Vehicle Routing Problem in Cold Chain Logistics: a Joint Distribution Model with Carbon Trading Mechanisms

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Abstract: Fierce competition and the mandate for green development have driven cold chain logistics companies to minimize total distribution costs and carbon emissions to gain a competitive advantage and achieve sustainable development. However, the cold chain logistics literature considers carbon trading mechanisms in sharing economy, namely the joint distribution, is limited. Our research builds a Joint Distribution-Green Vehicle Routing Problem (JD-GVRP) model, in which cold chain logistics companies collaborate among each other to deliver cold chain commodities by considering carbon tax policy. Based on the real business data from four cold chain companies and 28 customers, a simulated annealing (SA) algorithm is applied to optimize the model. The results indicate that joint distribution is an effective way to reduce total costs and carbon emissions when compared with the single distribution. The total cost is positively correlated with the carbon price, while the carbon emissions vary differently when the carbon price increases. In addition, carbon quotas have no effect on the delivery path. This research expands cold chain logistics literature by linking it with joint distribution and carbon trading mechanisms. Moreover, this research suggests that cold chain logistics companies could enhance delivery efficiency, reduce the business cost, and improve competitiveness by reinforcing the collaboration at the industry level. Furthermore, the government should advocate the mode of joint distribution and formulate an effective carbon trading policy to better utilize social and industrial resources to achieve the balanced economic and environmental benefits.

Keywords: green vehicle routing problem; cold chain logistics; joint distribution; carbon trading mechanism

1. Introduction

Recently, global warming has been growing increasingly severe, and the hotspot issue of reducing carbon emissions has drawn worldwide attention (Shen et al., 2018). Many countries and non-governmental organizations reached a meaningful contract to prevent further deterioration in climate change at 2009 United Nations Climate Change Conference. For example, China guaranteed to cut CO_2 per unit of GDP by 40% by 2020 (Wang et al., 2017). Transportation is one of the major components that produces carbon emissions, which occupies 14% of the total emissions all over the world. Among all types of transportation, road transportation discharges 75% of the total carbon emissions (Dekker et al., 2012). The cold chain logistics is an extremely important sub-branch of transportation, which may consume more fuel to preserve the appropriate temperature (Stellingwerf et al., 2018; Tsang et al., 2018). For example, Adekomaya et al. (2016) indicated that 40% of foods need the cold storage during delivery, which consumes 53% of the total power in operations. As investigated by Allied Market Research (2019), the cold chain logistics market all over the world had reached to 160,000 million dollars in 2018 and is expected to boost to reach 585,000 million dollars by 2026. The annual growth rate is projected as high as 17.9%. The market is segmented in 5 major categorizations based on end-use: 1) fruits and vegetables; 2) bakery; 3) milk products; 4) meat and seafood; 5) drugs and pharmaceuticals (Allied Market Research, 2019). Moreover, the Asia-Pacific region is the leading market in cold chain logistics, among which China contributes the most to generating market revenue. Since 2013, the market size of China's cold chain logistics grows 15% every year, and it is projected to generate 80 billion dollars revenue in 2024 (Dai et al. 2019). Although the cold chain logistics market is flourishing, cold chain logistics companies are usually small in scale and numerous in quantity. The collaboration among them are quite limited, which leads to high costs and high carbon emissions during transportation (Di et al., 2018; Li et al., 2020). Hence, reducing the total delivery cost and cutting down carbon emissions are key focuses of the whole industry and involving cold chain logistics companies.

The vehicle routing problem (VRP) was proposed to optimize transportation routes of products (Toth and Vigo, 2014). It aims to minimize the transportation cost and transportation distance through path optimization (Zhang et al., 2003; Hsiao et al., 2017). Unlike ordinary logistics, cold chain logistics would consume more fuel to keep the goods fresh, and thus, it is essential to consider a damage factor and refrigeration factor in the cold chain logistics (Wang et al., 2016). Under the requirement of green development, the amount of carbon emissions becomes another important factor that influences the delivery paths in the vehicle routing problems (Li et al., 2019). To better consider the carbon emissions factor in the model, some scholars began to add the carbon emissions trading cost (the carbon cost) into the objective function (Zhang et al., 2015; Liao, 2017; Niu et al., 2018). However, there is little literature that simultaneously considers the costs of damage, refrigeration, and carbon. Hence, this research holistically covers all of the related costs in a cold chain logistics delivery path, including the fixed cost, transportation cost, damage cost, refrigeration cost, penalty cost, and carbon cost. In addition, a carbon trading mechanism is introduced by focusing on the carbon price and the carbon quotas when calculating the carbon cost.

The current literature starts from the perspective of an individual cold chain logistics company, which overlooks synchronisation among similar businesses. Joint distribution means that multiple logistics companies share the transportation resources and customers, and work is conducted under unified planning and dispatching (Liu et al., 2018). From an industry perspective, joint distribution could effectively reduce total costs and carbon emissions by better utilising all available resources (Burns et al., 1985; Kuo and Chen, 2010). The neglect of joint distribution makes the VRP literature incomplete because this omission makes the total distribution cost and carbon emissions of the entire cold chain logistics industry remain unclear.

To fill this gap, the present paper aims to answer three research questions: 1) How to apply joint distribution in the cold chain logistics industry? 2) How to construct an optimization model that includes all of the related costs? 3) How do carbon prices and carbon quotas affect total costs and carbon emissions? VRP is a typical NP-hard problem (Raff, 1983; Shen et al., 2018). The proposed model is a derivative of VRP that considers more variables. The simulated annealing algorithm is used to analyse and simulate the scenarios as it is one of the most effective algorithms to answer NP-Hard problems that have large scale.

In this paper, Section 2 presents the literature review. Section 3 shows the targeted problem and the proposed model. The algorithm, the design of experiments and the computational results are described in Section 4. Section 5 provides a discussion and managerial suggestions. Section 6 presents the conclusions and future work.

2. Literature review

This section reviews the literature in three areas: the first area relates to VRP in cold chain logistics. The second area investigates the green vehicle routing problem (GVRP). The third concerns the joint distribution.

2.1 VRP in cold chain logistics

Dantzig and Ramser (1959) is the first work that brought up VRP, which has been extensively studied since then and becomes an important topic in the cold chain logistics industry. As cold chain logistics aims to reduce cargo damage and maintain product freshness, the delivery will consume more fuel for temperature preservation (Stellingwerf et al., 2018). Hence, how to cut carbon emissions and lower delivery costs are the key focuses in the cold chain logistics industry. Although previous studies have made great contributions to the cold chain logistics literature, they always neglect the cargo damage factor or the refrigeration factor. For example, Zhang and Chen (2014) established a VRP model to find the most economical delivery path for frozen products. However, the proposed model did not consider the cargo damage cost. Wang et al. (2016) covered the damage cost that was generated by door-opening during loading in the model but did not consider the damage cost that was generated by the long delivery time. Osvald and Stirn (2008) and Cai and Pan (2017) considered the cargo damage but ignored the refrigeration cost. Hence, the cargo damage cost and the refrigeration cost will be thoroughly investigated in this study.

Solomon (1984) is the first work that studied VRP with time window constraints where customers impose earliest or deadline time constraints on delivering routes. Compared with the delivered products of ordinary logistics, products distributed in cold chain logistics are more sensitive to time factors. Hsu et al. (2013), de Armas et al. (2015), and Sun et al. (2017) introduced time windows into cold chain logistics to ensure the quality of the cold chain products and to improve the customer satisfaction. Hence, this study involves time limits in the constraints. In addition, the unloading sequence of cold chain products will significantly affect the delivery path (Zachariadis et al., 2015). Under this circumstance, the shortest distribution path may not be the optimal path (Ahn and Rakha, 2008). Hence, the loading capacity is considered in this paper as suggested by Zhang and Chen (2014).

2.2 The green vehicle routing problem

In the past, most researchers focused only on the economic benefits of vehicle routing problems. Because of the increasing attention to climate change, the GVRP model was introduced by Erdoğan and Miller-Hooks (2012). It has been used to diminish the environmental influence, most often considered in terms of CO_2 emissions. With the purpose of reducing the fuel consumption and carbon emissions, Zhang et al. (2015) proposed a GVRP model to balance the economic and environmental impacts. Later, Naderipour and Alinaghian (2016) identified and discussed the delivery sequence and the travelling speed could significantly reduce the greenhouse gas emissions. Moreover, Xiao and Konak (2017) identified that carbon emissions could be reduced effectively by adjusting vehicle distribution routes and time. To better study GVRP, researchers take more environmental factors into consideration. For example, Liao (2017) proved that CO_2 emissions could be reduced significantly by including emission factors into the on-line GVRP model. Niu et al. (2018) identified that carbon emissions could be greatly cut by preventing vehicles from travelling with empty load. Hence, the open GVRP model, in which vehicles would not go back to the distribution centre after delivering the product to the final customer, could significantly reduce the environmental impacts. Wang et al. (2018) proposed that the total delivery cost and carbon emissions in cold chain logistics could be reduced by introducing carbon tax policies. Although previous GVRP studies investigated carbon emissions to some extent, no literature has fully explored the impacts of carbon trading mechanisms in cold chain logistics. Hence, the carbon trading mechanism including carbon price and carbon quota will be taken into consideration.

2.3 Joint distribution

In recent years, cold chain logistics companies normally conduct delivery independently, and thus, a large amount of research has focused on the single distribution model (Zhang and Chen, 2014; Wang, et al., 2017; Li et al., 2019). Obvious shortcomings of the single distribution are the poor full load rate, the very large quantity of hired vehicles and the high delivery cost. These shortcomings seriously restrict the cold chain logistics industry to grow. Joint distribution is a new way to deliver cold chain products, which can share the overall resources among companies, improve the full load rate, decrease the hired vehicles, as well as reduce the distribution cost (Zhang, 2009; Kuo and Chen, 2010). Thus, the joint distribution mode is a new choice for the current cold chain logistics companies to consider.

The Japanese government first proposed the concept of joint distribution in 1977, with the aim of improving the distribution efficiency through resource integration (Wang, 2018). Benjamin (1990) jointly optimized the inventory and distribution cost and explored the impact of different transportation decision-making approaches on the system's economic cost. Although the above literature considers the integration of resources, it is still a distribution problem for individual companies. The existing joint distribution literature concentrates on the distribution cost, depot locations, and the delivery route planning. Burns et al. (1985) proposed an analytical method to compare the total cost between the joint distribution strategy and the single direct distribution strategy; the results showed that the cost optimization had obvious advantages in the joint distribution model. Cheng et al. (2009) built a joint distribution mathematical model that optimises the total distribution cost. Zhang (2009) studied the problem of distribution centre locations and the vehicle routing problem, and the results proved that joint distribution could significantly reduce the travel distance and improve the route planning. Kuo and Chen (2010) had established a joint distribution model for food logistics, which provided a competitive advantage in reducing the damage cost during transportation. Although previous studies have proved the superiority of joint distribution, there is a shortage of research on carbon emissions for cold chain logistics. Thus, carbon emissions is introduced to the joint distribution vehicle routing problem in cold chain logistics in this study.

The key features of above-mentioned models are summarized in Table 1. The cargo damage cost, the refrigeration cost, and the carbon cost are all considered in the newly proposed Joint Distribution-Green Vehicle Routing Problem (JD-GVRP) model to better cope with cold chain logistics. The carbon trading mechanism is also introduced in the JD-GVRP model to reflect the real business environment.

Table 1. Key Features of Models

Model	Significant Factors	References
VRP in cold chain logistics	Cargo damage; Refrigeration; Time window; Load constraints	Zhang et al. (2003), Osvald and Stirn (2008), Zhang and Chen (2014), Wang et al. (2016), Cai and Pan (2017), de Armas et al., (2015); Sun et al. (2017)
Green VRP	Fuel consumption; Carbon emissions; Carbon cost; Carbon tax policy	Naderipour and Alinaghian (2016), Xiao and Konak, (2017), Zhang et al. (2015), Liao (2017), Niu et al. (2018), Wang et al. (2018)
Joint distribution	Sharing depots and vehicles	Cheng et al. (2009), Zhang (2009), Kuo and Chen (2010)
JD-GVRP	All related costs; Sharing depots and vehicles; Carbon trading mechanisms	

3. Model Formulation

3.1. Problem description

In real life, several cold chain logistics companies have their own depots and customers with a certain range, which is shown in Figure 1. As is shown in Figure 2, the single distribution mode refers to having each company use its own vehicles to serve its customers, and there is no contact between the companies. The main model of this study is the joined distribution mode, which can be described as all of the cold chain logistics companies sharing the depots, vehicles, and customers; a detailed description is in Figure 3.

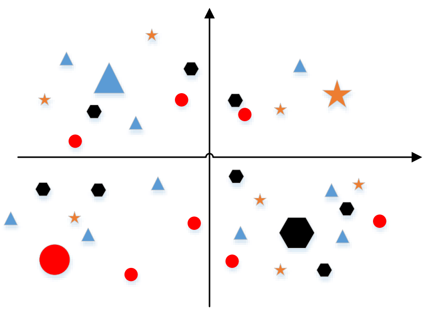


Figure 1. Regional depots and customers

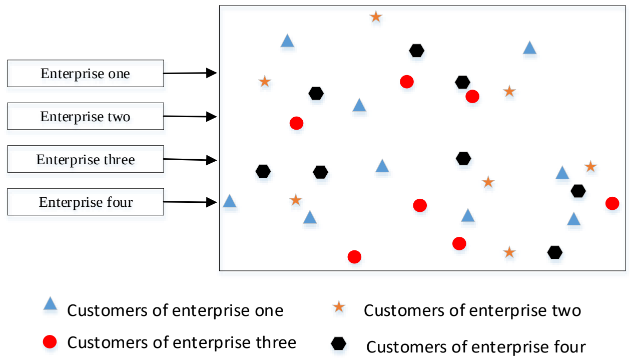


Figure 2. Single distribution mode

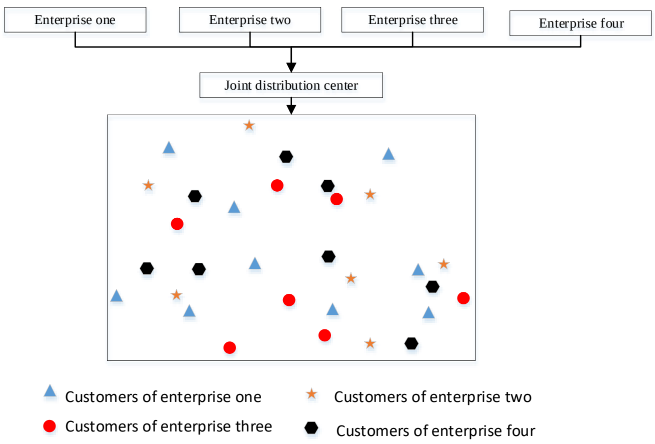


Figure 3. Joint distribution mode

3.2. Model assumptions

The JD-GVRP model will be set up by taking the following assumptions into considerations:

(1) The information regarding customers' sites, products demands, and preferred delivery time is known.

(2) Each customer is served only one time by one vehicle from one depot.

(3) All of the vehicles are refrigerated trucks, and they leave the depot simultaneously.

(4) Overload is not allowed during the delivery.

(5) There is no traffic jam and vehicles travel at a constant speed.

(6) The vehicle will not return to the depot after serving the final customer.

(7) Customers are not allowed to pick up products from the depot.

3.3 Symbols and parameters

Table 2 shows the symbols and parameters used in this paper.

Table 2. Description of symbols.

Symbols	Description
m	Number of depots (1, 2, ..., m)
n	Number of customers (m+1, m+2, m+3, ..., m+n)
K	Vehicle quantity
i, j	Index of nodes (i, j=1, 2, 3, ..., m+n)
k	Index of vehicles (k=1, 2, 3, ..., K)
d_{ij}	Distance between nodes i and j
q_i	Customer *i's demand*
q_j	Customer *j's demand*
F_1	Fixed cost of each vehicle
F_2	Transportation cost of per unit distance
F_3	Cold chain products' price per unit
F_4	Fuel price per unit
F_5	Waiting cost due to the early arrival
F_6	Punishment cost due to the late arrival
F_7	Carbon price
ε_1	The deterioration rate of the product freshness during transportation
ε_2	The deterioration rate of the product freshness during unloading
θ	Cold chain products' sensitivity factor
v_1	Vehicle speed
v_2	Unloading speed
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
ρ_0	The fuel consumption per unit distance (empty load)
ρ^*	The fuel consumption per unit distance (full load)
Q	The maximum load capacity of a refrigerated truck
Q_{ij}	Products quantity from customer i to customer j
Q_{in}	Products quantity when the vehicle leaves customer j
T_1	Time window's starting time
T_2	Time window's ending time
T_q	Carbon emissions quotas
η	The coefficient values of the carbon emissions
t_{jk}	Time point when vehicle k arrives at customer j
t_{dp}	Departure time of all vehicles
x_{ijk}	0-1 value, when refrigerated truck k delivers cargo from node i to node j, x_{ijk}=1; otherwise, x_{ijk}=0
y_{ijk}	0-1 value, when refrigerated truck k delivers cargo from depot i to customer j, y_{ijk}=1; otherwise, y_{ijk}=0

3.4 Objective function

The JD-GVRP model proposed in this paper includes six types of costs, namely fixed cost (C_1), transportation cost (C_2), damage cost (C_3), refrigeration cost (C_4), penalty cost (C_5) and carbon cost (C_6).

3.4.1 Fixed cost

The fixed cost includes the vehicle's daily maintenance cost, the depreciation cost, and the drivers' salary. It is linearly corelated with the number of refrigerated trucks, regardless of the travel distance. The fixed cost is given as follows:

$$C_1 = F_1 K \tag{1}$$

Where F_1 indicates the fixed cost of each vehicle; K is the number of refrigerated trucks.

3.4.2 Transportation cost

The transportation cost directly influences the variable cost, such as the labour cost and the fuel consumption cost. The travel distance plays a significant role in determining the transportation cost. They are positively correlated. Thus, the total transportation cost is given as follows:

$$C_2 = F_2 \sum_{i=1}^{\mathrm{m+n}} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} d_{ij} \tag{2}$$

Where F_2 represents the transportation cost of per unit distance; m is the number of depots; n is the number of customers; x_{ijk} is a 0-1 value, when refrigerated truck k delivers cargoes from node i to node j, x_{ijk}=1, otherwise x_{ijk}=0; d_{ij} represents the distance between node i to node j.

3.4.3 Damage cost

According to Zhang and Chen et al. (2014), Balaji and Arshinder (2016), Huang et al. (2018), Chen et al. (2019), and Heard et al. (2019), the damage cost arises mainly from two aspects: one is the deterioration of the freshness of cold chain products due to the length of delivery; and the other is the convection with the outside hot air that damages cold chain products' quality due to door opening during unloading.

(1) When the vehicle is on the way to deliver products, the door is closed. The damage cost C_{31} that is incurred in the delivery process is

$$C_{31} = F_3 \sum_{i=1}^{m} \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} y_{ijk} q_j \left(1 - \varepsilon_1 e^{-\theta(t_{jk} - t_{dp})}\right) \tag{3}$$

Where y_{ijk} is a 0-1 value, when refrigerated truck k delivers cargoes from depot i to customer j, y_{ijk}=1, otherwise y_{ijk}=0; F_3 is the unit price of cold chain products; q_j is the demand of customer j; $\mathcal{E}_1$ is the deterioration rate of the product freshness during transportation; θ is a sensitivity factor of cold chain products; t_{jk} represents the time point when the vehicle k arrives at customer j, t_{dp} represents time point when all vehicles depart from the depot.

(2) After vehicle arriving at customer *i's* location, the door will be opened to unload products. Because of the convection, the temperature of cold chain products will increase that changes the deterioration rate of the product freshness. The damage cost C_{32} pf unloading process is

$$C_{32} = F_3 \sum_{i=1}^{m} \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} y_{ijk} Q_{\text{in}} \left(1 - \varepsilon_2 e^{-\theta \frac{q_j}{v_2}} \right) \tag{4}$$

Where Q_{in} represents the product quantity when the vehicle leaves customer j; $\mathcal{E}_2$ is the deterioration rate of the product freshness during unloading; q_j/v_2 represents the service time at customer j; v_2 is the unloading speed.

Therefore, the total damage cost C_3 is

$$C_3 = C_{31} + C_{32} = F_3 \sum_{i=1}^{m} \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} y_{ijk} \left[q_j (1 - \varepsilon_1 e^{-\theta (t_{jk} - t_{dp})}) + Q_{in} (1 - \varepsilon_2 e^{-\theta \frac{q_j}{v_2}}) \right] \tag{5}$$

3.4.4 Refrigeration cost

According to the literature (Xiao et al., 2012; Defraeye, 2019), the refrigeration cost consists of two parts: one is the energy consumption cost of cooling during the delivery, and the other is the additional energy cost of maintaining the low temperature during unloading.

(1) The cost C_{41} of the energy consumption during the delivery is

$$C_{41} = F_4 \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \alpha_1 \frac{d_{ij}}{v_1} \tag{6}$$

Where F_4 represents the unit price of fuel; a_1 represents the fuel consumption of the refrigeration equipment per unit time during transportation.

(2) The cost C_{42} of the extra energy consumption during the process of unloading is

$$C_{42} = F_4 \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \alpha_2 \frac{\mathrm{q_j}}{\mathrm{v_2}} \tag{7}$$

Where a_2 represents the fuel consumption of the refrigeration equipment per unit time during unloading.

Therefore, the total refrigeration cost C_4 is

$$C_4 = C_{41} + C_{42} = F_4 \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \left(\alpha_1 \frac{d_{ij}}{v_1} + \alpha_2 \frac{\mathrm{q_j}}{\mathrm{v_2}} \right) \tag{8}$$

3.4.5 Penalty cost

In cold chain logistics, the condition of products when customers received is critical as it directly influences customers' revenues, inventory control, and quality management. As the deterioration of products during delivery will cause damage, cold chain logistics companies should deliver products according to customers' specific time requirements. If vehicles arrive too early, they must wait until the customer starts receiving the product. The condition of products may become worse during the waiting. If vehicles arrive too late, customers may meet problems of replenishment and sale. These problems are commonly seen in supermarkets, online shopping platforms, and local convenient stores. Hence, a penalty cost is generated if vehicles arrive outside customers' time windows (Lin et al. 2011; Chen et al. 2019; Wang et al., 2019). [T_1, T_2] represents the time window required by the customer. The penalty cost is

$$C_5 = \begin{cases} F_5 \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} \max(T_1 - t_{jk}, 0), t_{jk} < T_1 \\ 0, T_1 \le t_{jk} \le T_2 \\ F_6 \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} \max(t_{jk} - T_2, 0), t_{jk} > T_2 \end{cases}$$
$$= \sum_{j=m+1}^{m+n} \sum_{k=1}^{K} \left[F_5 \max(T_1 - t_{jk}, 0) + F_6 \max(t_{jk} - T_2, 0) \right] \quad (9)$$

Where F_5 represents the waiting cost due to the early arrival; F_6 represents the punishment cost due to the late arrival.

3.4.6 Carbon cost

The fuel consumption in cold chain logistics includes two aspects: one aspect is the fuel consumption of the vehicle travelling, and the other is the fuel consumption of the refrigeration equipment.

(1) The fuel consumption of the vehicle travelling is not only related to the travel distance, but also affected by the loading conditions of vehicles. According to Xiao et al. (2012), Clarke et al. (2019), and Wu et al. (2019), the fuel consumption per unit distance can be expressed as

$$\rho(X) = \rho_0 + \frac{\rho^* - \rho_0}{Q} X \quad (10)$$

Where ρ_0 represents the fuel consumption per unit distance when the vehicle is empty; ρ^* represents the fuel consumption per unit distance when the vehicle is fully loaded; Q is the maximum load capacity of the vehicle; X is the weight of the cargo.

Therefore, the fuel consumption of the vehicle travelling is

$$FC_1 = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \rho(Q_{ij}) d_{ij} = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} (\rho_0 + \frac{\rho^* - \rho_0}{Q} Q_{ij}) d_{ij} \quad (11)$$

Where Q_{ij} represents the quantity of products that are transported from customer i to customer j.

(2) The fuel consumption of the refrigeration equipment has been discussed in Section 3.4.4, which is

$$FC_2 = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \left(\alpha_1 \frac{d_{ij}}{v_1} + \alpha_2 \frac{q_j}{v_2} \right) \quad (12)$$

Therefore, the total fuel consumption can be obtained as follows:

$$FC = FC_1 + FC_2$$
$$= \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \sum_{k=1}^{K} x_{ijk} \left[\left(\rho_0 + \frac{\rho^* - \rho_0}{Q} Q_{ij} \right) d_{ij} + \left(\alpha_1 \frac{d_{ij}}{v_1} + \alpha_2 \frac{q_j}{v_2} \right) \right] \quad (13)$$

Carbon emission is the product of the fuel consumption and CO_2 emission coefficient (Ottmar, 2014). Thus, the carbon emission can be calculated by Equation (14).

$$EM = \eta \times FC \quad (14)$$

Where η is CO_2 emission coefficient.

If the cold chain logistics company exhaust more carbon emissions than its prescribed limited, the company must pay extra money to buy more carbon quota. However, the cold chain logistics company can sell the carbon quota to gain profit if its emissions are lower than the prescribed limit (Eberhart and Kennedy, 1995; Li et al., 2019; Li et al, 2019). Therefore, the carbon cost can be calculated as follows:

$$\begin{aligned} C_6 &= F_7(\eta \times FC - T_q) \\ &= F_7\left\{\eta \sum_{i=1}^{m+n}\sum_{j=1}^{m+n}\sum_{k=1}^{K} x_{ijk}\left[\left(\rho_0 + \frac{\rho^* - \rho_0}{Q} Q_{ij}\right) d_{ij} + \left(\alpha_1 \frac{d_{ij}}{v_1} + \alpha_2 \frac{q_j}{v_2}\right)\right] - T_q\right\} \end{aligned} \tag{15}$$

Where F_7 represents the carbon trading price; Tq is the carbon emission quota, which represents the highest carbon emissions that an company can emit for free.

3.5 Modelling

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

$$\begin{aligned} \min\ C &= C_1 + C_2 + C_3 + C_4 + C_5 + C_6 \\ &= F_1 K \\ &+ F_2 \sum_{i=1}^{m+n}\sum_{j=1}^{m+n}\sum_{k=1}^{K} x_{ijk} d_{ij} \\ &+ F_3 \sum_{i=1}^{m}\sum_{j=m+1}^{m+n}\sum_{k=1}^{K} y_{ijk}\left[q_j(1-\varepsilon_1 e^{-\theta(t_{jk}-t_{dp})}) + Q_{in}(1-\varepsilon_2 e^{-\theta\frac{q_j}{v_2}})\right] \\ &+ F_4 \sum_{i=1}^{m+n}\sum_{j=1}^{m+n}\sum_{k=1}^{K} x_{ijk}\left(\alpha_1 \frac{d_{ij}}{v_1} + \alpha_2 \frac{q_j}{v_2}\right) \\ &+ \sum_{j=m+1}^{m+n}\sum_{k=1}^{K}\left[F_5 \max(T_1 - t_{jk}, 0) + F_6 \max(t_{jk} - T_2, 0)\right] \\ &+ F_7\left\{\eta \sum_{i=1}^{m+n}\sum_{j=1}^{m+n}\sum_{k=1}^{K} x_{ijk}\left[\left(\rho_0 + \frac{\rho^* - \rho_0}{Q} Q_{ij}\right) d_{ij} + \left(\alpha_1 \frac{d_{ij}}{v_1} + \alpha_2 \frac{q_j}{v_2}\right)\right] - T_q\right\} \end{aligned} \tag{16}$$

Constraints:

$$\sum_{i=1}^{m+n}\sum_{m=1}^{m}\sum_{k=1}^{K} x_{ijkm} = 1, j \in \{m+1, m+2, ..., m+n\} \tag{17}$$

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

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

$$\sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{m=1}^{m} x_{ijkm} = 0, \forall k \in \{1,2,...,K\} \tag{20}$$

$$\sum_{i=1}^{m+n}\sum_{j=m+1}^{m+n}\sum_{k=1}^{K}\sum_{m=1}^{m} q_i x_{ijkm} \le Q, \forall k \in \{1,2,...,K\} \tag{21}$$

$$t_{jk} = t_{ik} + \frac{d_{ij}}{v_1} + \frac{q_i}{v_2} \tag{22}$$

Equation (17) represents that each customer can only be served one time by one vehicle. Equation (18) and (19) regulate that the vehicle starts from the depot and does not need to return to the depot after serving the last customer. Equation (20) avoids the vehicle travelling directly form one depot to another. Equation (21) shows that the vehicle cannot overload during the delivery. Equation (22) characterizes that the delivery process is continuous.

4 Computation and Experiments

4.1 Algorithm design

Although taking more variables and constraints into consideration, the proposed JD-GVRP model is a derivative of the VRP model. They share the same calculation principles and natures. As VRP is an NP-hard problem (Raff, 1983; Shen et al., 2018), whereupon JD-GVRP is an NP-hard problem as well. To work out this complex model efficiently, heuristic algorithms are required to be applied (Kuo, 2010). As one of the heuristic algorithms, Simulated Annealing (SA) is inspired by an analogy presenting the physical annealing in solids. This paper adopts SA algorithm to solve the proposed model for the following reasons: firstly, SA is one of the most flexible and promising algorithms to solve combinatorial optimization problems (Kirkpatrick et al., 1983). It has a simple calculation structure, a good generality, and the strong robustness. Secondly, SA aims to gradually generate the optimal solution through continuously decreasing the temperature. Therefore, compared with the wide area search algorithm (such as genetic algorithm), SA can reflect the depth of excavation feature. Thirdly, SA randomizes the local search procedure and accepts changes that worsen the solution with some probability (i.e., Boltzmann distribution). This could avoid the optimization process be captured in a suboptimal solution to some extent. As a neighborhood search heuristic, SA helps to improve the intensification and exploitation of the solution. Finally, scholars found SA can fit well for solving VRP, especially for optimizing multi-variable and multi-degree-of-freedom composite systems. VRP and associated problems have been solved effectively by applying SA (e.g., Chiang et al., 1996; Kuo, 2010; Lin et al., 2011; Mousavi and Tavakkoli-Moghaddam, 2013; Yu and Lin, 2015; Shaabani and Kamalabad, 2016; Yu et al., 2017; Wei et al. 2018). For example, Lin et al. (2011) investigated the truck routing problem by considering the time window. They found that SA could generate the optimal solution quickly. Moreover, Yu and Lin (2015) and Yu et al. (2017) also verified that SA could significantly save computation time by quickly generating more accurate solution. Furthermore, Van Breedam (1995, 2001) compared SA and other heuristic approaches and summarized that SA has advantages in reducing the ‘run time’ and accuracy. The existing literature verifies SA’s effectiveness in solving VRP and its variants. Hence, to effectively solve the defined problem in this study and to overcome the early convergence (Chiang et al., 1996; Lee et al., 2007; He et al., 2014), SA is selected to efficiently deal with multiple variables and a large number of constraints. The analysis steps of SA are shown in Figure 4.

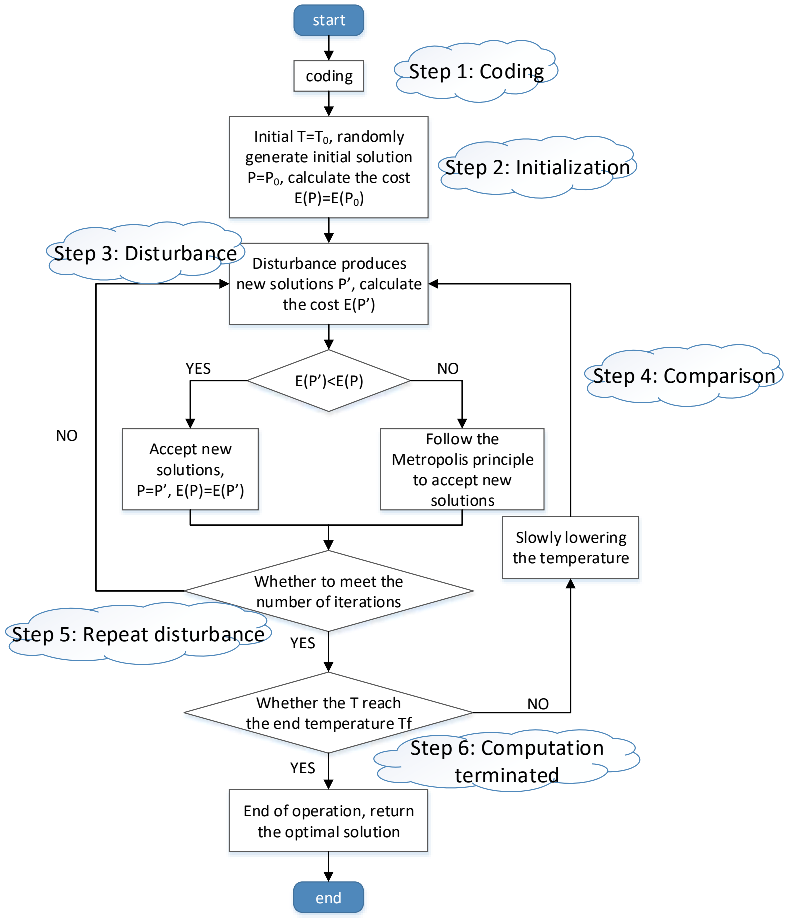


Figure 4. The analysis steps of SA

Step 1: Coding

This paper uses real numbers for coding. Negative numbers (-1, -2, -3 ..., -n) indicate depots, and positive numbers (1, 2, 3 ..., m) indicate customers. For example, the code numbers "-1, 1, 2, 4, -2, 3" express that two vehicles are needed to service four customers from two depots, and the detailed routes are O_1-1-2-4 and O_2-3.

Step 2: Initialization

We start with T=T_0, which is the initial temperature when the annealing starts. The initialization parameters are set, and an initial solution P_0 is randomly generated. For every customer, we assign one vehicle from one distribution randomly, which means generating m different paths, and each vehicle does not exceed its maximum load. For example, P_0 = "-4, 1, -2, 3, -3, 2 ..., -1, m". Then, we calculate the cost of route P=P_0, which is $E(P)$ =$E(P_0)$.

Step 3: Disturbance

In the process of cooling, we make T=T'. The disturbance is performed according to the present solution P, and a new solution P' is generated; next, the cost $E(P')$ is calculated.

Step 4: Comparison

If $E(P')$ is smaller than $E(P)$, we accept P' as the present state to optimize the solution; otherwise, we accept the new solution P' following the probability of $\exp((E(P)-E(P'))/T_i)$.

Step 5: Repeat disturbance

Repeat the disturbance and acceptance process at temperature T_i until it meets the specified number of the iterations.

Step 6: Computation terminated

Determine whether the temperature T has reached the end temperature T_f. If it arrives at this end temperature, the algorithm stops and outputs the optimal distribution scheme. Otherwise, continue cooling down and repeat step 3, step 4.

4.2 Case study

The empirical data comes from four cold chain logistics companies in Chengdu, China. They distribute the same frozen food to their customers who are located in the central regions of Chengdu. Each cold chain logistics company operates independently and has one depot that serves seven customers, which is relatively small in scale. As a result of adopting the single distribution mode, each company has a large upfront investment in the depot and a high distribution cost, which results in a low profit level for a long time. In addition, the specific cold chain product and the uncertainty of the market demand lead to a low customer demand but a high distribution frequency. Hence, the cold chain logistics companies need to distribute a very low amount of cold chain products serval times every day. These characteristics of the empirical data used in this study conform to the real situation of the cold chain logistics industry. Thus, the selected data can represent the Chinese cold chain logistics industry and reflects its features. The empirical data for our case study is taken from Wang (2018). Wang (2018) studied the optimal deliver path of cold chain products to minimize the total deliver cost by conducting joint distribution. However, it ignored the environmental impact during the transportation. Therefore, this paper takes carbon trading mechanisms into consideration to extend the environmental focus of GVRP in the cold chain logistics industry.

The location of each depot and the original group information on the customers are shown in Table 3. The first customer to the 7th customer belong to depot one (O_1), the 8th customer to the 14th customer belong to depot two (O_2), the 15th customer to the 21st customer belong to depot three (O_3), and the 22nd customer to the 28th customer belong to depot four (O_4). Table 4 shows customer locations, customer demands, and customer preferred time windows. Based on the real business data, we set parameters by following the standard procedure in works of Wang et al. (2018), Huang et al. (2018), and Chen et al. (2019). Table 5 shows the detailed settings of parameters.

Table 3. The location of each depot

Depots	X(km)	Y(km)	Customers
O_1	12.2	23.6	1.2.3.4.5.6.7
O_2	25	17.7	8.9.10.11.12.13.14

O_3	2	2.1	15.16.17.18.19.20.21
O_4	18	7.5	22.23.24.25.26.27.28

Table 4. Customer locations, demands, and time windows

Customers	X (km)	Y (km)	Demands (*t*)	Time window
1	14.1	14.4	0.6	10:30-11:00
2	25	15	0.4	10:00-10:30
3	17.2	15.8	0.9	10:30-11:00
4	12.6	11.8	0.9	10:00-10:30
5	11.6	16.1	1.3	10:30-11:00
6	13.3	18.9	0.6	11:00-11:30
7	14.45	11.1	0.4	10:30-11:00
8	7.1	21.4	1.2	10:00-10:30
9	1.2	25.7	0.6	11:00-11:30
10	18.7	12.5	1.2	10:00-10:30
11	15.47	13.5	1.2	10:00-10:30
12	17.8	16	1	10:00-10:30
13	14.64	15.56	0.2	10:00-10:30
14	10.8	14.05	1	11:00-11:30
15	11.5	11.3	0.5	11:00-11:30
16	18.2	16	0.9	11:00-11:30
17	6.2	12.8	1.3	10:00-10:30
18	14.03	9.5	1.2	10:00-10:30
19	16	9.1	0.5	11:00-11:30
20	10.2	18.2	0.7	10:00-10:30
21	16.3	15.3	0.3	11:30-12:00
22	22.1	6.9	0.8	10:30-11:00
23	5.8	8.6	0.3	10:00-10:30
24	17.6	14.14	1.2	11:00-11:30
25	11	10.2	0.2	10:00-10:30
26	13.1	15.8	0.8	11:00-11:30
27	17.1	17	0.6	10:30-11:00
28	21.9	6.6	0.6	10:00-10:30

Table 5. Parameter settings in the case study

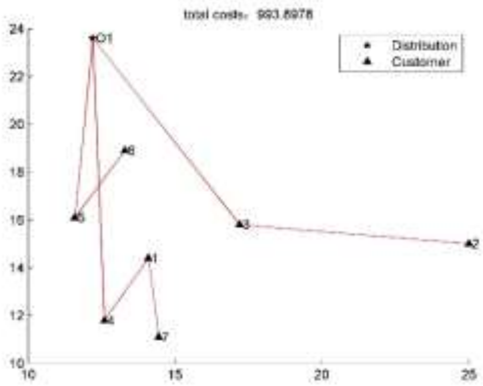
Symbols	Description	Unit	Value
m	Number of depots	none	4
n	Number of customers (all)	none	28
F_1	Fixed cost of each vehicle	RMB/car	200
F_2	Transportation cost of per unit distance	RMB/km	3
F_3	Cold chain products' price per unit	RMB/t	5000
F_4	Fuel price per unit	RMB/L	6.68
F_5	Waiting cost due to the early arrival	RMB/h	50
F_6	Punishment cost due to the late arrival	RMB/h	50
F_7	Carbon price	RMB/kg	0.25
$\mathcal{E}_1$	The deterioration rate of the product freshness during transportation	none	1
$\mathcal{E}_2$	The deterioration rate of the product freshness during unloading	none	0.9
θ	Cold chain products' sensitivity factor	none	0.002
v_1	Vehicle speed	km/h	40
v_2	Unloading speed	t/h	3.6
α_1	The fuel consumption of refrigeration equipment per unit time during transportation	L/h	2
α_2	The fuel consumption of refrigeration equipment per unit time during unloading	L/h	2.5
ρ_0	The fuel consumption per unit distance (empty load)	L/km	0.165
ρ^*	The fuel consumption per unit distance (full load)	L/km	0.377
Q	The maximum load capacity of a refrigerated truck	t	2
Tq	Carbon emissions quotas	kg	100
η	The coefficient values of the carbon emissions	kg/L	2.63

4.3 Evaluation of the model

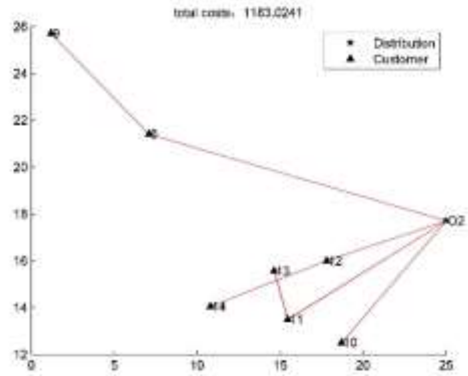
By comparing the single and joint distribution modes, we set the carbon price to 0.5 RMB/kg. the 25 kg carbon quotas are given for each company in the single distribution mode. For the join distribution, a total of 100 kg carbon quotas is given. After conducing 20 times comparison (results are identical), the optimal solutions are summarized in Table 6. Figures 5 and 6 shows the optimized deliver paths.

Table 6. The comparison between the single and joint distribution mode

Distribution mode	Total costs (RMB)	Carbon emissions (kg)	Fleet size	Distance (km)
Single distribution	4195.36	230.28	13	203.73
Joint distribution	3910.08	172.09	12	132.61
Rate of decline	6.80%	25.27%	7.69%	34.91%



(a)



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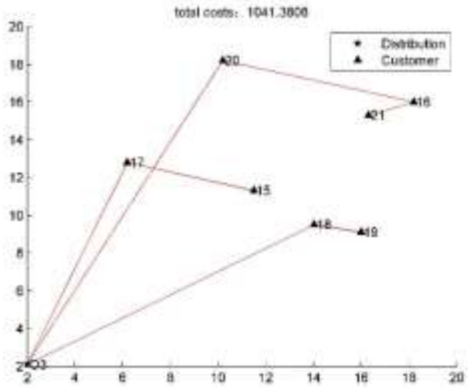

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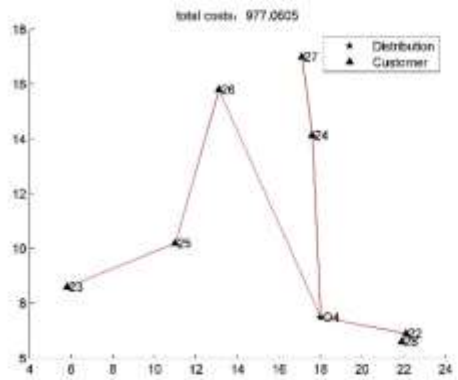


(d)

Figure 5. The optimized delivery routes for the single distribution mode

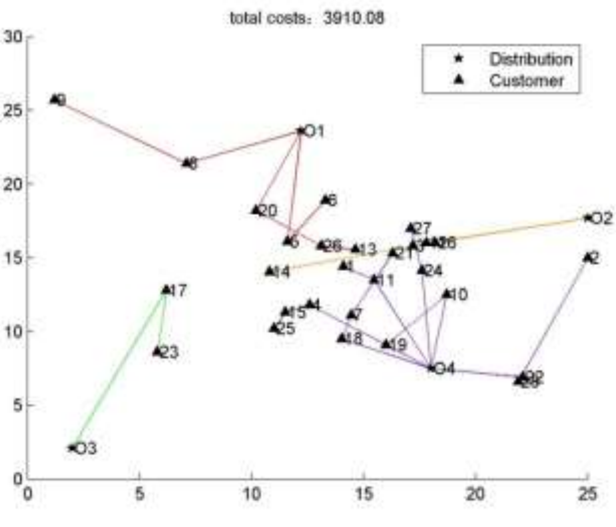


Figure 6. The optimized delivery routes for the joint distribution mode

According to Table 6, the total cost of the joint distribution mode is 3910.08 RMB, which is lower than the figure of the single distribution. Hence, cold chain logistics companies could save 6.8% cost by collaborating to adopt joint distribution. Moreover, carbon emissions are greatly dropped 25.27% by conducting joint distribution. Hence, JD-GVRP model could significantly contribute to reducing the environmental impacts. In addition, when joint distribution is applied, the fleet size can be reduced approximately 7.69%, and the delivery distance can be reduced by approximately 34.91%. In summary, adopting the JD-GVRP model could achieve both economic and environmental benefits simultaneously.

4.4 Analysis of the carbon price and carbon quotas

4.4.1 Analysis of the carbon price

In the above section, we adopted the average carbon price in the market. As time goes by, the carbon price is likely to rise or fall. Thus, this section considers 23 different sets of carbon prices with fixed carbon quotas (100 kg) in joint distribution to analyse the changing trends of carbon emissions, carbon costs, and total costs.

Table 7. The results of a comparative test in which the carbon price changes.

Carbon price (RMB/kg)	Carbon emissions (kg)	Carbon cost (RMB)	Total costs (RMB)	Carbon cost / Total costs
0	167.0981	0	3851.85	0.00%
0.25	171.0061	17.75	3866.51	0.46%
0.5	172.0927	36.05	3910.08	0.92%
0.75	168.6557	51.49	3918.93	1.31%
1	166.2666	66.27	3923.73	1.69%
2	163.5253	127.05	4021.48	3.16%
3	160.7612	182.28	4059.10	4.49%
4	159.7335	238.93	4112.71	5.81%
5	158.9456	294.73	4168.41	7.07%
6	158.1267	348.76	4213.52	8.28%
7	156.6943	396.86	4287.78	9.26%
8	155.4470	443.58	4369.30	10.15%
9	154.5189	490.67	4384.63	11.19%
10	153.0256	530.26	4396.52	12.06%
12	151.1894	614.27	4489.67	13.68%
14	149.2872	687.22	4569.63	15.04%
16	147.3684	757.89	4631.18	16.37%
18	145.6749	822.15	4741.94	17.34%
20	144.9528	899.06	4855.45	18.52%
24	144.7535	1074.08	5048.53	21.28%
28	144.8535	1255.90	5336.22	23.54%
34	144.4331	1510.73	5668.28	26.65%
40	144.6923	1787.69	5872.99	30.44%

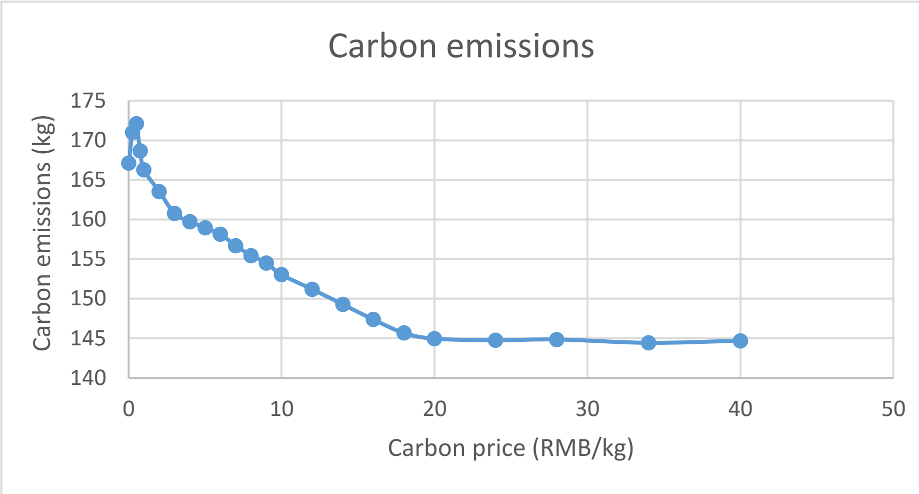


Figure 7. The changing trend of carbon emissions

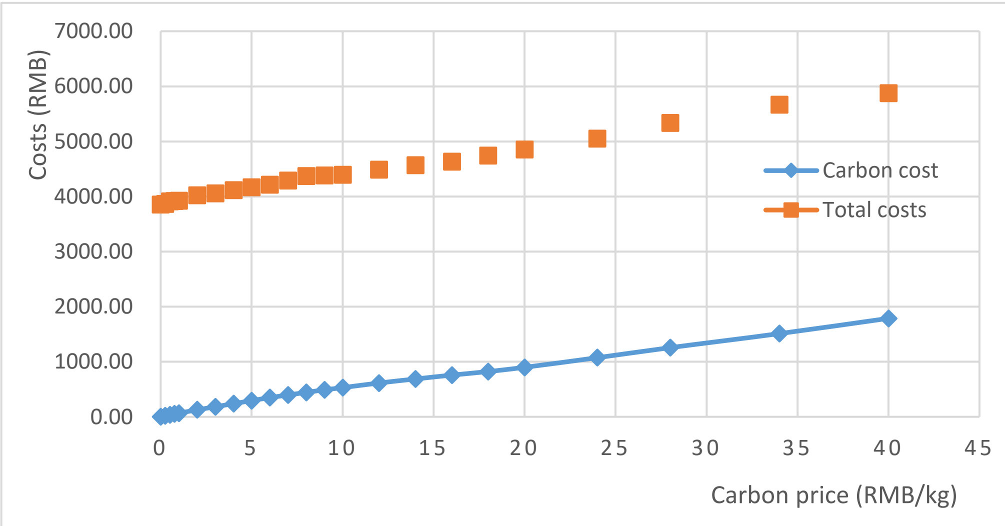


Figure 8. The changing trend of carbon costs and total costs

According to Table 7 and Figures 7 and 8, carbon emissions increase when the carbon price is in the [0, 0.5] interval. When the carbon price increases to the [0.5, 20] interval, carbon emissions continuously decrease, especially in the interval [0.5, 3]. The reduction of carbon emissions in [0.5, 3] interval occupies 41.75% of the total reduction of carbon emissions with an average reduction rate of 1.69%. In the interval [3, 20], the average reduction rate of carbon emissions is only 0.86%. When the carbon price jumps to the [20, 40] interval, the carbon emissions basically remain unchanged.

As the carbon price rises, the carbon cost increases. According to Equation (15) and Figure 7, although carbon emissions are reduced, carbon costs still rise due to the high carbon prices. In addition, total costs increase with the mounting carbon price. From Table 7, carbon costs occupy up to 30.44% of total costs, which identifies that the cost of carbon emissions significantly determines total costs as the carbon price becomes more and more expensive.

4.4.2 Analysis of carbon quotas

The effect of carbon quotas on carbon emissions, carbon costs, and total costs will be studied in this section. We selected three sets of data (carbon prices at 0.5 RMB/kg, 0.75 RMB/kg, and 1 RMB/kg) in which the carbon emissions could be effectively reduced. We then studied the impact of six different sets of carbon quotas on the optimal distribution solution. The results are shown in Table 8 and Figures 9 to 16.

Table 8. The results of the comparative test when the carbon quotas are changed

Carbon price (RMB/kg)	T_q (kg)	Carbon emissions(CE) (kg)	CE - T_q (kg)	Carbon cost (RMB)	Total costs (RMB)
0.5	0	172.0927	172.0927	86.05	3960.08
	50	172.0927	122.0927	61.05	3935.08
	100	172.0927	72.0927	36.05	3910.08
	150	172.0927	22.0927	11.05	3885.08
	200	172.0927	-27.9073	-13.95	3860.08
	250	172.0927	-77.9073	-38.95	3835.08
0.75	0	168.6557	168.6557	126.49	3993.93
	50	168.6557	118.6557	88.99	3956.43
	100	168.6557	68.6557	51.49	3918.93
	150	168.6557	18.6557	13.99	3881.43
	200	168.6557	-31.3443	-23.51	3843.93
	250	168.6557	-81.3443	-61.01	3806.43
1	0	166.2666	166.2666	166.27	4023.73
	50	166.2666	116.2666	116.27	3973.73
	100	166.2666	66.2666	66.27	3923.73
	150	166.2666	16.2666	16.27	3873.73
	200	166.2666	-33.7334	-33.73	3823.73
	250	166.2666	-83.7334	-83.73	3773.73

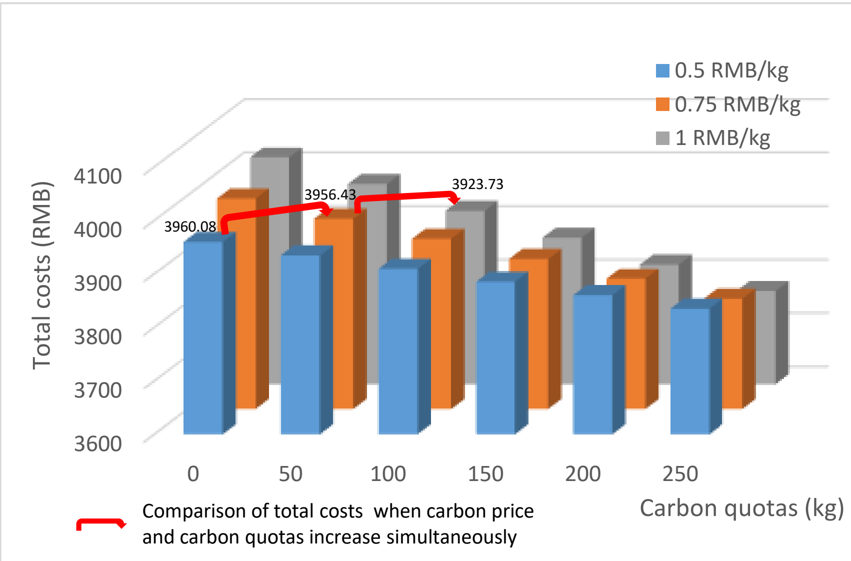


Figure 9. The total costs under different carbon prices and carbon quotas

According to Table 8, for each data set, carbon costs and total costs decline when carbon quotas increase. Based on Equation (15), the carbon cost is determined by carbon emissions and carbon quotas (i.e., CE-T_q). Therefore, when the carbon price is fixed, carbon quotas regulate carbon costs and total costs. When the carbon quota is fixed, the higher the carbon price is, the greater the absolute value of carbon costs. In addition, with the increasing carbon price, total costs will change more and more drastically.

As shown in Figure 9, the red line demonstrates that total costs continuously decline when both the carbon quota and the carbon price are increasing. This trend proves that when the carbon price and the carbon quota increase at the same time, both the total cost and the carbon emission can be reduced simultaneously. Therefore, the government can achieve energy conservation and emissions reduction without increasing the cost incurred on the companies by carefully adjusting the carbon price and the carbon quota.

The delivery path could significantly influence carbon emissions as the travel distance directly determines the fuel consumption. However, the relationship between the delivery path and the carbon quota is not well explored. Thus, by setting the carbon price at a fixed value (i.e., 0.75 RMB/kg), Figures 10 to15 show the optimal delivery path with different carbon quotas. The delivery path remains the same when the carbon quota increases. The same results have been generated after experimenting with multiple sets of carbon prices. Thus, the distribution path is independent from the carbon quota when the carbon price is fixed.

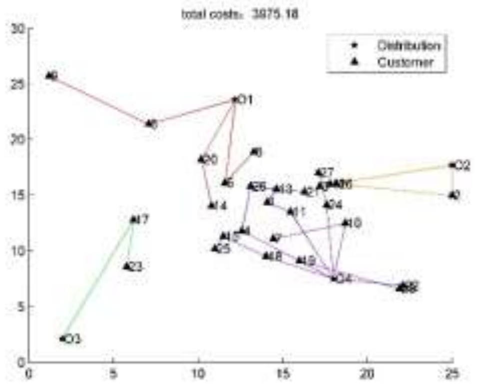


Figure 10. Distribution paths when T_q is 25.

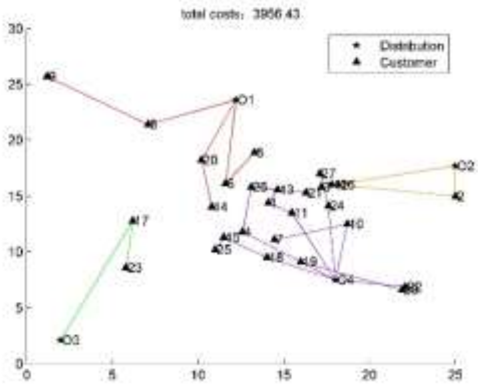


Figure 11. Distribution paths when T_q is 50.

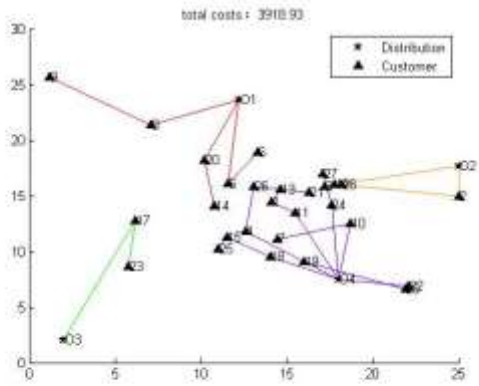


Figure 12. Distribution paths when T_q is 100.

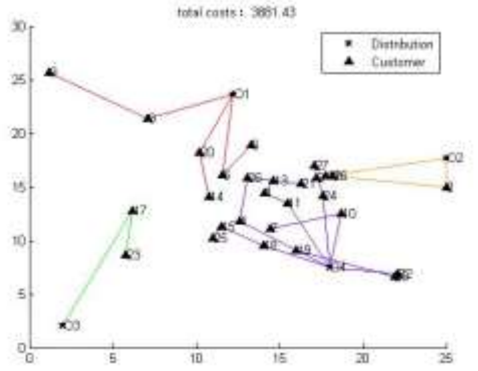
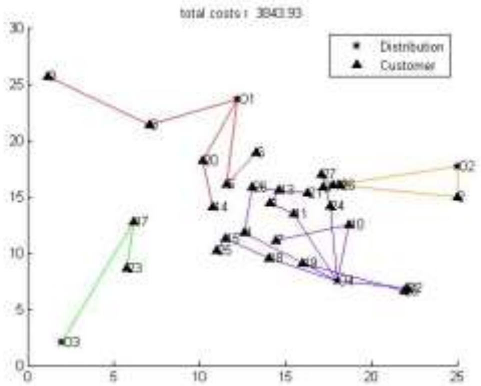


Figure 13. Distribution paths when T_q is 150.



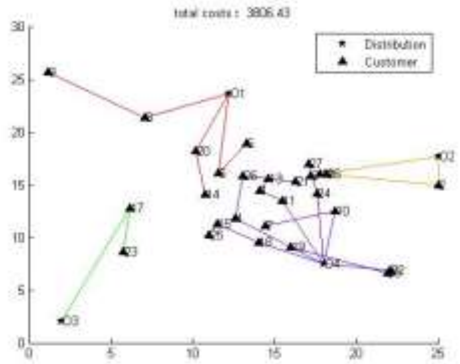


Figure 14. Distribution paths when T_q is 200. **Figure 15.** Distribution paths when T_q is 250.

Furthermore, to advance the impact of the carbon trading mechanism on the total cost, we use all carbon prices in Table 7 and all carbon quotas in Table 8 to perform a full simulation. Figure 16 presents the results, which are consistent with previous experiments. When the carbon price is fixed, the total cost decreases with the increasing carbon quotas. When the carbon quota is fixed, the total cost will fluctuate more and more drastically with the rising carbon price. It means that the total cost will increase with the rising carbon price if the carbon emission exceeds the carbon quota. Otherwise, the total cost will keep decreasing with the rising carbon price as the cold chain logistics could sell the surplus carbon quota. Furthermore, the redline indicates that the total cost could be reduced by simultaneously increasing the carbon price and the carbon quota.

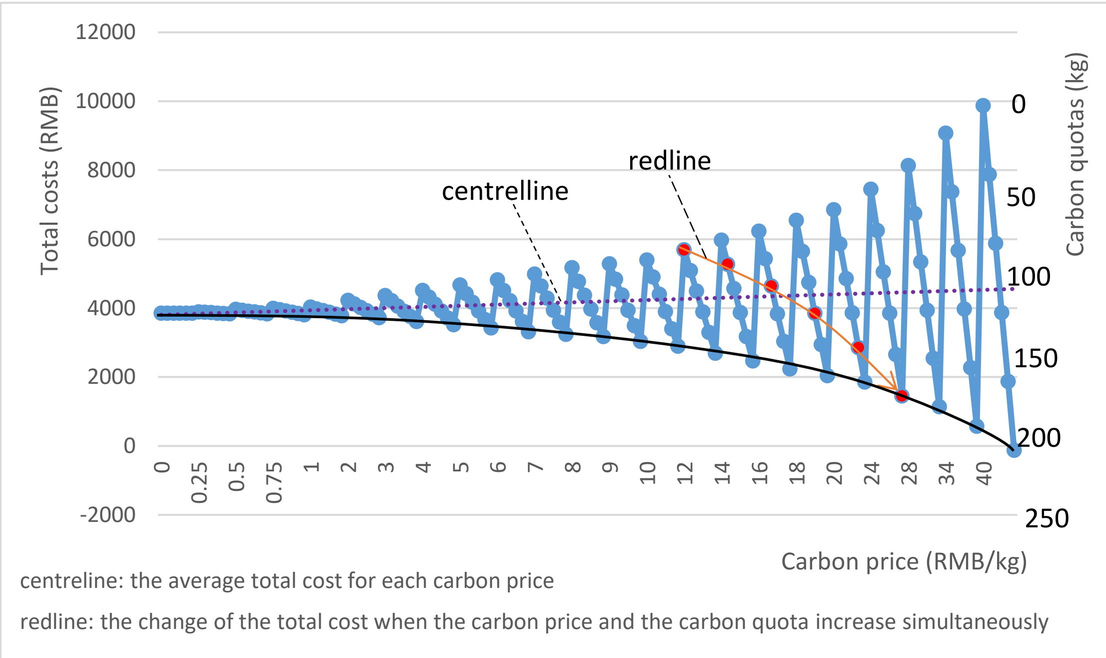


Figure 16. The simulated results of the carbon trading mechanism

5 Discussion and Managerial Implications

This paper proposes the JD-GVRP model to reduce the total distribution cost and carbon emissions. By conducting joint distribution through the industrial level collaboration, cold chain logistics companies could save costs, hire fewer vehicles, travel shorter distances, and contribute more to the environment. The government could motivate cold chain logistics companies to participate in joint distribution by carefully adjusting the carbon price and the carbon quota. The discussion is itemized as follows:

(1) The JD-GVRP model can simultaneously consider the damage cost, the refrigeration cost, and the carbon cost, which results in a more practical solution to cope with the real business environment of the cold chain logistics industry. By running experiments with the empirical data, this study verifies that conducting joint distribution by sharing resources among cold chain logistics companies could effectively achieve economic and environmental benefits.

(2) The carbon price is an essential factor in optimizing the cold chain product delivery. When the carbon price is in a very low range [0, 0.5], companies do not make efforts to optimize transportation arrangements as the carbon cost is extremely low. Thus, they would not pay much attention to how to reduce carbon emissions or even resist reducing carbon emissions. As the carbon price goes up to the interval [0.5, 20], carbon emissions can be reduced effectively. The prominent carbon emission reduction in the interval [0.5, 3] indicates that the carbon price could significantly regulate cold chain logistics companies to exhaust greenhouse gas. In this carbon price interval, companies are sensitive to the carbon price and they will shorten the distribution distance and lower the refrigeration cost to reduce the fuel consumption, which in turn reduce the carbon emissions. In the carbon price interval [3, 20], companies keep trying to reduce carbon emissions by optimizing the delivery paths. However, the reduction rate of carbon emissions is lower than that of the interval [0.5, 3]. As the carbon price continues to rise, the carbon emission will almost remain the same. This illustrates that cold chain logistics companies will experience increasing difficulties in reducing carbon emissions by routes optimization when the carbon price rise to 20 RMB/kg. As the technical ability of the cold chain logistics companies is limited, they will definitely suffer profit loss to meet the everchanging customer demands.

(3) The carbon quota dose not determine the delivery path but significantly influences the total cost. When the carbon price is fixed, the total cost decreases with the increasing carbon quota. However, carbon emissions will remain the same. When the carbon quota is lower than the carbon emission, the total cost is positively correlated to the carbon price. In contrast, when carbon quota is higher than the carbon emission, the total cost is negatively correlated to the carbon price.

(4) By simultaneously increasing the carbon price and the carbon quota, an optimal result that is both economically beneficial and environmentally friendly will be achieved. Therefore, the government can achieve the sustainable development goal without bring the economic burden to cold chain logistics companies by setting reasonable carbon prices and allocating sufficient carbon quotas.

Based on the above discussion, some recommendations for cold chain logistics companies and the government are provided below.

For cold chain logistics companies, they are obliged to pay more attention to reduce the total distribution cost and carbon emissions to cope with the ferocious competition and sustainable development agenda. In order to achieve these goals, firstly, they should consider adopting joint distribution. By working closely with each other and reinforcing the collaboration at the industry level (e.g., sharing depots and vehicles, jointly planning delivery schedules and paths), cold chain logistics companies could significantly reduce the delivery distance, carbon emissions, total cost, and fleet size. Hence, they can ultimately improve operational efficiency and achieve competitiveness. Secondly, as the carbon quota is being tightened, cold chain logistics companies need to implement new technologies to ensure their carbon emissions comply with the government's policy. Efforts should be made to improve the delivery route planning, develop more efficient engines, and replace normal transportation facilities/equipment by electronic vehicles and others that consume renewable resources. As the government and customers have more in-depth understandings of sustainability, cold chain logistics companies should cogently consider the carbon tax policy in delivery path planning to improve their awareness of environmental protection, actively work in concert with the government's low-carbon policy, and build up their business reputation in the society.

The government is the significant actor of reducing carbon emissions by setting the policy (e.g., regulations, taxation, and incentives). Hence, providing the good governance will be conducive to the sustainable development of the cold chain logistics industry. Firstly, the government needs to promote the joint distribution model to individual companies and the whole industry. For example, the government should urge companies to establish cold chain logistics alliances and encourage cooperation among cold chain logistics companies by providing preferential tax policy. Secondly, the government should advocate the cooperation between logistics companies and manufacturers of transportation facilities to better develop green logistics technology. Moreover, the government should invest the infrastructure to ensure the application of new technology. For example, the number of charging pile should be significantly enlarged. Thirdly, the government should set the carbon price at a suitable level to motivate cold chain logistics companies to cut carbon emissions. For example, in our case, cold chain logistics companies are most sensitive to the carbon price range [0.5, 3]. Hence, setting the carbon price in this range can effectively urge cold chain logistics companies to shorten the delivery distance, optimize delivery path, lower refrigeration usage, and reduce fuel consumption.

6 Conclusions and Future Work

The severe environmental pollution and the high energy consumption make the green economy extremely important in present, especially in the cold chain logistics industry. This study proposes the JD-GVRP model to minimize the total cost and carbon emissions. It makes three contributions to the theory and the industry. First, it fills the gap of insufficient research on joint distribution by applying the JD-GVRP in the cold chain logistics industry. The results prove that joint distribution makes a great improvement in terms of both the economic efficiency and environmental protection. Second, this study contributes to the VRP model. Six different costs (i.e., the fixed cost, the transportation cost, the damage cost, the refrigeration cost, the penalty cost, and the carbon cost) are considered to expand the VRP model to cope with the characteristics of the cold chain logistics industry. Third, the carbon trading mechanism is introduced to the cold chain logistics industry. The impact of carbon prices and carbon quotas on carbon emissions and total costs are analysed, which verifies the positive effects of the carbon trading mechanism on reducing carbon emissions.

This study provides constructive advices for the cold chain logistics industry to develop effectively. Some decision support approaches are proposed for managers in third-party logistics companies. The logistics companies will consider re-engineering the distribution paths, and the government can also formulate more valuable carbon emission policies. Companies and governments should work together to create a good carbon emissions environment and to promote green economic development.

There are several limitations that guide the future research directions. This paper assumes that the speed at which the vehicle is transported is constant without considering uncertain factors, such as traffic congestion or driver factors. In addition, after adopting joint distribution, the changes in the efficiencies of the individual companies are not accounted for. Thus, the improvement of profits for each company is a further research direction.

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