistics center joint distribution with the goal of minimum total cost. In view of the joint distribution problem under the pick-up and delivery problem, Ren et al. [17], aiming at the problems of high no-load rate and high expenditure cost in urban logistics distribution, constructed a mathematical model for joint distribution path optimization with the goal of minimizing the total expenditure of individual customers, e-commerce enterprise customers, and transportation departments on the basis of analyzing the delivery of e-commerce orders and pick-up and delivery of intra-city orders by the transportation department. Wang et al. [18] have studied a multi-center joint distribution vehicle routing problem with time windows and mixed distribution and pick-up, constructed a mixed integer programming model, and solved it using the genetic particle swarm hybrid algorithm, proving that this method can effectively allocate and utilize transportation resources. Sheng et al. [19] have studied a rural e-commerce logistics distribution problem, and constructed a mathematical model of the integrated vehicle routing problem based on the joint distribution strategy with the goal of minimizing the total distribution cost. Padmanabhan et al. [20] have studied a carrier cooperation mode in the pick-up and delivery state, adopting centralized collaborative planning to allocate transportation operations to carriers and reduce the total transportation cost.

With the increasing demand for green development of the economy, scholars have begun to incorporate carbon emissions into the path solution, especially for the study of carbon emissions considering the carbon trading mechanism. Among many studies focused on carbon emissions, Kuo et al. [21] have studied a drone vehicle routing problem and introduced the calculation for carbon emissions while taking into account the environmental benefits. Zhou et al. [22] have studied a dual-objective green vehicle routing problem that considers time dependence and simultaneous pick-up and delivery, considering the influence of time-varying speed, real-time load, and other factors on fuel consumption and carbon emissions. Duan [23] has introduced a carbon trading mechanism into the traditional cold chain distribution location–route problem, considering that an enterprise should also take into account social benefits while obtaining economic benefits, and established a joint optimization model for the location problem and distribution route of cold chain logistics. Kabadurmi et al. [24] have proposed a green vehicle routing problem that minimizes the total amount of carbon emissions and maximizes the service level. Their results indicated that, with an improvement in the service level, the number of vehicles and carbon emissions also increase. With an increase in carbon emissions and the reduction in violation time windows, more vehicles and alternative fuel stations are used. Wen et al. [25] have studied a multi-warehouse vehicle routing problem, established a model with the goals of including carbon emissions, fuel consumption, and vehicle rental and driver costs, and proposed an improved self-adaption large neighborhood search algorithm to efficiently solve the multi-depot green vehicle routing problem with time windows. Guo et al. [26], considering the timeliness impact caused by traffic congestion, have established a time window model for the timely green vehicle routing problem of cold chain logistics, and proposed a two-order hybrid search algorithm. The effectiveness and superiority of the model and hybrid search algorithm were verified through examples. Yin et al. [27] have focused on reducing energy consumption and the carbon emissions generated in the process of urban logistics transportation and distribution. On the premise of meeting customer cargo needs and time requirements, the distribution vehicle routing problem was optimized, and the NSGA-II algorithm based on the multi-factor evolutionary algorithm was adopted. The results obtained by the algorithm demonstrated that the designed multi-objective path optimization model has great value for reducing carbon emissions on the premise of meeting customer cargo needs and time requirements.

According to the above studies, it can be seen that adopting the model of simultaneous pick-up and delivery can address the problem of no-load return in the vehicle routing problem and improve the operating efficiency of enterprises. Furthermore, joint distribution has a good effect on integrating logistics resources, improving the efficiency of urban logistics distribution, and reducing environmental pollution, and it is of practical significance to include carbon trading in the transportation costs of logistics enterprises for research. Although the above-mentioned problems have been studied in all directions, there are few studies which have combined them. Therefore, this study considers the joint distribution model of simultaneous pick-up and delivery under the background of carbon trading to provide a reference for enterprises to make decisions under the opening of the carbon trading market, thus enriching the application research of carbon trading in the logistics field.

3. Model Building

3.1. Model Description

The goal of this research is to explore the advantages of the simultaneous pick-up and delivery vehicle routing problem with a joint distribution model, compared with the simultaneous pick-up and delivery vehicle routing problem with an independent distribution model in reducing logistics costs and carbon emissions. Therefore, this paper constructs the model of simultaneous pick-up and delivery of independent distribution and the model of simultaneous pick-up and delivery of joint distribution at this stage. The two models are described in detail as follows:

(1) For the simultaneous pick-up and delivery model of independent distribution, with the minimum total cost including carbon emission cost as the optimization goal, each logistics company in the region has a distribution center, which is responsible for customers in the company's area, and each distribution center sends transportation vehicles from the distribution center to serve their own customers. Each transportation vehicle has a load limit, and if the vehicle is fully loaded, the distribution center needs to send more transportation vehicles to meet the needs of other customers. When serving customers, it is necessary to complete the customer's pick-up and delivery needs at the same time, and each customer has its own time window, and the transportation vehicle should arrive within the customer's time window as far as possible, otherwise it will be punished accordingly. After serving all customers, it returns to the distribution center. For example, there are three enterprises in this area: A, B, and C, each of which completes its own pick-up and delivery tasks. The representation is shown in Figure 1.

(2) For the simultaneous pick-up and delivery model of joint distribution, the same optimization goal is to minimize the total cost including carbon transaction costs. Under the joint distribution model, various logistics companies in the region cooperate to share distribution centers, transportation vehicles, and customer information. Transportation vehicles can start from any distribution center of each company and serve customers of any company in the region. They return to any distribution center after serving all customers. The load limits for transport vehicles and the customer's time window requirements are consistent with the independent distribution model. The representation is shown in Figure 2.

This study considers many factors, including time window constraints, load constraints, the pick-up and delivery mechanism, and the carbon trading mechanism, which makes the vehicle routing problem more complicated. In order to facilitate research, it is necessary to abstract the actual problem into a mathematical model. The basic assumptions of the two models to be constructed in this article are as follows:

(1) This paper assumes that the goods distributed by various enterprises in the region are the same commodity and same price.

(2) The distribution centers and the locations of customers for each enterprise are determined, and the customer needs and requirements are known. The quantity of the goods of each enterprise is sufficient to meet the needs of all customers in the region.

(3) During the pick-up and delivery process, the transportation vehicle models of each enterprise are the same and it is believed that the maximum transportation distance of the vehicle is sufficient to serve all customers. The vehicle has a maximum load limit and cannot be overweight during transportation.

(4) Transportation vehicles operate in accordance with the principle of "unloading before loading" in the process of serving customers, ensuring that the load after unloading and loading will not exceed the maximum load capacity, and each customer can only meet the demand for pick-up and delivery by one transportation vehicle.

(5) Transportation vehicles ignore traffic problems in the process of pick-up and delivering goods, and keep a constant speed throughout the whole process, as well as the speed during the handling of customer unloading and loading.

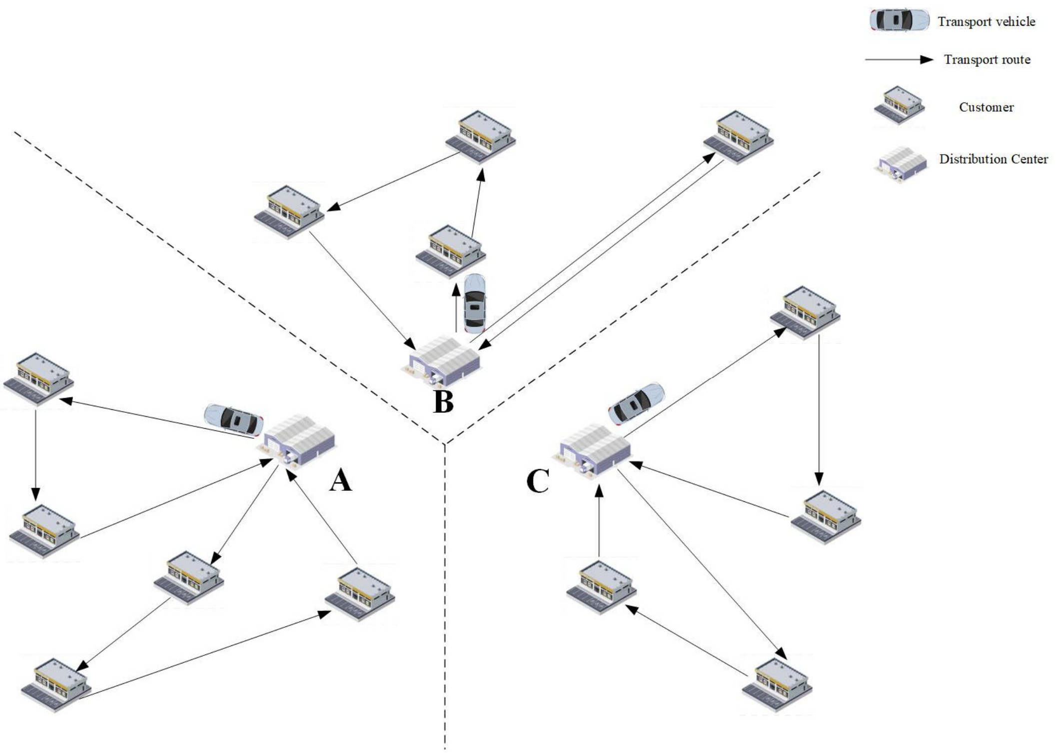


Figure 1. Independent distribution model. A, B, and C represent three logistics companies that carry out logistics and transportation activities in this area.

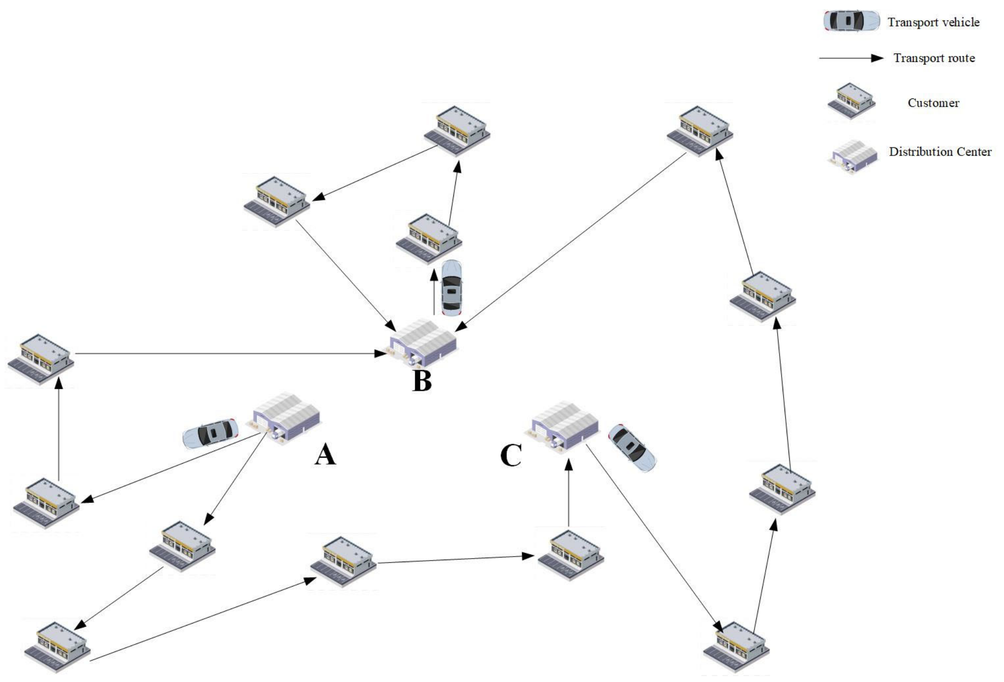


Figure 2. Joint distribution model. A, B, and C represent three logistics companies that carry out logistics and transportation activities in this area.

According to the above description of the two models that need to be constructed, the two models constructed in this paper both aim at the lowest total cost including fixed transportation cost, variable transportation cost, time penalty cost, and carbon emission cost. And the objective functions of the two models are consistent. Therefore, this paper first analyzes the cost composition of the two models in Section 3.2. Then, a simultaneous pick-up and delivery model for independent distribution is constructed in Section 3.3. Finally, on the basis of Section 3.3, a simultaneous pick-up and delivery model for joint distribution is constructed in Section 3.4. A description of symbols and parameters used in this paper is shown in Table 1. Among them, x_{ijvm} represents the decision variable.

Table 1. Parameter description table.

Symbol	Explanation
m	Represents a collection of distribution centers $(1,\ 2,\ 3,\ldots,m)$
n	Represents a collection of customers $(m+1, m+2,\ldots,m+n)$
V	Represents a collection of vehicles $(1,\ 2,\ 3,\ldots,v)$
i,j	Represents each node in the pick-up and delivery process, including the distribution center and the customer $i,j \in \{1,\ 2,\ 3\ldots,m+n\}$
c_1	Represents unit fixed transportation cost
c_2	Represents variable transportation cost per unit distance
c_3	Represents unit time waiting cost
c_4	Represents late cost per unit time
c_5	Indicates the carbon trading price
C_1	Represents fixed transportation costs
C_2	Represents variable costs
C_3	Indicates time penalty cost
C_4	Represents carbon transaction costs
d_{ij}	Represents the distance from node i to node j
$[T_1, T_2]$	Time window representing customer needs
t_{jv}	Represents the time point when the vehicle v arrives at j
f	Represents the fuel consumption per unit distance of the vehicle
F	Represents fuel consumption during driving
CO	Indicates carbon dioxide emissions
G_v	Represents the weight of the vehicle
G_{ij}	Represents the load of vehicles i to j
T_{cq}	Indicates carbon quota
q_j	Express j customer point delivery quality
p_j	Represents j customer point pick-up goods quality
v_1	Indicates that the vehicle is traveling at a constant speed
v_2	Indicates unloading and loading speed
x_{ijvm}	Indicates whether the transportation vehicle v is used for transportation between the vehicle transportation nodes i and j starting from the distribution center m; if so, then x_{ijvm} = 1, otherwise x_{ijvm} = 0

3.2. Cost Composition Analysis

Considering the logistics and distribution situation in the city and the environmental factors of carbon trading, the optimization goal is to minimize the total cost of the enterprise in the logistics and transportation process. The objective function of the lowest total cost constructed in this article mainly includes fixed transportation costs, variable transportation costs, time penalty costs, and carbon emission costs. The following is an analysis of these costs:

① Fixed transportation costs:

The fixed transportation cost of a vehicle is usually not related to the number of customers served and the distance traveled by the transportation vehicle. It refers to the loss caused by the fixed vehicle during the driving process and the driver's salary. Each vehicle issued will have such a cost. Therefore, it has a linear relationship with the number of transportation vehicles used. If a transportation vehicle V is used, there will be a cost of c_1, and the fixed transportation cost C_1 is expressed as

$$C_1 = c_1 V. \tag{1}$$

② Variable transportation costs:

The variable transportation costs of vehicles mainly include the daily maintenance and maintenance costs of transportation vehicles. With the increase in driving distance, vehicle parts, engine oil, etc., will wear out. In addition, more vehicles need to be cleaned in daily life. Therefore, the driving distance plays an important role in determining the variable transportation costs. There is a positive correlation between them. For every d distance traveled by a vehicle V, there will be a cost of c_2, and the variable transportation cost C_2 can be expressed as follows:

$$C_2 = c_2 \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} d_{ij}. \tag{2}$$

③ Time penalty cost:

In logistics transportation, the situation when the customer receives the product is crucial. It directly affects the customer's income, inventory control, and quality management, thus affecting the customer's satisfaction with the logistics enterprise. If the vehicle comes too early, it must wait until the customer starts to receive the product. During the waiting period, waiting costs such as parking fees may be incurred. If the vehicle arrives too late, the customer may encounter replenishment and sales problems; that is, the vehicle arrives outside of the customer's time window, which will incur a penalty fee. According to the literature [28,29], if $[T_1, T_2]$ is used to represent the time window required by the customer, then the time penalty cost C_3 can be expressed as

$$\begin{aligned} C_3 &= \begin{cases} c_3 \sum\limits_{j=m+1}^{m+n} \sum\limits_{v=1}^{V} \max(T_1 - t_{jv}, 0), t_{jv} < T_1 \\ 0, T_1 \le t_{jv} \le T_2 \\ c_4 \sum\limits_{j=m+1}^{m+n} \sum\limits_{v=1}^{V} \max(t_{jv} - T_2, 0), t_{jv} > T_2 \end{cases} . \\ &= \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} [c_3 \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} \max(T_1 - t_{jv}, 0) + c_4 \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} \max(t_{jv} - T_2, 0)] \end{aligned} \tag{3}$$

④ Carbon emissions costs:

Carbon emissions mainly derive from the combustion of fossil fuels; specifically, in the process of logistics and transportation, they come from the consumption of fuel in the process of vehicle driving. In order to solve the carbon emissions in the process of vehicle transportation, the fuel consumption in the process of vehicle transportation must be solved first, then converted according to the carbon dioxide emissions coefficient to obtain carbon emissions. According to the literature [30], the carbon emission cost is calculated as follows:

The fuel consumption in vehicle transportation is mainly related to the distance traveled by the vehicle and the weight and load of the vehicle. If f_0 represents the unit distance fuel consumption of the vehicle in the no-load state, $f_{\max}$ represents the unit distance fuel consumption of the vehicle in the full-load state, G_v represents the weight of the transportation vehicle, and G represents the quality of the transportation goods, then the fuel consumption per unit distance can be specifically expressed as Formula (4):

$$f(G) = f_0 + \frac{f_{\max} - f_0}{G_v} G. \tag{4}$$

When the traveling distance of the transport vehicle is d, the fuel consumption of the transport vehicle traveling from i to j is expressed as Formula (5):

$$F = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} f(G) d_{ij} = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} (f_0 + \frac{f_{\max} - f_0}{G_v} G_{ij}) d_{ij}. \quad (5)$$

As the main vehicle fuel combustion emission is carbon dioxide, the conversion from fuel consumption to carbon emission requires the use of carbon dioxide emissions factor β. Therefore, the carbon emissions generated during vehicle transportation can be expressed as Formula (6):

$$CO = \beta \times F. \quad (6)$$

According to the carbon emissions trading mechanism of the carbon trading market, every logistics company has a prescribed carbon quota T_{cq}. If the carbon emissions emitted by the logistics company exceed the carbon quota, the company must pay additional funds to purchase more carbon credits; if the emissions of the logistics company are lower than the carbon quota, they can sell the remaining carbon quota to make profits. The carbon emissions cost of the carbon trading mechanism can be expressed as Formula (7) [31]:

$$\begin{aligned} C_4 &= c_5(\beta \times F - T_{cq}) \\ &= c_5[\beta \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} (f_0 + \tfrac{f_{\max} - f_0}{G_v} G_{ij}) d_{ij} - T_{cq}] \end{aligned} . \quad (7)$$

3.3. Simultaneous Pick-Up and Delivery Vehicle Routing Problem with Independent Distribution Model

After analyzing the composition of the cost, this section will construct a simultaneous pick-up and delivery vehicle routing problem with an independent distribution model. In addition to the model description and basic assumptions in Section 3.1, according to the characteristics of the independent distribution problem, the following assumptions need to be added to the basic assumptions:

(1) In the case of independent distribution, each enterprise has a distribution center in the region, and is responsible for its own customers without interfering with each other;
(2) Under independent distribution, the pick-up and delivery process starts from the respective distribution centers, and the respective transportation vehicles complete the distribution of their customers and return to the respective distribution centers.

Therefore, the model of the simultaneous pick-up and delivery vehicle routing problem with the independent distribution model can be expressed as

$$\begin{aligned} &MinC = C_1 + C_2 + C_3 + C_4 \\ &= c_1 V \\ &+ c_2 \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} d_{ij} \\ &+ \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} [c_3 \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} \max(T_1 - t_{jv}, 0) + c_4 \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} \max(t_{jv} - T_2, 0)] \\ &+ c_5[\beta \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} (f_0 + \tfrac{f_{\max} - f_0}{G_v} G_{ij}) d_{ij} - T_{cq}] \end{aligned} \quad (8)$$

In the model, Formula (8) is the objective function, and the goal is the lowest total cost in the logistics transportation process, including fixed transportation costs C_1, variable transportation costs C_2, time penalty costs C_3, and carbon emissions costs C_4 in the transportation process.

The constraints are as follows:

$$\sum_{i=1}^{m+n}\sum_{m=1}^{m}\sum_{v=1}^{V} x_{ijvm} = 1 \forall\, j \in \{m+1, m+2, \ldots, m+n\} \tag{9}$$

Formula (9) represents that each customer i can only be a transport vehicle V service from the distribution center m.

$$\sum_{j=m+1}^{m+n} x_{ijvm} = 1 \forall v \in \{1,2,3,\ldots,V\}, m \in \{1,2,3,\ldots,m\}, i = m \tag{10}$$

$$\begin{gathered}\sum_{i=m+1}^{m+n} x_{i\mu vm} - \sum_{j=m+1}^{m+n} x_{\mu jvm} = 0 \\ \forall \mu \in \{m+1, m+2, \ldots, m+n\}, v \in \{1,2,3,\ldots,V\}, m \in \{1,2,3,\ldots,m\}\end{gathered} \tag{11}$$

$$\sum_{i=m+1}^{m+n} x_{ijvm} = 1 \forall v \in \{1,2,3,\ldots,V\}, m \in \{1,2,3,\ldots,m\}, j = m \tag{12}$$

Formulas (10)–(12) represents the transport vehicle V from the distribution center m, continuous service several customers, vehicles do not stop service during the intermediate process, and then returns to the distribution center m.

$$\begin{gathered}G_{ij} - q_j + p_j \le G_{\max} \\ \forall i \in \{1,2,3,\ldots,m+n\}, j \in \{m+1, m+2, \ldots, m+n\}\end{gathered} \tag{13}$$

Formula (13) indicates that after the transport vehicle completes the delivery q_j and pick-up p_j operations at the customer point j, the cargo quality G_{ij} cannot exceed its maximum load G_{max}.

$$\begin{gathered}\sum_{i=1}^{m+n} G_{i\mu} - q_\mu + p_\mu = \sum_{j=m+1}^{m+n} G_{\mu j} \\ \forall \mu \in \{m+1, m+2, \ldots, m+n\}, i \ne \mu \ne j\end{gathered} \tag{14}$$

Formula (14) is the recursive formula for the load between the transport paths, indicating that the load $G_{i\mu}$ on the $i\mu$ path is equal to the load $G_{\mu j}$ on the μj path after the delivery q_μ and pick-up p_μ operations at the μ point.

$$t_{jv} = t_{iv} + \frac{d_{ij}}{v_1} + \frac{q_i + p_i}{v_2}. \tag{15}$$

Formula (15) indicates that the time during transportation is continuous, and the time to reach the customer point j is equal to the time to reach the customer point i plus the travel time on the ij path and the time to deliver and pick up goods at the i point.

3.4. Simultaneous Pick-Up and Delivery Vehicle Routing Problem with Joint Distribution Model

The simultaneous pick-up and delivery vehicle routing problem with the joint distribution model to be constructed in this section is established on the basis of the model constructed in Section 3.3. Unlike the independent distribution model, the joint distribution model realizes the sharing of distribution centers, customer information, and vehicles between enterprises. In addition to the model description and basic assumptions in Section 3.1, according to the characteristics of the joint distribution problem, the following assumptions need to be made:

(1) In the case of joint distribution, each enterprise realizes the sharing of distribution centers, customer information, and vehicles. Each enterprise can start transportation tasks from each distribution center, and at the same time be jointly responsible for all customers in the region and cooperate with each other.

(2) Under the joint distribution, the pick-up and delivery process starts from any distribution center, and the transportation vehicle completes the distribution tasks of all customers in the area and returns to any distribution center.

Therefore, the simultaneous pick-up and delivery vehicle routing problem of the joint distribution model can be expressed as

$$\begin{aligned} &MinC = C_1 + C_2 + C_3 + C_4 \\ &= c_1 V \\ &+ c_2 \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} d_{ij} \\ &+ \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} [c_3 \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} \max(T_1 - t_{jv}, 0) + c_4 \sum_{j=m+1}^{m+n} \sum_{v=1}^{V} \max(t_{jv} - T_2, 0)] \\ &+ c_5 [\beta \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{v=1}^{V} x_{ijv} (f_0 + \tfrac{f_{\max} - f_0}{G_v} G_{ij}) d_{ij} - T_{cq}] \end{aligned}, \tag{16}$$

In the model, Formula (16) is the objective function. Like Formula (8), the goal is the lowest total cost in the logistics transportation process, including fixed transportation costs C_1, variable transportation costs C_2, time penalty costs C_3, and carbon emissions costs C_4 in the transportation process.

With the constraints of

$$\sum_{i=1}^{m} \sum_{j=1}^{m} x_{ijvm} = 0 \forall v \in \{1, 2, 3, \ldots, V\}, m \in \{1, 2, 3, \ldots, m\} \tag{17}$$

Formula (17) means that the transportation vehicle V cannot go directly from one distribution center m to another m.

$$\sum_{i=1}^{m+n} \sum_{m=1}^{m} \sum_{v=1}^{V} x_{ijvm} = 1 \forall j \in \{m+1, m+2, \ldots, m+n\} \tag{18}$$

Formula (18) represents that each customer i can only be a transport vehicle V service from the distribution center m.

$$\sum_{i=1}^{m} \sum_{j=m+1}^{m+n} x_{ijvm} = 1 \forall v \in \{1, 2, 3, \ldots, V\}, m \in \{1, 2, 3, \ldots, m\} \tag{19}$$

$$\begin{aligned} &\sum_{i=m+1}^{m+n} x_{i\mu vm} - \sum_{j=m+1}^{m+n} x_{\mu jvm} = 0 \\ &\forall \mu \in \{m+1, m+2, \ldots, m+n\}, v \in \{1, 2, 3, \ldots, V\}, m \in \{1, 2, 3, \ldots, m\} \end{aligned} \tag{20}$$

$$\sum_{i=m+1}^{m+n} \sum_{j=1}^{m} x_{ijvm} = 1 \forall v \in \{1, 2, 3, \ldots, V\}, m \in \{1, 2, 3, \ldots, m\} \tag{21}$$

Formulas (19)–(21) indicate that the transport vehicle V starts from any distribution center m and continuously serves multiple customers of any enterprise. During the intermediate process, the vehicle V does not stop service and then returns to any distribution center m.

$$\begin{aligned} &G_{ij} - q_j + p_j \leq G_{\max} \\ &\forall i \in \{1, 2, 3, \ldots, m+n\}, j \in \{m+1, m+2, \ldots, m+n\} \end{aligned} \tag{22}$$

Formula (22) indicates that after the transport vehicle completes the delivery q_j and pick-up p_j operations at the customer point j, the cargo quality G_{ij} cannot exceed its maximum load G_{max}.

$$\begin{aligned}&\sum_{i=1}^{m+n} G_{i\mu} - q_\mu + p_\mu = \sum_{j=m+1}^{m+n} G_{\mu j}\\ &\forall \mu \in \{m+1, m+2, \ldots, m+n\}, i \neq \mu \neq j\end{aligned} \tag{23}$$

Formula (23) is the recursive formula for the load between the transport paths, indicating that the load $G_{i\mu}$ on the $i\mu$ path is equal to the load $G_{\mu j}$ on the μj path after the delivery q_μ and pick-up p_μ operations at the μ point.

$$t_{jv} = t_{iv} + \frac{d_{ij}}{v_1} + \frac{q_i + p_i}{v_2}. \tag{24}$$

Formula (24) indicates that the time during transportation is continuous, and the time to reach the customer point j is equal to the time to reach the customer point i plus the travel time on the ij path and the time to deliver and pick up goods at the i point.

4. Algorithm Design

4.1. Improvement and Design of Genetic Algorithm

In this section, in order to solve the two models constructed above, appropriate algorithms need to be used to implement them. However, due to the conditions of time window constraints, capacity constraints, and simultaneous pick-up and delivery constraints, the two models are more complex and belong to the NP-hard problem. Heuristic algorithms are suitable for solving this. In heuristic algorithms, the genetic algorithm is one of the most widely used algorithms in the field of vehicle routing problems, so this paper will use the genetic algorithm for solving it. The genetic algorithm has the advantages of a wide coverage of search and easier implementation of overall optimization, which can effectively reduce the risk of falling into the search for local optimum solutions [32,33]. Although the basic genetic algorithm can solve the model constructed in this paper, due to the weak local search ability of the basic genetic algorithm, it is easy to fall into the local optimum, and with the increase in data volume and solving difficulty, the solving efficiency of the genetic algorithm in the later stage of evolution is low. These shortcomings of the basic genetic algorithm can no longer meet the needs of solving the two complex models constructed in this paper. Therefore, this paper first constructs the basic genetic algorithm, and then adds the self-adaption cross-mutation probability and the damage and repair mechanism of the neighborhood search algorithm on this basis to improve the genetic algorithm.

First, the basic genetic algorithm steps are as follows:

Step 1: Initialization. Set the evolution iteration counter $g = 0$, set the maximum evolution algebra G, and randomly generate N_P individuals as the initial population $P(0)$.

Step 2: Individual evaluation. Calculate the fitness of each individual in the population $P(t)$.

Step 3: Selection operation. The selection operator is applied to the population and, according to the individual's fitness, with respect to certain rules or methods, some excellent individuals are selected and passed on to the next generation.

Step 4: Crossover operation. The cross-operator is applied to a group of selected pairs of individuals to exchange some chromosomes between them, with a certain probability to produce new chromosomes.

Step 5: Mutation operation. The mutation operator is applied to the population to change the value of one or some genes to other alleles with a certain probability for the selected individual.

Step 6: Cyclic operation. The population $P(t)$ yields the next-generation population $P(t+1)$ after selection, crossover, and mutation operations. The fitness value of this generation is calculated, and it is sorted according to the fitness value to prepare for the next genetic operation.

Step 7: Termination condition judgment: If $g \leq G$, then $g = g + 1$, go to step (2); if $g > G$, the individual with the maximum fitness obtained in this evolution process is output as the optimal solution and the calculation is terminated.

The genetic algorithm constructed in this paper is improved on this basis, where the improvements are as follows:

(1) Self-adaption crossover mutation probability

The original genetic algorithm specifies the probability of cross mutation in the process of the cross-mutation operation, which means that no matter whether the chromosomes are excellent or poor, there will be the same probability of cross mutation to generate new chromosomes, which may lead chromosomes with high fitness to be replaced by the chromosomes with low fitness, increasing the difficulty of obtaining an optimal solution. In order to protect the chromosomes with high fitness in the process of cross-mutation, the self-adaption cross-mutation probability mechanism is introduced; that is, the cross-mutation probability changes with the chromosome fitness value, where the probability of cross mutation of chromosomes with high fitness becomes lower, while the probability of cross mutation of chromosomes with low fitness is higher [34]. Using the self-adaption cross-mutation probability, it can take a larger mutation and cross probability to search in the early stage of evolution to maintain the diversity of the population, and search with a smaller probability in the late stage of evolution to refine the search direction and prevent the destruction of the population. The optimal solution is to speed up the convergence. Therefore, from an individual perspective, this is conducive to the survival of chromosomes with high fitness, reducing the possibility of high-fitness chromosomes being replaced by low-fitness chromosomes, retaining more excellent individuals, and helping to improve the solution efficiency of the algorithm and the ability to jump out of local optimum. From a group perspective, the probability of self-adaption cross mutation can ensure better convergence of the algorithm while maintaining the diversity of the group. The self-adaption probability cross- and self-adaption mutation probability formulas are shown in Formulas (25) and (26), respectively.

$$P_c = \begin{cases} P_{x1} - \frac{(P_{x1}-P_{x2})(f-f_{avg})}{f_{\max}-f_{avg}} & , f \geq f_{avg} \\ P_{x1} & , f < f_{avg} \end{cases}, \tag{25}$$

$$P_m = \begin{cases} P_{y1} - \frac{(P_{y1}-P_{y2})(f'-f_{avg})}{f_{\max}-f_{avg}} & , f' \geq f_{avg} \\ P_{y1} & , f' < f_{avg} \end{cases}, \tag{26}$$

where P_{x1}, P_{x2} and P_{y1}, P_{y2} respectively represent the maximum and minimum crossover probability and the maximum and minimum mutation probability; f and f' represent the individual fitness values; $f_{\max}$ represents the maximum fitness value; and f_{avg} represents the average fitness value. When the individual fitness value is higher than the average population fitness value, it is considered that its fitness value is high, and it is necessary to reduce its crossover mutation probability to protect the chromosomes with high fitness value. At this time, the higher the individual fitness value, the lower the crossover mutation probability; when the individual fitness value is lower than the average value, the probability of individual cross mutation remains unchanged.

(1) Damage and repair mechanism

The neighborhood in the large neighborhood search algorithm can be understood as a collection of neighbors of the current solution, and the surrounding solution is actually slightly different from the current solution. The process can be described as destroying the existing path by using two operations of breaking the ring and repairing, and then connecting the disconnected path with other points through the repair operation to form a new path [35,36]. In fact, this process is a local search, removing a certain proportion of customers through destruction, and then inserting the removed customers again through reorganization. Such an operation will greatly change the structure of the solution. By searching for more satisfactory solutions in multiple neighborhoods of the current solution, the search range of the algorithm in the solution space can be greatly expanded. Due to the weak local search ability of the basic genetic algorithm, the destruction and repair mechanism of the large-scale neighborhood search algorithm can effectively improve the local search ability of the algorithm, and it is more conducive for the genetic algorithm to jump out of the local optimum trap. The specific operations are as follows:

① Destroy: Randomly delete customer c in the current solution, save it to the removed customer collection s, remove the customer with the largest correlation with c from the remaining customers to s, and randomly select the customer s_i according to the s cycle operation, remove the customer with the largest correlation with s_i from the remaining customers to s. This is repeated until s reaches a pre-determined size, shortening the route where customers are deleted. The correlation calculation formula is shown in Formula (27) as follows:

$$R(i,j) = \frac{1}{\frac{d_{ij}}{d_{ijmax}} + V_{ij}}. \tag{27}$$

② Repair: Re-construct the solution by inserting deleted customers; simply scan all idle customers and repeatedly insert customers with the lowest cost until all customers are inserted.

Adding the self-adaptive cross-mutation probability and the damage repair mechanism of the large-scale neighborhood search algorithm on the basis of the original genetic algorithm, the algorithm flow chart of the improved genetic algorithm constructed in this paper is shown in Figure 3 as follows:

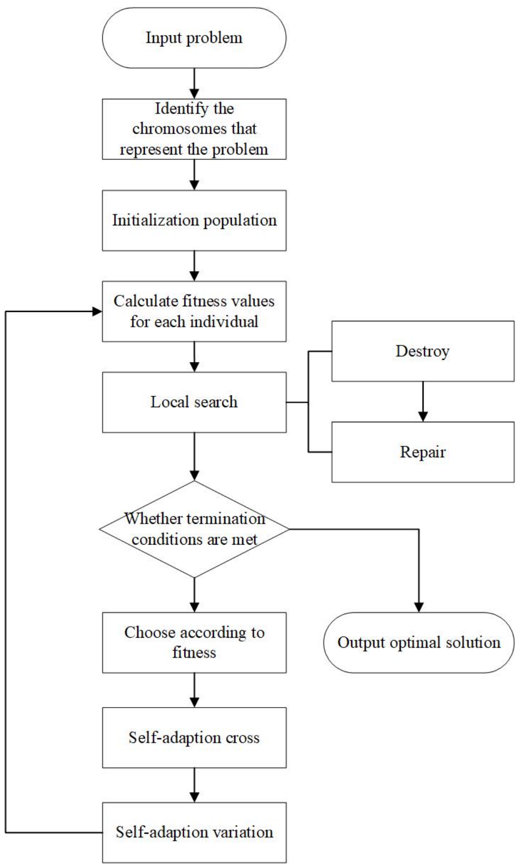


Figure 3. Flowchart of improved genetic algorithm.

4.2. Joint Distribution Solution Strategy

As the problem changes from independent distribution to joint distribution and the considered number of distribution centers changes from one to multiple, the difficulty of solving the vehicle routing problem increases significantly. In the process of solving, the original search customer area will change to searching both for distribution centers and customers, and the number of distribution vehicles is uncertain. Therefore, in order to quickly and accurately find the optimal solution, a special solution method is needed to deal with the multi-distribution center problem. Many studies have adopted the strategy of transforming the multi-distribution center problem into a single distribution center. Although this can simplify the complex problem, it cannot solve the different situations between the initial distribution center and the end distribution center of each path, and it is impossible to realize the sharing of distribution center resources in joint distribution. Therefore, this paper divides the entire vehicle routing problem of multi-distribution centers into two layers as follows:

Step 1: The first layer uses the genetic algorithm to traverse the entire system, with the lowest total cost as the goal. In this way, the distribution center and the vehicle are paired, and the lowest cost combination in the set of the starting distribution center and ending distribution center combinations is determined. For each vehicle, the corresponding start and end points are obtained.

Step 2: The second layer is based on the pairing found in the first layer and uses an improved genetic algorithm to optimize the path. Therefore, the vehicle routing problem considering multiple distribution centers is solved.

4.3. Algorithm Validity Test

After designing the improved genetic algorithm, before using the case to explore the advantages of the common distribution mode, this paper first uses part of the data of the three Qingdao express logistics companies in the Section 4.1 case to test the effectiveness of the improved genetic algorithm designed in this paper. The main purpose is to calculate through the data; first, verify that the improved genetic algorithm can obtain the model constructed in this paper, and second, verify that the improved genetic algorithm can achieve faster and better results than the basic genetic algorithm. The model parameter settings at this stage are shown in Table 2, and the distribution center data and customer data for the example are shown in Tables 3 and 4.

Table 2. Model parameter setting for verification algorithm.

Symbol	Description	Unit	Numerical
m	Number of distribution centers	Piece	3
n	Number of customers	Piece	21
c_1	Fixed fee per vehicle	CNY/vehicle	100
c_2	Variable cost per unit distance	CNY/km	1.61
c_3	Penalty price per unit of waiting time	CNY/h	20
c_4	Penalty price for unit late time	CNY/h	20
c_5	Carbon price	CNY/kg	2
v_1	Vehicle speed	km/h	60
v_2	Unloading and loading speed	T/h	3.6
f_0	Fuel consumption per unit distance when the vehicle is empty	L/km	0.165
f_{max}	Fuel consumption per unit distance when the vehicle is fully loaded	L/km	0.377
G_V	Vehicle weight	T	3
G_{max}	Maximum vehicle load	T	3
T_{cq}	Carbon quota	kg	50
β	Conversion efficiency of carbon emissions	kg/L	2.63

Table 3. Distribution center data in verification algorithm.

Distribution Center	X (km)	Y (km)	Customer
O1	12.1	22.5	1, 2, 3, 4, 5, 6, 7
O2	24	17.8	8, 9, 10, 11, 12, 13, 14
O3	7	10.1	15, 16, 17, 18, 19, 20, 21

Table 4. Customer data in verification algorithm.

Customer	X (km)	Y (km)	Delivery (t)	Pick-Up (*t*)	Time Window
1	14.1	14.4	0.6	0.3	22:30–23:00
2	25	15	0.4	0.2	22:00–22:30
3	17.2	22.1	0.9	0.2	22:30–23:00
4	12.6	11.8	0.9	0.1	22:00–22:30
5	11.6	16.7	1.3	0.6	22:30–23:00
6	13.3	18.9	0.6	1	23:00–23:30
7	14.45	11.1	0.4	0.3	22:30–23:00
8	7.1	21.4	1.2	0.7	22:00–22:30
9	1.3	25.7	0.6	0.4	23:00–23:30
10	18.7	12.5	1.2	0.4	22:00–22:30
11	15.47	13.5	1.2	1	22:00–22:30
12	21	16	1	1	22:00–22:30
13	17.64	15.56	0.2	0.6	22:00–22:30
14	10.8	14.05	1	0.5	23:00–23:30
15	11.5	11.3	0.5	0.3	23:00–23:30
16	17.9	20	0.9	0.7	23:00–23:30
17	6.2	12.8	1.3	1	22:00–22:30
18	14.03	9.5	1.2	0.5	22:00–22:30
19	16	9.1	0.5	0.6	23:00–23:30
20	10.2	18.2	0.7	0.7	22:00–22:30
21	19.3	15.3	0.3	0.4	23:30–24:00

4.3.1. Independent Distribution Model of Simultaneous Pick-Up and Delivery Vehicle Routing Problem Model

The effectiveness of the improved genetic algorithm for the independent distribution model in the context of the simultaneous pick-up and delivering vehicle routing problem model was verified. MATLAB R2021b was used to compile and run the algorithm proposed in this paper. According to the design and analysis of the genetic algorithm in the existing literature [37–39], and combined with the actual algorithm design in this paper, the algorithm parameters were set as follows: The population size was 100, the number of iterations was 80, the crossover probability in the original genetic algorithm was 0.9, and the mutation probability was 0.05. The original genetic algorithm and the improved genetic algorithm were used to solve the model under the independent distribution model. The iteration convergence results are shown in Figures 4 and 5. In these figures, the blue line represents the convergence process of the algorithm, the abscissa represents the number of iterations, and the ordinate represents the fitness.

From the iteration convergence result graphs for the original genetic algorithm and the improved genetic algorithm regarding the three distribution center points, on the one hand, the improved genetic algorithm outperformed the original genetic algorithm, with a faster convergence rate and had a stronger ability to jump out of local optima. On the other hand, from the convergence results, it can be seen that the total cost with the improved genetic algorithm was 1407.64 CNY, while the total cost with the original genetic algorithm was 1489.58 CNY, yielding an improvement of approximately 5.5%.

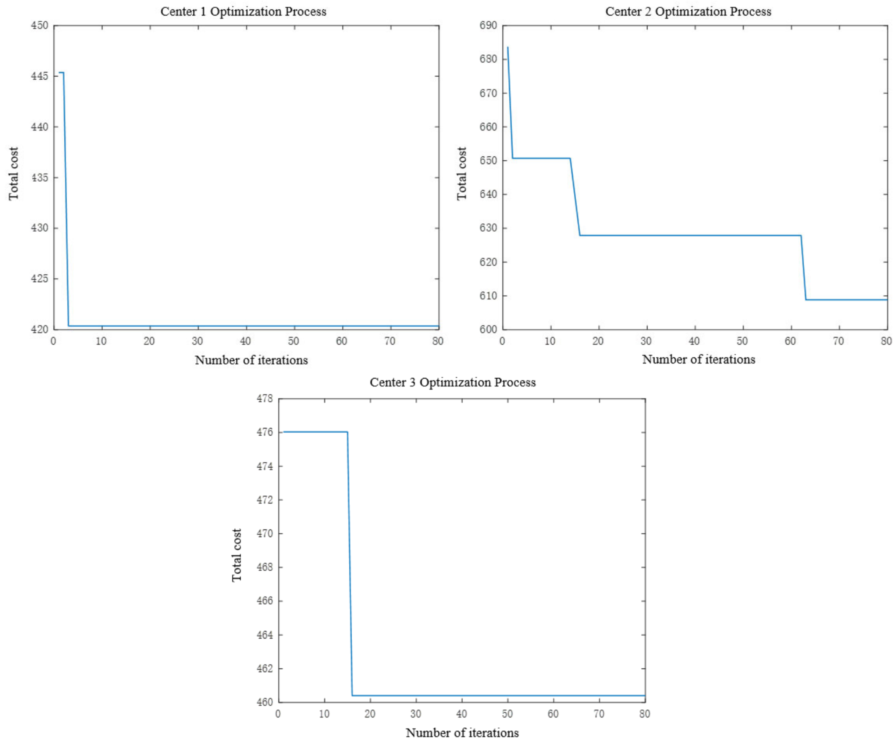


Figure 4. Independent pattern model iteration convergence results obtained with original genetic algorithm.

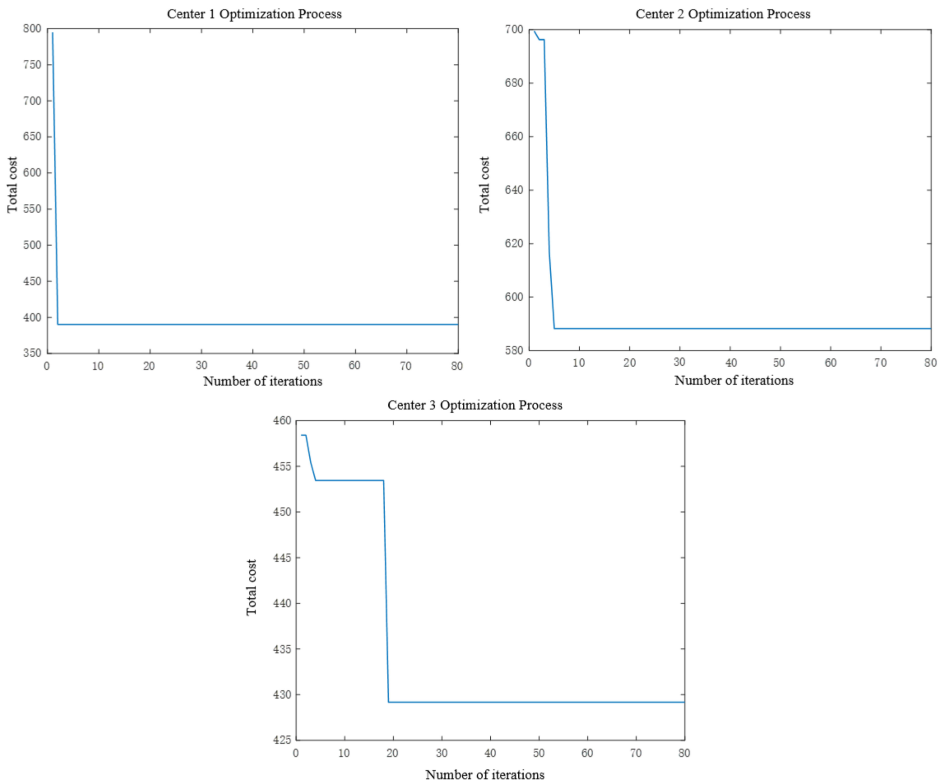
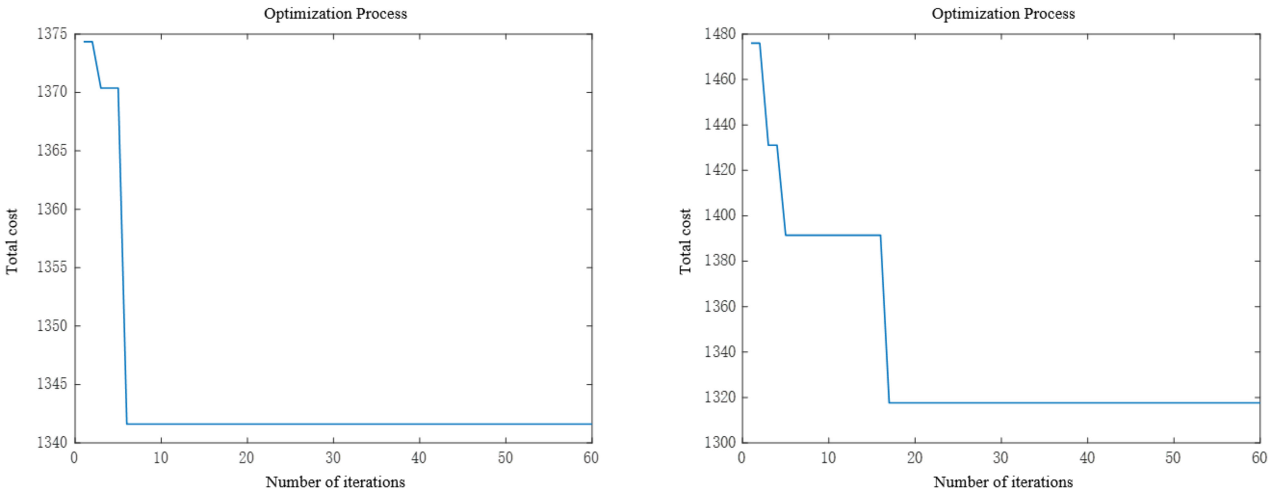


Figure 5. Independent pattern model iteration convergence results obtained with improved genetic algorithm.

4.3.2. Joint Distribution Model Simultaneous Pick-Up and Delivery Vehicle Routing Problem Model

According to the parameters given in Tables 3 and 4, the algorithm parameters were set as follows: The population size was 300, the number of iterations was 60, the crossover probability in the original genetic algorithm was 0.9, and the mutation probability was 0.05. The effectiveness of the improved genetic algorithm for the joint distribution model was verified by using the original genetic algorithm and the improved genetic algorithm to solve the model in the joint distribution model. The iteration convergence result is shown in Figure 6. Similarly, in this figure, the blue line represents the convergence process of the algorithm, the abscissa represents the number of iterations, and the ordinate represents the fitness.



(**a**) Before improvement (**b**) After improvement

Figure 6. Genetic algorithm joint distribution model iteration convergence result.

From the iteration convergence results obtained with the original genetic algorithm and the improved genetic algorithm under the joint distribution model, it can be seen that the improved genetic algorithm had a stronger ability to jump out of local optima than the original genetic algorithm, as the original genetic algorithm has a higher convergence point and could not jump out of the local optimum. The improved algorithm jumped out of the local optimum and further converged. Compared with the original algorithm, the total cost after convergence was lower: from the convergence results, it can be seen that the improved genetic algorithm had a total cost of 1317.62 CNY in the process of solving the joint distribution model, while the total cost with the original genetic algorithm was 1341.61 CNY. Therefore, the improved genetic algorithm yielded an improvement of approximately 1.79%, compared with the original genetic algorithm.

In sum, for the independent distribution model and the joint distribution model constructed in this paper, the improved genetic algorithm can solve the result, and it is more effective than the basic genetic algorithm.

5. Case Analysis

5.1. Case Introduction

As a branch industry in the logistics industry, express delivery has developed rapidly in China in recent years with the continuous growth of online shopping consumption. The process of an express delivery service in cities can be divided into two stages. One is to use trucks from the city's transfer station to transport to each express outlet. The other is to use small vehicles such as electric vehicles or electric tricycles from each express outlet to transport to customers. In the first stage, it is necessary to use trucks to carry and deliver express delivery from the transfer station to each outlet to unload the express delivery in the area that the outlet is responsible for, and install the express delivery sent in the area that the outlet is responsible for. Therefore, this article selects the distribution business data of three express logistics companies (Company A, Company C, and Company Y) in Qingdao City, and mainly selects the pick-up and delivery data from the transfer station to the outlets as is the case of this article, and further solves exploration in the advantages of the joint distribution model.

This article selects the logistics and distribution data of three companies in Qingdao City from the transfer station to the outlet in a certain period of time. Under these data, the customer's pick-up and delivery information and the geographic location information of the transfer station and the outlet are known. Since this article mainly explores the advantages of the common distribution mode, for the convenience of calculation, the model constructed in this article ignores the impact of urban road traffic, converts the location information of the transfer station and the outlet into plane coordinates, and uses the European distance to describe the distance between the points. Suppose that the same type of truck is used in the process of logistics distribution. The case parameter values are given in Table 5, and the case data are shown in Tables 6 and 7.

Table 5. Model parameter setting for case solving.

Symbol	Description	Unit	Numerical
m	Number of distribution centers	Piece	3
n	Number of customers	Piece	21
c_1	Fixed fee per vehicle	CNY/vehicle	100
c_2	Variable cost per unit distance	CNY/km	1.61
c_3	Penalty price per unit of waiting time	CNY/h	20
c_4	Penalty price for unit late time	CNY/h	20
c_5	Carbon price	CNY/kg	2
v_1	Vehicle speed	km/h	60
v_2	Unloading and loading speed	T/h	3.6
f_0	Fuel consumption per unit distance when the vehicle is empty	L/km	0.165
f_{max}	Fuel consumption per unit distance when the vehicle is fully loaded	L/km	0.377
G_V	Vehicle weight	T	4
G_{max}	Maximum vehicle load	T	5
T_{cq}	Carbon quota	kg	50
β	Conversion efficiency of carbon emissions	kg/L	2.63

Table 6. Distribution center data in case solving.

Distribution Center	X (km)	Y (km)	Customer
O1	7.8	22.5	1, 2, 3, . . ., 16
O2	20	19	17, 18, 19, . . ., 33
O3	8	9.5	34, 35, 36, . . ., 50

Table 7. Customer data in case solving.

Customer	X (km)	Y (km)	Delivery (t)	Pick-Up (t)	Left Time Window	Right Time Window
1	13	16	0.6	0.5	1320	1380
2	22	13	0.4	0.2	1320	1350
3	18.2	24.5	0.5	0.2	1350	1380
4	11.5	11.8	0.8	0.1	1350	1380
5	13.7	11.8	1	0.6	1350	1380

Table 7. *Cont.*

Customer	X (km)	Y (km)	Delivery (*t*)	Pick-Up (*t*)	Left Time Window	Right Time Window
6	13.3	18.9	0.6	1	1380	1410
7	14.4	11.1	0.4	0.3	1350	1380
8	10.4	12.4	1.1	0.8	1320	1350
9	2.5	9.5	0.6	0.5	1380	1410
10	14.8	12.5	1.2	0.5	1320	1350
11	15.4	13.5	1.2	1	1320	1350
12	20	15.6	0.8	1	1320	1350
13	16.7	17.7	0.2	0.6	1320	1350
14	10.8	14	1	0.6	1380	1410
15	11.5	11.3	0.5	0.3	1380	1410
16	18	19.3	0.9	0.7	1380	1410
17	6.2	12.8	1.3	1	1320	1350
18	14.3	9.5	1.2	0.5	1320	1350
19	16	9.1	0.5	0.6	1380	1410
20	10.2	18.2	0.7	0.7	1320	1350
21	19.3	15.3	0.3	0.4	1410	1440
22	15	1.5	1.1	0.1	1320	1410
23	17.2	12	0.4	0.7	1320	1380
24	18.5	17.5	0.2	0.2	1320	1380
25	20.1	19.1	1.2	0.3	1350	1380
26	4.7	10.6	0.8	0.2	1410	1440
27	8	21.5	0.5	0.7	1320	1380
28	10.2	10	0.5	1.1	1320	1380
29	17	18.1	0.8	0.2	1350	1380
30	21	18.6	0.2	0.7	1320	1380
31	21.1	20.8	0.4	0.5	1380	1440
32	11	15.6	0.3	0.1	1380	1440
33	10.6	21.1	1.3	0.6	1380	1440
34	20	4.5	1.2	0.4	1350	1440
35	3.5	10.7	1.5	0.8	1410	1440
36	10.2	16.4	1.3	1	1410	1440
37	16.2	10.5	1.4	0.9	1380	1440
38	15.3	17.4	0.4	0.4	1380	1440
39	7.2	15.3	0.2	0.4	1380	1440
40	5.8	4.6	0.7	0.2	1350	1380
41	4	17.2	0.5	0.5	1410	1440
42	2.4	20.2	0.5	0.8	1380	1410
43	9.9	15.4	0.7	0.3	1380	1440
44	16.5	8.7	1.1	0.4	1380	1440
45	23	18.5	1	0.1	1350	1380
46	24.5	20.1	0.8	0.2	1410	1440
47	13.2	7.6	0.2	0.6	1380	1380
48	6.6	7.8	0.5	0.3	1380	1440
49	6.2	9.9	0.2	1	1380	1440
50	8.2	13.4	0.5	0.4	1350	1380

5.2. Simultaneous Pick-Up and Delivery Vehicle Routing Problem Model Solution

5.2.1. Solving Independent Distribution Model

First, the improved genetic algorithm was used to solve the model of the simultaneous pick-up and delivery vehicle routing problem under the independent distribution model. The roadmap of the optimal distribution scheme is shown in Figure 7. In the figure, lines of different colors represent the transportation paths of different transportation vehicles, blue squares represent distribution centers, and circles represent customer points. And the solution results for the three distribution centers are provided in Table 8.

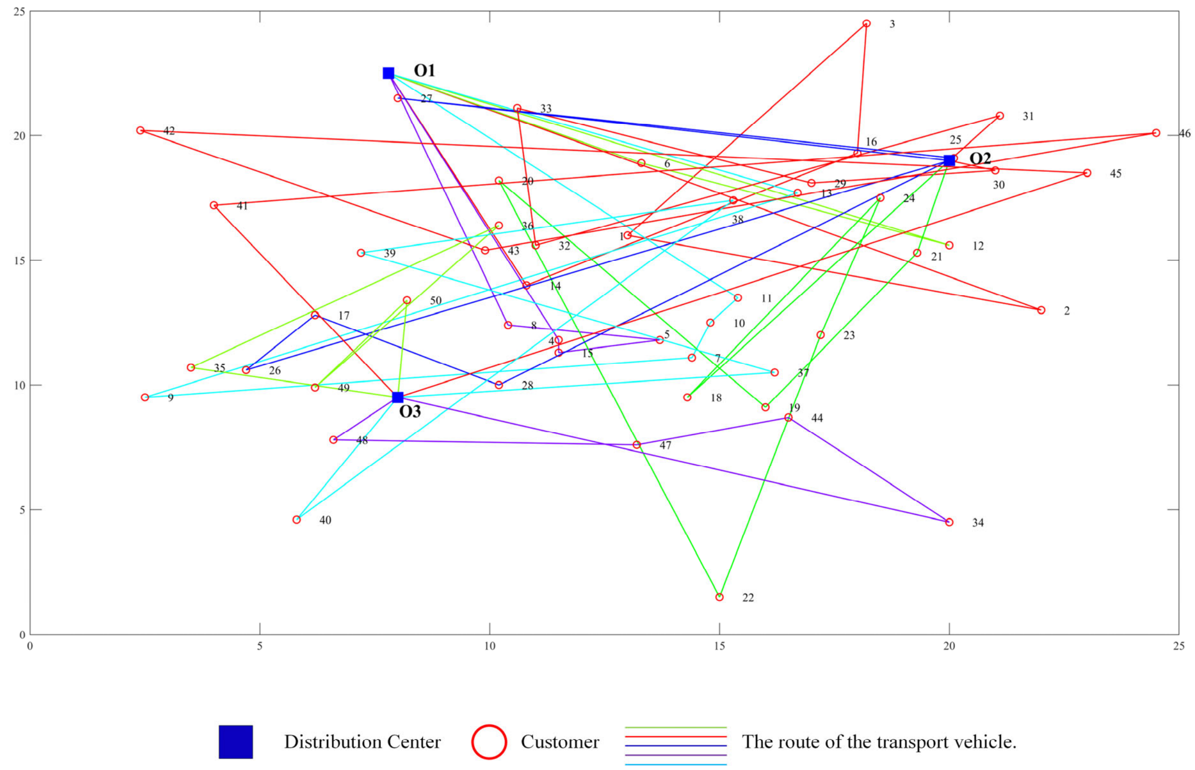


Figure 7. Optimal distribution roadmap in independent model. O1, O2 and O3 represent the respective distribution centers of the three enterprises, and the lines of different colors represent the transportation routes of different transportation vehicles issued from one distribution center.

Table 8. Distribution center route solution results.

Distribution Center	Delivery Route	Number of Vehicles	Transport Distance	C1	C2	C3	C4	Total Cost
O1	0 -> 2 -> 1 -> 3 -> 16 -> 14 -> 0 0 -> 12 -> 6 -> 0 0 -> 11 -> 10 -> 7 -> 9 -> 13 -> 0 0 -> 4 -> 15 -> 5 -> 8 -> 0	4	168.53	400	271.34	115.69	236.95	1023.98
O2	0 -> 30 -> 29 -> 33 -> 32 -> 31 -> 0 0 -> 18 -> 24 -> 23 -> 22 -> 20 -> 19 -> 21 -> 0 0 -> 27 -> 25 -> 28 -> 17 -> 26 -> 0	3	169.65	300	273.14	130.41	277.43	980.98
O3	0 -> 45 -> 42 -> 43 -> 46 -> 41 -> 0 0 -> 50 -> 49 -> 36 -> 35 -> 0 0 -> 40 -> 38 -> 39 -> 37 -> 0 0 -> 48 -> 47 -> 44 -> 34 -> 0	4	199.70	400	321.51	119.73	285.99	1127.23

From the solution results, it can be seen that the O1 and O3 distribution centers dispatched four vehicles, while the O2 distribution center dispatched two vehicles. In terms of transportation distance, the transportation distance for the O1 and O2 distribution centers was equivalent. The transportation distance of the O3 distribution center is the largest, at 199.70 km, while the shortest distribution distance is the O1 distribution center, at 168.53 km. From the time penalty cost point of view, the highest was observed for the O2 distribution center, which was 130.41 CNY, while the lowest was obtained by the O1 distribution center, which was 115.69 CNY. From the carbon emissions cost point of view, the highest was for the O3 distribution center, at 285.99 CNY, while the lowest was obtained for the O1 distribution center, which was 236.95 CNY. The total solution results are shown in Table 9.

Table 9. Solution results for the three distribution centers.

Distribution Center	Delivery Route	Number of Vehicles	Transport Distance	C1	C2	C3	C4	Total Cost
O1	0 -> 2 -> 1 -> 3 -> 16 -> 14 -> 0 0 -> 12 -> 6 -> 0 0 -> 11 -> 10 -> 7 -> 9 -> 13 -> 0 0 -> 4 -> 15 -> 5 -> 8 -> 0	4						
O2	0 -> 30 -> 29 -> 33 -> 32 -> 31 -> 0 0 -> 18 -> 24 -> 23 -> 22 -> 20 -> 19 -> 21 -> 0 0 -> 27 -> 25 -> 28 -> 17 -> 26 -> 0	3	537.88	1100	865.99	365.83	800.37	3132.19
O3	0 -> 45 -> 42 -> 43 -> 46 -> 41 -> 0 0 -> 50 -> 49 -> 36 -> 35 -> 0 0 -> 40 -> 38 -> 39 -> 37 -> 0 0 -> 48 -> 47 -> 44 -> 34 -> 0	4						

5.2.2. Joint Distribution Model

Next, the resources of the three distribution centers were integrated together, and the improved genetic algorithm was used to solve the model of the simultaneous pick-up and delivery vehicle routing problem under the joint distribution model. The optimal distribution roadmap is shown in Figure 8. The same as above, in the figure, lines of different colors represent the transportation paths of different transportation vehicles, blue squares represent distribution centers, and circles represent customer points. The solution results are shown in Table 10.

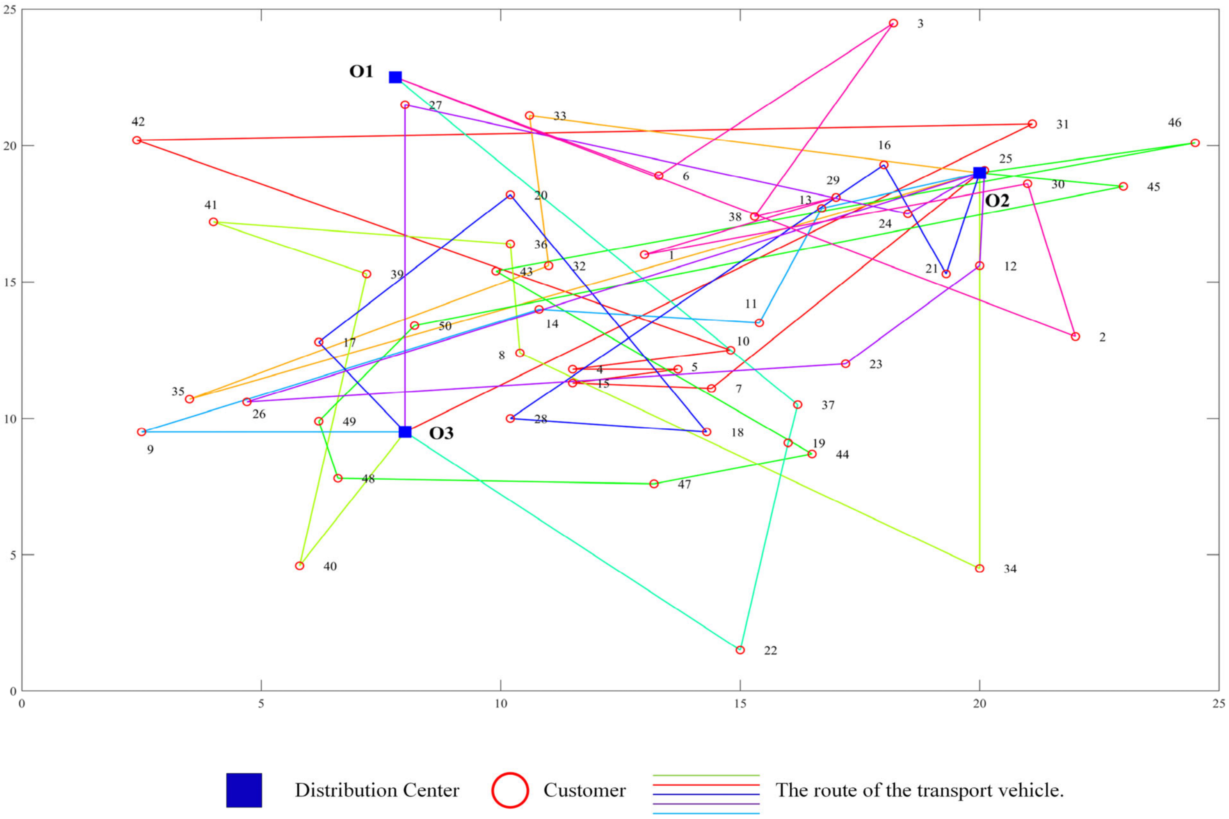


Figure 8. Optimal distribution roadmap in joint model. O1, O2 and O3 represent the respective distribution centers of the three enterprises, and the lines of different colors represent the transportation routes of different transportation vehicles issued from one distribution center.

Table 10. Solution results.

Delivery Route	Transport Distance	C1	C2	C3	C4	Total Cost
① C2 -> 7 -> 15 -> 5 -> 4 -> 10 -> 42 -> 31 -> C3 ② C2 -> 33 -> 32 -> 35 -> C2 ③ C3 -> 40 -> 39 -> 41 -> 36 -> 8 -> 34 -> C2 ④ C2 -> 45 -> 50 -> 49 -> 48 -> 47 -> 44 -> 43 -> 46 -> C2 ⑤ C3 -> 22 -> 19 -> 37 -> C1 ⑥ C2 -> 13 -> 11 -> 14 -> 9 -> C3 ⑦ C3 -> 17 -> 20 -> 18 -> 28 -> 16 -> 21 -> C2 ⑧ C3 -> 27 -> 24 -> 25 -> 12 -> 23 -> 26 -> C2 ⑨ C1 -> 2 -> 30 -> 1 -> 29 -> 38 -> 3 -> 6 -> C1	464.02	900	747.07	523.48	754.53	2925.08

As can be seen in Table 10, under the joint distribution model for the pick-up and delivering vehicle routing problem model, the three distribution centers were jointly distributed using a total of nine vehicles, for which the starting distribution center and the ending distribution center on six paths were different. The vehicles drove a total of 464.02 km, resulting in a time penalty cost of 523.48 CNY and a carbon emissions cost of 754.53 CNY, with a total cost of 2925.08 CNY after completing all pick-up and delivery tasks.

5.2.3. Comparative Analysis of Two Models

MATLAB R2021b was used to implement the improved genetic algorithm to solve the case of the simultaneous pick-up and delivery vehicle routing problem model under the two modes. The results of the two models were compared and analyzed, and the results are shown in Table 11 and Figure 9.

Table 11. Comparison of the results for the two models.

Model	Number of Vehicles	Transport Distance	C1	C2	C3	C4	Total Cost
Independent distribution model	11	537.88	1100	865.99	365.83	800.37	3132.19
Joint distribution model	9	464.02	900	747.07	523.48	754.53	2925.08

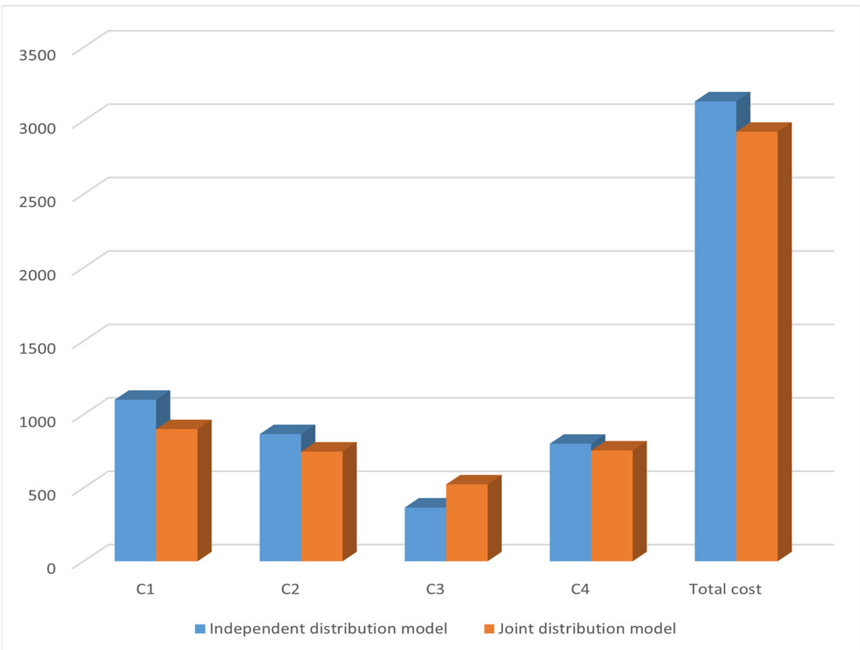


Figure 9. Comparison of two distribution models.

Analysis of the data in Table 11 and Figure 9 shows that the total cost under the joint distribution model is lower. For one transportation scenario, the joint distribution model is reduced by 207.11 yuan compared with the independent distribution model. It can be found that the joint distribution model can save the enterprise about 6.61% of the total cost. A detailed analysis of each cost can obtain the following conclusions:

(1) The number of transportation vehicles used in each transportation of the joint distribution model is two fewer than that of the independent distribution model, and the fixed transportation cost C1 is reduced by 200 yuan and optimized by about 18.18%. Because the joint distribution model integrates the distribution center, customer information, and vehicles, it reduces the waste of transportation capacity that may exist in the distribution process and reduces the vehicles issued by the distribution center, thus reducing the fixed transportation cost.
(2) Compared with the independent distribution model, the transportation distance of the joint distribution model is shortened by 73.86 km, which is optimized by 13.73%. Due to the positive proportion between the variable transportation cost and the distance, the transportation cost C2 of each transportation change is reduced by 118.92 yuan, which is also optimized by about 13.73%. Because the vehicle can serve the customers of all enterprises under the joint distribution model, the customers of a certain enterprise were far away from the distribution center, but now because of the sharing of the distribution center, there are distribution centers closer to the customer, which makes the transportation distance shortened. Therefore, the joint distribution can better shorten the transportation distance, so the variable transportation cost is better optimized.
(3) Compared with the independent distribution model, the time penalty cost C3 increased by 157.65 yuan; this is due to the higher transportation efficiency under the joint distribution model. And the transportation vehicles can reach the customer point earlier, which makes it unable to meet the left time window of some customers, resulting in an increase in the time penalty cost. In reality, the impact of early arrival on customer satisfaction is smaller than late arrival, so the transportation side can negotiate with the customer and arrange the distribution reasonably.
(4) Compared with the independent distribution model, the carbon emission cost C4 of each transportation is reduced by 45.84 yuan, which is equivalent to a reduction of 61.46 kg of carbon emissions per transportation, which is optimized by about 5.73% compared with the route optimization of the independent distribution model. This is because the joint distribution model uses fewer vehicles and the transportation distance is also shortened, which leads to fewer vehicles capable of generating carbon dioxide emissions and fewer carbon dioxide distances, thus better reducing carbon emissions. Therefore, the adoption of the joint distribution model by enterprises is more conducive to reducing atmospheric carbon dioxide emissions.

In sum, the solution result of the simultaneous pick-up and delivery vehicle path optimization model under the joint distribution mode is better than that of the simultaneous pick-up and delivery vehicle path optimization model under the independent distribution mode. Therefore, enterprises can better reduce the respective logistics costs of enterprises and reduce the carbon emission of enterprises when carrying out joint distribution. It can enable logistics enterprises to obtain greater profits in their business activities and better social benefits.

5.3. Sensitivity Analysis of Carbon Trading Mechanism Based on Simultaneous Pick-Up and Delivery Vehicle Routing Problem with Joint Distribution Model

In order to further explore the impact of carbon trading mechanism on enterprise logistics distribution costs, the model under the joint distribution model was studied from the perspectives of carbon price and carbon quota.

5.3.1. Impact of Carbon Price on Distribution Cost

With the passage of time, the carbon price is not static, and an increase or decrease in the carbon price can be expected. In this section, in the context of the joint distribution model, the impact of different carbon prices on the distribution cost of enterprises is discussed. First, a fixed carbon quota of 50 kg was set and the carbon price was set to 0, 2, 4, 6, 8, and 10 CNY/kg. Then, the cost results were obtained for each carbon price many times and the lowest value was selected. The change trend of the total distribution cost under different carbon prices is shown in Figure 10.

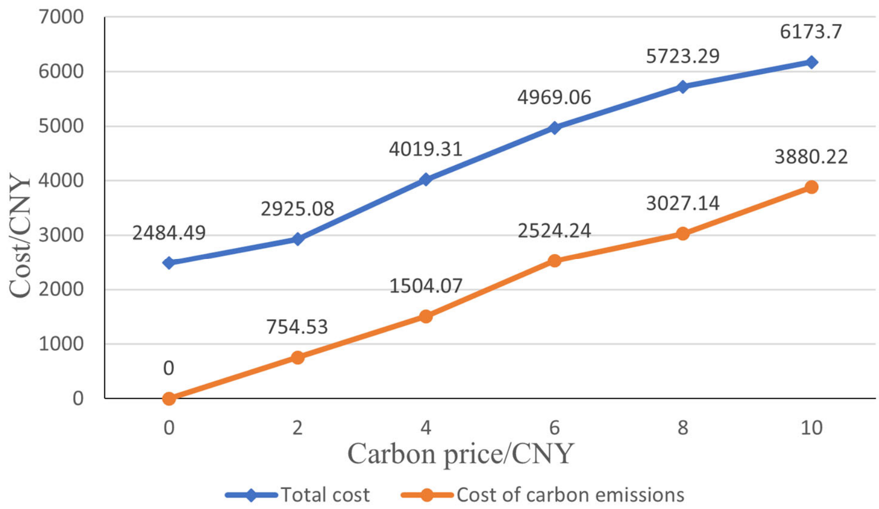


Figure 10. Trends in carbon emissions and total costs under changes in carbon prices.

It can be seen, from Figure 10, that with an increase in carbon price, the carbon emissions cost gradually increases, such that the total cost also increases continuously. The trend of carbon emissions cost is basically consistent with the trend of total cost, and it can be seen that a change in the carbon price directly affects the total distribution cost of enterprises. Therefore, under the influence of the carbon trading mechanism, when the carbon price increases, enterprises may be forced to find a more low-carbon way to carry out their distribution activities, encouraging enterprises to reduce their carbon emissions.

5.3.2. Impact of Carbon Quotas on Distribution Costs

Different carbon quotas have a certain impact on the carbon emissions cost of an enterprise. A larger carbon quota means that the enterprise can emit more carbon emissions. Therefore, the impact of different carbon quotas on the distribution cost of the enterprise was explored in the context of a joint distribution model. The carbon price was set to 2 CNY/kg, and the carbon quota was set to 0, 50, 100, 150, 200, or 250 kg. The change trend of the total distribution cost was then solved under the different carbon quotas. The results are shown in Figure 11.

From the data shown in Figure 11, it can be seen that, when the carbon price is fixed, a higher carbon quota allocated to an enterprise in the carbon trading market reduces the carbon emissions cost and, consequently, the total cost of the enterprise. According to the calculation formula of the carbon emissions cost $c_5(\beta F - T_{cq})$, it can be seen that, when the carbon price is fixed, the factor that determines the carbon emissions cost is the carbon quota T_{cq}. As the carbon quota increases, the impact of the carbon emissions of automobiles on the carbon emissions cost decreases. Therefore, when the carbon emissions of automobiles βF is fixed, the carbon quota increases, and the carbon emissions cost and total cost are lower.

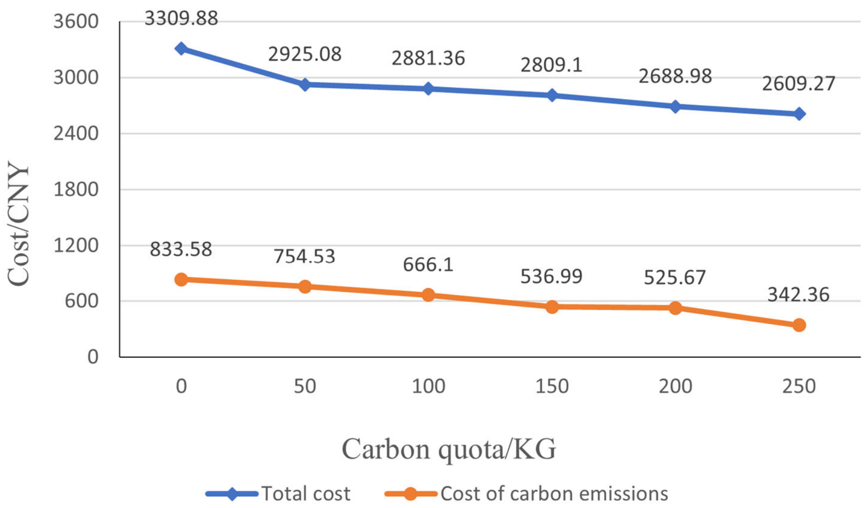


Figure 11. Trends in carbon emissions and total costs under changes in carbon quotas.

In summary, according to the research on carbon prices and carbon quotas under the carbon trading mechanism considered in this section, it was found that, under the background of the joint distribution model constructed in this paper, the carbon trading market can control enterprises to reduce their carbon emissions by adjusting carbon prices while, at the same time, it can also reduce the cost increase caused by the increase in carbon prices by adjusting the carbon quotas of enterprises. Therefore, when making distribution decisions, enterprises should pay attention to the changes in carbon prices and carbon quotas in the carbon trading market. When the carbon price is high, they should reasonably reduce the order volume in the distribution process, thereby reducing the transportation distance of distribution, thus reducing carbon emissions and their costs; when the carbon quota is given in sufficient quantities, the impact of carbon emissions on the carbon emissions cost is weakened, and the order volume in the distribution process can be appropriately increased to obtain more profits.

6. Conclusions

In this study, by constructing a simultaneous pick-up and delivery vehicle routing problem model under the independent and joint distribution models, then designing an improved genetic algorithm to solve the models, the joint distribution model was compared with the independent distribution model, particularly in terms of the advantages gained regarding cost reduction. The following conclusions can be drawn:

(1) Through the research, it can be found that the joint distribution by enterprises can effectively reduce the vehicles used in transportation and shorten the transportation distance, thus reducing the fixed transportation cost and variable transportation cost generated in the transportation process, and effectively reducing the carbon emission cost. Reduce the carbon dioxide emissions of enterprises, so that enterprises can better find a balance between economic factors and social factors, and promote the sustainable development of enterprises.

(2) As for the application of the joint distribution mode in practice, through the research of this article, because the joint distribution mode can integrate the resources of various enterprises, compared with independent distribution, it can shorten the distance of logistics and the vehicles transported, and reduce the cost of logistics. In the actual operation process of logistics enterprises, it is difficult for enterprises to organize the service network when facing the vast and sparsely populated areas with scattered residence, fewer customers, and long transportation lines. Due to the lack of sufficient business volume support and the high logistics cost, the timing, fixed-point, and fixed-line end distribution service methods based on a single enterprise cannot be

carried out. At this time, logistics enterprises can adopt the mode of joint distribution and integrate the distribution centers, customers, and vehicle resources of various enterprises in the region, which can effectively save the distribution cost in such areas and solve the logistics bottleneck of "the last kilometer" in sparsely populated areas.

(3) By studying the impact of the carbon trading mechanism on the logistics costs of enterprises, enterprises should make reasonable use of the changes in carbon prices and carbon quotas, arrange distribution rationally when the carbon price rises, and reduce the impact of the increase in carbon emission costs. The government should also formulate carbon quotas rationally. While controlling the carbon emissions of enterprises, it should reduce the cost pressure caused by the increase in low-carbon prices by increasing carbon quotas, balance the relationship between carbon emissions and enterprise costs, and promote the sustainable development of logistics enterprises.

Finally, in order to eliminate the interference of other factors, the corresponding assumptions and constraints are put forward on the model during the research of this article, and there are still deficiencies in some parts of the research. Therefore, for future research, it can also be expanded from the following aspects:

(1) In the process of constructing the optimization model of simultaneous pick-up and delivery routes, this paper did not consider the situation of road congestion. In real life, with the development of the economy, there are more and more cars on the roads, resulting in frequent congestion on urban roads. Therefore, for future research, the problem of road congestion can be considered at the same time, and dynamic emergencies can be added to make the research closer to reality.

(2) From the perspective of enterprise logistics decision makers, this article studies the problem of optimizing the delivery route with the joint distribution model, and simply discusses the impact of two different route optimization modes on the transportation costs and carbon emissions of logistics enterprises. In fact, in addition to considering the impact of its own transportation costs and carbon emissions, the benefit distribution between enterprises is also an aspect. In China, the government can play a role in promoting the implementation of joint distribution. Therefore, future research can also further elaborate on the benefit distribution of joint distribution and how the government promotes enterprises to participate in the construction of the joint distribution model on the basis of path optimization research.

(3) Due to the wide application of electric vehicles in recent years, for the problems in this paper, the research on the route problem model of electric vehicles [40,41] applied to the simultaneous pick-up and delivery vehicles under the joint distribution model can be further carried out to further explore the low-carbon management and sustainable development of enterprises.

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