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# An Improved Distribution Cost Model Considering Various Temperatures and Random Demands: A Case Study of Harbin Cold-Chain Logistics

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**ABSTRACT** This paper explores a more applicable distribution scheme to reduce the distribution cost from the perspective of various influencing factors in the distribution process. We comprehensively considers the effect of temperature changes on the decay rate of fresh products during unloading, the carbon emission costs during transportation and cold storage, customer satisfaction, as well as the traffic situation of the actual distribution route. On this basis, a distribution cost model is constructed. And the improved genetic algorithm is used to solve the problem. In addition, we also conducted sensitivity analysis on different customer demands, so as to put forward some management enlightenment to business managers. An analytical investigation of a case study in Harbin indicates that reasonable transportation path planning can effectively reduce the total distribution cost. Hence, the proposed distribution scheme can serve as an effective and socially feasible method in cold chain logistics management to reduce logistics costs.

**INDEX TERMS** Cold chain logistics, vehicle routing problem, cargo damage cost, genetic algorithm, carbon emission.

## I. INTRODUCTION

With the increasing scale of cold chain logistics, the problem of cold chain logistics distribution has become increasingly serious. This issue has caused many negative effects, including direct economic losses caused by the spoilage of fruits, vegetables, meat, etc., and an increase in the operation cost of enterprises. The data show that agricultural products suffer serious losses after entering the circulation field. The spoilage rates of fruits and vegetables, meat, and aquatic products have reached 30%, 12%, and 15%, respectively.

Among them, the annual loss of fruits and vegetables exceeds \$12.5 billion, accounting for more than 30% of the output value of the entire industry [1]. Path planning is a distribution management method that has proven to be effective in some cases [2], [3]. Previous studies showed that it can rationally plan the distribution path and shorten the transportation time, thereby reducing the spoilage rate and increasing the benefits of enterprises.

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In rapidly developing countries such as China, most fresh food still circulates at room temperature, so it is necessary to plan reasonable paths to shorten the distribution time as much as possible. Statistics show that the hardware facilities of cold chain logistics in China are relatively perfect, but unreasonable path planning leads to an increase in distribution time. For example, the ''Report on the Development of Cold Chain Logistics for Agricultural Products'' in 2018 showed that by the end of 2017, the warehousing area of cold chain logistics in China had increased by 13.7% to 119.37 billion cubic meters, and the number of refrigerated vehicles increased by 16.5% year-over-year to 134,000 [1]. However, due to unreasonable path planning, the annual economic loss caused by the decay of fruits and vegetables in China is as high as \$1.07 million. Therefore, to solve the problem of cold chain logistics distribution, the key point is to plan a reasonable path.

The basic principle of path planning is to realize the minimum transportation cost or the shortest path [4], [5]. By adding constraints such as load, running route, and working time, we can design the route and manage the distribution time. Therefore, we need to consider various constraints to meet the actual situation of cold chain logistics and transportation of fresh products and develop an effective path planning method to achieve optimal transportation efficiency.

For example, many studies have considered the linear or non-linear decay rate of fresh food in the actual transportation process [6]. But in fact, the change of temperature has a great influence on the reaction rate of deterioration, especially in the process of unloading. In addition, at present, low-carbon economy is the only way for the sustainable development of cold chain logistics, and it is also an important direction of economic development. Only by reducing carbon emissions can we achieve a win-win situation of economic development and environmental protection [7]. In cold chain logistics distribution, researchers should consider not only the above constraints but also the customer satisfaction degree and the traffic situation of the actual distribution route.

Some researchers have explored path planning to obtain the shortest route. For example, Clarke and Wright (1964) [8] proposed a change in the solution of the classical vehicle routing problem (VRP) and generated a metaheuristic algorithm. They found that a metaheuristic algorithm can improve the computational efficiency of VRP. This lays a foundation for researchers to develop a variety of calculation methods.

In addition, Mohammed and Ghani (2017) [9] designed an improved genetic algorithm for solving the VRP model. This can reduce the distribution time. Experimental results showed that compared with existing linear programming methods, the designed genetic algorithm has better optimization ability.

In recent years, research on cold chain logistics distribution has concentrated on solving the VRP [10]–[14]. However, considering the spoilage of fresh food and the complex traffic environment, researchers found that the shortest paths may not necessarily lead to the lowest distribution cost. In 2014, P. Amorim [15] studied the spoilage of fresh food and developed a distribution model with the goal of maximizing freshness. They found that if the shortest path is chosen, then the goods need to be unloaded and loaded many times, which increases the overall distribution time. Moreover, due to frequent loading and unloading, the spoilage rate of fresh food increases rapidly. Therefore, researchers need to consider different processes of cold chain logistics distribution such as transportation, loading, and unloading. Thus far, few studies can comprehensively consider the influencing factors mentioned above.

Moreover, we should also conducted sensitivity analysis on some parameters in the model and discuss the influence of parameter changes on distribution costs, so as to give enterprises some inspiration on how to reduce distribution costs. Masudin *et al.* (2019) [16] develops the remanufacturing inventory model considering the storage capacity. He also indicates that factors such as warehouse capacity and number of cycles have an impact on the total inventory cost which provides management implications that companies can make appropriate policies to minimize total inventory cost.

Therefore, this paper comprehensively considers the effect of temperature changes on the decay rate of fresh products during unloading, the carbon emission costs during transportation and cold storage, customer satisfaction, as well as the traffic situation of the actual distribution route. On this basis, a distribution cost model is constructed. And the improved genetic algorithm is used to solve the problem. In addition, we also conducted sensitivity analysis on different customer demands, so as to put forward some management enlightenment to business managers. This study tries to provide theoretical references and practical insights for the effective analysis of distribution decision-making as well as an optimization of the distribution cost.The remainder of this paper is organized as follows. In Section 2, we present a review on cold chain logistics distribution in general. Section 3 analyzes the influencing factors during cold chain logistics distribution. The methodology, including variable selection and distribution cost model construction, is discussed in Section 4. Section 5 reviews the algorithm design for the model. Section 6 presents a case study. This paper concludes with Section 7, in which the authors summarize their findings and discuss the study limitations and directions for future research.

## II. LITERATURE REVIEW

The majority of the studies on cold chain logistics distribution focused on reducing the distribution cost. Some of them used economic theories including marginal cost pricing, price elasticity, and performance pricing to calculate distribution costs. For example, Bonney (1992) [17] used economic theories to analyze the composition of third-party logistics costs and pointed out that the benefits of enterprises can be improved by reducing distribution costs. These studies seldom considered the impact of other conditions such as customer satisfaction on distribution cost.

Certain studies focused on distribution decision-making under the influence of fresh food characteristics. G. Viji *et al.* (2018) [18] treated the spoilage rate of fresh food as a multifactor influence function or a normal distribution function and constructed an optimization objective model. They found that by converting the spoilage rate into an exponential function, the process of spoilage can be determined more accurately to find methods to slow down the spoilage, thereby reducing the distribution cost. Qi *et al.* (2020) [19] considered the damage of goods over time and the traffic situation of the actual distribution route to establish the emergency cold chain logistics scheduling model. Guike Liu *et al.* (2020) [20] and Chen *et al.* (2019) [6] divided the cost of cargo damage into the transportation process and the unloading process. But the above studies only considered the cost of cargo damage over time, and did not consider the impact of temperature changes on the corruption rate of fresh products during the unloading process. And apart from Qi *et al.* (2020) [19] considering the traffic situation of the actual distribution route, most other studies did not consider the traffic situation of the actual distribution route.

Mingxi Wang *et al.* (2021) [21] combines different aspects, such as considering the refrigeration energy consumption, the damage costs and the customer satisfaction. Although he considered the impact of temperature changes on product loss during unloading, they did not analyze the specific changes in temperature during unloading and their effects on the rate of deterioration reactions. Therefore, this paper will consider the influence of the change of temperature on the decay rate of fresh products during unloading, the customer satisfaction and the traffic situation of the actual distribution route.

Moreover, Zhang *et al.* (2019) [22] and Leng L *et al.* (2020) [23] found that there is little research on the cost of carbon emissions in logistics, especially in cold chain logistics, but now low-carbon logistics is more and more concerned by enterprises and scholars, and reducing carbon emissions is an inevitable trend in the logistics industry. how to cut carbon emissions and lower delivery costs are the key focuses in the cold chain logistics industry. Therefore, we also consider the carbon emission costs in the transportation process and the refrigeration process.

There are also some studies about solving VRP to obtain the lowest distribution cost. For example, Omar Dib *et al.* [24] used a metaheuristics method to solve routing problems in road networks. The results indicated that by optimizing the distribution path and shortening the distribution time, the distribution cost can be effectively reduced. A. I. Diveev and O.V. Bob (2017) [25] conducted an in-depth study on a metaheuristic method for solving VRP and introduced the successful application of genetic algorithms in solving vehicle routing problems. The research results showed that compared with existing linear programming methods, the genetic algorithm has better optimization ability and efficiency in finding the optimal path and calculating the lowest distribution cost.

Based on the findings of the above studies, in many distribution cost model studies, the traffic situation of the actual distribution route and the influence of the change of temperature on the decay rate of fresh products during unloading is not considered by many people. We also found that low carbon and customer satisfaction has gradually become the highest goal of cold chain logistics management. However, there are few studies on distribution cost comprehensively consider the influencing factors mentioned above. The majority of the studies consider only some but not all of the influencing factors. In addition, the sensitivity analysis of the changes of the parameters on model should be considered to understand the impact of the changes to the objective functions.

## III. FACTOR ANALYSIS

### A. REQUIREMENT ANALYSIS

In the cold chain logistics distribution, customer satisfaction is one of the important standards to measure the level of enterprise distribution [26]–[28]. We need to meet customer demand not only for the quantity and quality of fresh products but also for the distribution time under uncertain circumstances.

#### 1) CUSTOMER DEMAND ANALYSIS

Customer demand varies and is affected by many factors. For example, in different seasons, the quantity of fresh food purchased by customers is different. Previous studies assumed that customer demand is a known constant. However, in real distribution, constant customer demand cannot reflect the actual demand. Surveys have shown that the demand for small and medium supermarkets changes every day. Therefore, to meet the various distribution demands, this paper will convert customer demand into a random demand that obeys the normal distribution and set the satisfaction rate of customer demand.

#### 2) TIME DEMAND ANALYSIS

In addition to meeting various customer demands, we also need to meet the customer demand for time. However, real traffic conditions such as traffic jams, vehicle scheduling, and other issues invalidate hard time window constraints. Therefore, to solve the customer demand for time, the use of soft time windows is more suitable. In this paper, we will transform customer demand for time into soft time window constraints and simultaneously establish penalty-cost constraints.

### B. THREE-LAYER CARGO DAMAGE ANALYSIS

Osvald and Stirn found that the fresh-keeping cycle is divided into three stages and linearly decreases with time [29]–[31]. Chakrabarty introduced a more universal Weibull function in his research and considered that compared with the previous linear deterioration rate, the treatment of the deterioration rate of goods by a Weibull function is more in line with the actual deterioration [29]. The quality rate of goods in three stages is shown in Fig. 1:

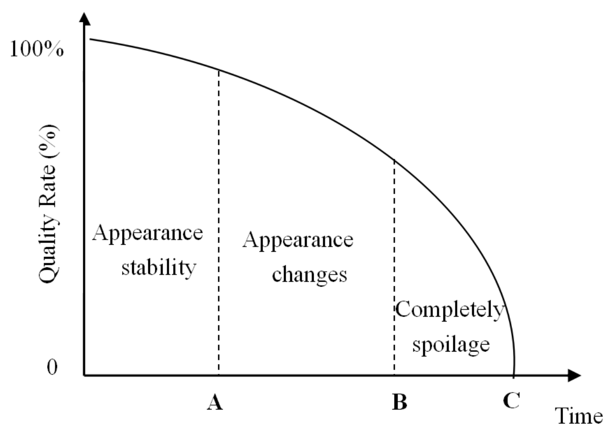


**FIGURE 1.** Three stages of fresh-keeping cycle.

As shown in Fig. 1, in general, the distribution time and temperature have a great impact on the quality of fresh food. The temperature will inevitably vary during the process of loading and unloading. Therefore, we should pay attention to the change in temperature to minimize the second-layer damage cost. Based on the above considerations, this paper divides the cargo damage in distribution into three layers.

The first-layer damage occurs when fresh food is transported from supply point $S$ to distribution center $D_i$, the second-layer damage occurs the process of $D_i$ inventory turnover in the distribution center, and the third layer involves damage from distribution center $D_i$ to demand point $B_j$.

### C. DISTRIBUTION LINK ANALYSIS

To decrease the spoilage rate, cold chain logistics distribution should ensure a refrigerated environment in the vehicle. However, the process of loading, unloading, and handling will inevitably increase the spoilage rate of fresh food. According to the analysis of cargo damage in Section 3.2, we will consider the cooling cost during transportation, loading, and unloading [32]–[34].

## IV. DETERMINATION OF DISTRIBUTION COST MODEL

### A. VARIABLE SPECIFICATION

Based on the factor analysis in Section 3, it is innovative to consider the cargo damage cost and related cost of the distribution link while meeting the random customer demand. In this paper, we use refrigerated trucks to distribute from one distribution center to multiple inventory points and customers. Therefore, we need to consider fixed costs and transportation costs. In cold chain logistics distribution, fresh foods need to be kept fresh at a constant temperature, so refrigeration costs will be incurred. At the same time, the distribution center and customers have corresponding constraints on the distribution time, so there will be cargo damage costs during transportation.

If the distribution center and inventory are out of stock, then a shortage cost will be incurred. In addition, if fresh food is not delivered within the specified time, then a penalty cost should be considered. Therefore, considering the fixed cost, transportation cost, refrigeration cost, cargo damage cost, shortage cost, and penalty cost, we construct a distribution cost model with the goal of maximizing social benefits. The variables are listed in Table 1. In addition, the following basic assumptions are made in this paper:

(1) Customer demand obeys a constant random distribution $F$.

(2) The refrigerated trucks start from a distribution center, pass through the inventory points and customers, and finally return to the distribution center.

(3) There is no midway assignment; that is, once the vehicle starts from a certain point, the next distribution point is determined.

### B. MODELING

#### 1) FIXED COST

The fixed cost includes the cost of purchasing or renting refrigerated trucks and the salary of the driver. We define the fixed cost of the $k$-$th$ refrigerated truck as $h$. In this paper, the fixed cost is expressed as follows:

$$C_1 = h \sum\nolimits_{j=1}^{n} \sum\nolimits_{k=1}^{m} x_{0,j}^{k} \tag{1}$$

**TABLE 1. Variables in distribution cost model.**

| Variable | Description | Variable | Description |
|---|---|---|---|
| $x_i$ | $i$-$th$ distribution link ($i$=1,2, …, $n$) | $X_0$ | distribution center |
| $k$ | $k$-$th$ refrigerated truck ($k$=1,2, …, m) | $c$ | transportation cost (CNY/h) |
| $h$ | fixed cost (CNY) | $f_e$ | refrigeration cost during transportation (CNY/h) |
| $\beta$ | shape parameter (β>0) | $f'_e$ | refrigeration cost during transportation (CNY/h) |
| $\alpha$ | scale parameter (α>0) | $\gamma$ | position parameter (γ>0) |
| $\varepsilon$ | Unit fuel carbon emission price (CNY/kg) | $P^*$ | Fuel consumption per unit time of vehicle under full load (L/h) |
| $\varphi$ | Carbon emission coefficient per unit fuel (kg/L) | $P_0$ | Fuel consumption per unit time of vehicle under no load (L/h) |
| $E$ | activation energy of reaction | $U$ | frequency factor |
| $L$ | molar constant of gas | $\theta$ | carbon emissions caused by refrigeration in process of vehicle distribution per unit mass of goods driving per unit time. |
| $\mathsf{T}$ | shortage cost (CNY/h) | $t^k_{i,j}$ | travel time of $k$-$th$ refrigerated truck |
| $p_i$ | unloading time of distribution link $x_i$ | $t^k_i$ | travel time when $k$-$th$ refrigerated truck arrives at distribution link $x_i$ |
| $Q_i$ | demand of distribution link $x_i$ | $z_k$ | carrying capacity of $k$-$th$ refrigerated truck |
| $Q_{max}$ | max carrying capacity of the $k$-$th$ refrigerated truck | $d_k$ | total demand of customer served by $k$-$th$ refrigerated truck |
| $a$ | cost of waiting time (CNY/h) | $b$ | penalty cost (CNY/h) |
| $[e_i,l_i]$ | time window of the distribution link $x_i$ | $[e_i,L_i]$ | acceptable time window of distribution link $x_i$ |
| $x^k_{i,j}$ | decision variable | $y^k_j$ | decision variable |
| $T$ | time point when spoilage rate is 100% | $T_0$ | time point when fresh food begins to deteriorate |
| $\sigma^k_{i,j}$ | intact rate of fresh food | $C_t$ | damage cost during transportation |
| $C_l$ | damage cost during loading and unloading | $z$ | price of fresh food (CNY) |

#### 2) TRANSPORTATION COST

In this paper, we choose the actual transportation time to calculate the transportation cost, and the impact of carbon emissions during vehicle transportation is considered to ensure the practicability of the model. The transportation cost $C_{21}$ is expressed as follows:

$$C_{21} = c \sum\nolimits_{k=1}^{m} \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{n} t_{i,j}^{k} x_{i,j}^{k} \tag{2}$$

The vehicle fuel consumption $P_{I,J}$ and cost of carbon emissions in the course of transportation $C_{22}$ can be expressed as follows [35]:

$$P_{i,j} = (P_0 + \frac{P^* - P_0}{Q_{max}} Q_i) t_{i,j}^{k} \tag{3}$$

$$C_{22} = \varepsilon \sum\nolimits_{k=1}^{m} \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{n} \varphi P_{i,j} x_{i,j}^{k} \tag{4}$$

Therefore, the total transportation cost $C_2$ is calculated as follows:

$$\begin{aligned} C_2 &= C_{21} + C_{22} \\ &= c\sum_{k=1}^{m}\sum_{i=0}^{n} t_{i,j}^{k} x_{i,j}^{k} \\ &\quad +\varepsilon\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}\varphi P_{i,j} x_{i,j}^{k} \end{aligned} \tag{5}$$

### 3) THREE-LAYER DAMAGE COST

Based on an analysis of the three-layer damage in Section 3.2, the deterioration rate of cold chain logistics goods obeys a Weibull distribution, and the function of the deterioration rate is as follows:

$$F_{(t)} = \begin{cases} 1 - e^{-\alpha(t-\gamma)^{\beta}}, & t > \gamma \\ 0, & t \leq \gamma \end{cases} \tag{6}$$

When the *k-th* refrigerated truck moves from distribution link $x_i$ to $x_j$, the intact rate of fresh food is as follows:

$$\delta_{i,j}^{k} = 1 - \left[1 - e^{-\alpha(t-\gamma)^{\beta}}\right] = e^{-\alpha(t-\gamma)^{\beta}} \tag{7}$$

where $\beta > 0$ is the shape parameter, $\alpha > 0$ is the scale parameter, and $\gamma > 0$ is the position parameter.

To better describe the function, the Arrhenius equation is introduced to express the relationship between the reaction rate $g(T)$ and temperature $T$. The improvements of $\delta_{i,j}^{k}$ are as follows [36]:

$$g(T) = Ue^{-E/LT} \tag{8}$$

$$\delta_{i,j}^{k} = e^{-g(T)\alpha(t-\gamma)^{\beta}} \tag{9}$$

In this paper, the three-layer damage cost $C_3$ can be simplified into two linear functions: the damage cost during transportation $C_t$ and that during loading and unloading $C_l$.

The damage cost during transportation $C_t$ can be expressed as follows:

$$C_t = z\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} y_j^k Q_i \left(1 - e^{-g(T_1)\alpha\left(t_{i,j}^{k}-\gamma\right)^{\beta}}\right) \tag{10}$$

where $T_1$ is the temperature during the transportation of the refrigerated car and is a constant.

After opening the door of the refrigerated car, the temperature in the car changes, and the temperature change function $T_{in}$ is as follows [37]:

$$T_{in} = \begin{cases} 2.38lnt + 17, & 0 < t < t_1 \\ T_2, & t_1 \leq t \leq t_2 \\ -3.2t + 3.6t_i + 4.3, & t_2 < t \leq t_i \end{cases} \tag{11}$$

The damage cost during the loading and unloading of $C_l$ can be expressed as follows:

$$C_l = z\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} y_j^k Q_i \left(1 - e^{-g(T_{in})\alpha(p_i-\gamma)^{\beta}}\right) \tag{12}$$

Therefore, the three-layer damage cost $C_3$ can be calculated as follows:

$$\begin{aligned} C_3 &= C_t + C_l \\ &= z\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} y_j^k Q_i \left(1 - e^{-g(T_1)\alpha\left(t_{i,j}^{k}-\gamma\right)^{\beta}}\right) \\ &\quad + z\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} y_j^k Q_i \left(1 - e^{-g(T_{in})\alpha(p_i-\gamma)^{\beta}}\right) \end{aligned} \tag{13}$$

### 4) REFRIGERATION COST

Similarly, the refrigeration cost can be divided into two parts: the refrigeration cost during transportation $C_t'$ and that during loading and unloading $C_l'$. These are defined as follows:

$$C_t' = f_e\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} x_{i,j}^{k}\hat{t}_{i,j}^{k} \tag{14}$$

$$C_l' = f_e'\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} y_j^k p_i \tag{15}$$

where $\hat{t}_{i,j}^{k} = t_{i,j}^{k} + max\{e_j - t_j^k, 0\}$, in which $\max\{e_j - t_j^k, 0\}$ is the waiting time.

At the same time, the impact of refrigeration carbon emissions should also be taken into account. The carbon emission cost $C_{41}$ in the refrigeration process is

$$C_{41} = \varepsilon\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}\theta Q_i(t_{i,j}^{k} + p_i)y_j^k \tag{16}$$

Therefore, the refrigeration cost $C_4$ is shown in Eq. (17):

$$\begin{aligned} C_4 &= C_t' + C_l' + C_{41} \\ &= \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}(f_e x_{i,j}^{k} \\ &\quad \hat{t}_{i,j}^{k} + f_e' y_j^k p_i + \varepsilon\theta Q_i(t_{i,j}^{k} + p_i)y_j^k) \end{aligned} \tag{17}$$

### 5) PENALTY COST

The time for the refrigerated truck to reach the demand links in advance is $max\{e_j - t_j^k, 0\}$, and the late time is $max\{t_j^k - l_i, 0\}$. Therefore, the penalty cost $C_5$ is as follows:

$$C_5 = \sum_{k=1}^{m}\sum_{i=0}^{n}(amax\{e_j - t_j^k, 0\} + bmax\{t_j^k - l_i, 0\}) \tag{18}$$

### 6) SHORTAGE COST

Due to the limited load capacities of refrigerated trucks, they are often unable to meet the demand of inventories or customers, which results in shortage costs. The shortage cost can be defined as follows:

$$C_6 = \tau\sum_{k=1}^{m} max\{d_k - z_k, 0\} \tag{19}$$

According to the objectives and constraints, the distribution cost model can be expressed as follows:

$$\begin{aligned} minC &= h\sum_{j=1}^{n}\sum_{k=1}^{m} x_{0,j}^{k} + c\sum_{k=1}^{m}\sum_{i=0}^{n} t_{i,j}^{k} x_{i,j}^{k} \\ &\quad +\varepsilon\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}\varphi P_{i,j} x_{i,j}^{k} \end{aligned}$$

$$
\begin{aligned}
&+z\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}y_j^k \\
&\times Q_i\left(1-e^{-g(T_1)\alpha\left(t_{i,j}^k-\gamma\right)^{\beta}}\right) \\
&+z\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}y_j^k \\
&\times Q_i\left(1-e^{-g(T_{in})\alpha(p_i-\gamma)^{\beta}}\right) \\
&+\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}(f_e x_{i,j}^k \hat{t}_{i,j}^k + f_e' y_j^k p_i \\
&+\varepsilon\theta Q_i(t_{i,j}^k+p_i)y_j^k) \\
&+\sum_{k=1}^{m}\sum_{i=0}^{n}(a\, max\{e_j-t_j^k,0\} \\
&+b\, max\{t_j^k-l_i,0\})+\tau\sum_{k=1}^{m} max\{d_k-z_k,0\}
\end{aligned}
\tag{20}
$$

$$s.t.\ \sum_{k=1}^{m}y_i^k=\left\{1,{}_{i=1,2\ldots n}^{m,\ i=0}\right. \tag{21}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m}x_{i,j}^k\le m\ i=0 \tag{22}$$

$$\sum_{j=1}^{n}x_{i,j}^k=\sum_{j=1}^{n}x_{j,i}^k\le 1\quad i=0,\ k=1,2,\ldots,m \tag{23}$$

$$\sum_{i=0}^{n}x_{i,j}^k=y_j^k,\quad j=0,1,2,\ldots,n,\ k=1,2,..,m \tag{24}$$

$$\sum_{j=0}^{n}x_{i,j}^k=y_j^k,\quad i=0,1,2,\ldots,n,\ k=1,2,..,m \tag{25}$$

$$\sum_{j=0}^{n}\sum_{k=1}^{m}x_{i,j}^k=1,\quad i=0,1,2,\ldots,n,\ i\ne j \tag{26}$$

$$\sum_{i=0}^{n}\sum_{k=1}^{m}x_{i,j}^k=1,\quad j=0,1,2,\ldots,n,\ i\ne j \tag{27}$$

$$x_{i,j}^k(max\{t_i^k,e_i+p_i+t_{i,j}^k-t_i^k)\le 0 \tag{28}$$

$$t_i^k\le L_i,\quad k=1,2,\ldots,n,\ i=1,2,\ldots,n \tag{29}$$

$$z_k\le Q_z,\quad k=1,2,\ldots,n \tag{30}$$

$$P\sum_{k=1}^{m}z_k\ge\sum_{k=1}^{m}d_k=q \tag{31}$$

$$x_{i,j}^k\in\{0.1\},\quad k=1,2,\ldots,m,\ j=1,2,\ldots,n \tag{32}$$

$$y_j^k\in\{0.1\},\quad k=1,2,\ldots,m,\ j=1,2,\ldots,n \tag{33}$$

$$Q_i\sim F \tag{34}$$

Formula (21) indicates the number of services, that is, a refrigerated vehicle serves one demand point at a time; formula (22) indicates the relationship between the route and the vehicle, that is, the number of vehicles is greater than or equal to the number of routes; formula (23) indicates that the distribution center is the starting point of the refrigerated vehicle; formula (24) and formula (25) mean that each vehicle leaves after unloading; formula (26) and formula (27) indicate that the delivery frequency is one time; formula (28) indicates the departure time constraint of the refrigerated vehicle; formula (29) means to ensure that the refrigerated vehicle must meet the customer time window; formula (30) indicates the vehicle load limit; formula (31) indicates to ensure that the customer demand satisfaction rate is met; formula (32) and (33) represent the 0-1 decision variable; formula (34) indicates that the customer demand obeys the random distribution F.

## V. ALGORITHM DESIGN

In this paper, we use an improved genetic algorithm to solve the distribution cost model. The improved genetic algorithm uses a random method to generate the population in the method of generating the initial population, and uses the roulette wheel selection and Partially Matched Exchange (PME) to set the initial population and genetic operations. By judging the evaluated population, this algorithm selects, crosses, and mutates the parameters that do not meet the conditions to generate a new population and continues to evaluate until satisfactory results are obtained.

### A. CODING DESIGN

In this paper, we assume that the distribution center should be separated from the demand link. All serial numbers should have 1 added to them in the process of encoding and decoding, that is, the code of distribution center 0 is 1, and the code of demand link 1 is 2. Each sort of permutation sequence is a customer ordering order. For example, (9, 5, 3, 1, 6, 8, 7, 2, 4) is the code of each demand link. First, demand link 9 is arranged in the first path, and then link 5 is searched to check whether the constraint conditions are met.

### B. INITIAL POPULATION GENERATION

Generally, the individual N in the initial population is generated randomly, and its range is [100, 200]. In this paper, according to the number of customers, we use the integer permutation coding method in Section 5.1. In this paper, we randomly generate N chromosomes by permutation of the sequence numbers of the client sites, where N is the size of the initial population.

### C. IMPROVING GENETIC MANIPULATION

#### 1) IMPROVED SELECTION OPERATOR

The purpose of the selection operator is to directly inherit the optimized individual (or solution) to the next generation or generate a new individual through a pairing crossover and then inherit the next generation. Based on preceding studies, we use the improved roulette selection method as the selection method to determine the selection probability. In roulette selection, the higher the individual's fitness, the more likely it will be selected to pass on to the next generation.

However, when individuals with high fitness values appear in the population, it is easy to produce a large number of reproductions of the dominant population. Then, the algorithm optimization will be limited only in the vicinity of the individual and stop approaching the optimal solution.

To solve this problem, this paper introduces a ranking method to improve roulette. According to the fitness value of all individuals in the population, we arrange their orders and determine the probability of individual selection. The probability of individual selection $p_i$ in this paper is shown in Eq. (36):

$$c = \frac{0.1}{1-0.9^M} \tag{35}$$

$$p_i = c(1-c)^{i-1} \tag{36}$$

where $p_i$ is the selection probability of individual $i$, and $M$ is the size of the population.

### 2) IMPROVED CROSSOVER AND MUTATION OPERATION

Generally, genetic algorithms mostly use a certain crossover probability $p_c$ and mutation probability $p_m$ to solve problems. However, they cannot fully determine the specific value, which leads to the convergence and precocity of the algorithm. In this paper, we introduce an adaptive mechanism to maintain the dynamic balance of crossover and mutation probability to reduce the possibility of cross-mutation of excellent individuals and preserve excellent genes. The crossover probability $p_c$ and mutation probability $p_m$ are defined as follows:

$$p_c = \begin{cases} \dfrac{h_1(f_0 - f')}{f_0 -}, & f' \geq \bar{f} \\ h_2, & f' \leq \bar{f} \end{cases} \tag{37}$$

$$p_m = \begin{cases} \dfrac{h_3(f_0 - f')}{f_0 -}, & f' \geq \bar{f} \\ h_4, & f' \leq \bar{f} \end{cases} \tag{38}$$

where $f_0$ and $\bar{f}$ represent the maximum current fitness and average fitness of all individuals, respectively. $f'$ is the higher fitness of the expected crossover individuals, and $f$ represents the fitness of the mutant individuals. $h_1$, $h_2$, $h_3$, and $h_4$ ($h_1$, $h_2$, $h_3$, $h_4 \in [0, 1]$) are constants.

## VI. CASE STUDY

In this section, we choose an urban area of Harbin to illustrate the properties and performance of the proposed distribution schemes. The relevant data are taken from the Harbin survey dataset. According to the survey results, under the regular demand, 12 vehicles are needed, and the total cost of distribution is about 9340.5.

### 1) DETERMINATION OF DISTRIBUTION LINKS

Based on the data from the Harbin survey dataset, we obtain the basic data of distribution links, including the distribution demand, schedule between links, and other parameter values, and illustrate the results in Table 2.

### 2) DETERMINATION OF DISTRIBUTION PATH

In this paper, to reflect the influence of changes in customer demand on the path choice, we assume that customer demand obeys an independent normal distribution. In this case, we also consider the changes of various costs under different customer demands. We assume that the satisfaction rate of customer demand is 95% and obeys the independent normal distribution of $X \sim N(\mu, \sigma^2)$. When $X = \mu + z_\alpha \times \sigma$ and $z_\alpha = z_{0.05} = 1.65$, we define that the demand variances $\sigma$ are 1, 2, 3, 4, 5, and 6, respectively. Then, we calculate the distribution path for each variance.

**TABLE 2. Distribution data.**

| $x_i$ | Name | Expected value $e$ | $e_i$/min | $l_i$/min | $p_i$/min |
|---|---|---|---|---|---|
| 0 | distribution center | — | 0 | 100 | 0 |
| 1 | Yufu Market | 8.9 | 12.3 | 79 | 3 |
| 2 | Daqiang Market | 7.4 | 2.3 | 37.9 | 6 |
| 3 | Yili Community | 11.6 | 10.8 | 78.9 | 5 |
| 4 | Lu Community | 14 | 13.1 | 78 | 6 |
| 5 | Lin Community | 23.4 | 3.1 | 40.9 | 7.5 |
| 6 | Xin Home | 4.1 | 7.5 | 54.9 | 2.2 |
| 7 | Hai Home | 6.1 | 6.8 | 46.8 | 2.2 |
| 8 | Mi Community | 8.5 | 8.7 | 54.5 | 3.1 |
| 9 | Jia Community | 14.9 | 7.2 | 57.5 | 8.6 |
| 10 | Xi Community | 11.4 | 12.1 | 85.2 | 6.3 |
| 11 | Lu Home | 13.1 | 5.4 | 41 | 6.8 |
| 12 | Han Market | 17 | 5.9 | 40.8 | 9.1 |
| 13 | Peace Home | 20.3 | 12.9 | 85.9 | 10.1 |
| 14 | Jing Park | 22.4 | 3.4 | 43.6 | 12 |
| 15 | Qin Market | 6.4 | 3.5 | 41.8 | 13.4 |
| 16 | Ka Community | 17.1 | 4.5 | 46.5 | 8.7 |
| 17 | Feng Market | 3.3 | 11.5 | 79.8 | 3.1 |
| 18 | Hua Home | 17 | 7.3 | 50.2 | 3 |
| 19 | Longxing | 13.7 | 4.2 | 50.3 | 1.5 |
| 20 | Peace Square | 9.8 | 11.4 | 87.4 | 5.6 |

**TABLE 3. Distribution path for demand variances.**

| No. | $\sigma$=1 | $\sigma$=2 | $\sigma$=3 | $\sigma$=4 | $\sigma$=5 | $\sigma$=6 |
|---|---|---|---|---|---|---|
| 1 | 0-15-13-10-0 | 0-14-1-10-0 | 0-8-13-1-0 | 0-13-6-14-0 | 0-3-6-12-0 | 0-8-16-0 |
| 2 | 0-16-14-0 | 0-17-12-8-0 | 0-9-16-0 | 0-10-3-0 | 0-20-19-0 | 0-14-3-0 |
| 3 | 0-19-12-2-0 | 0-9-19-13-0 | 0-11-15-2-0 | 0-19-8-17-0 | 0-10-14-0 | 0-5-4-10-0 |
| 4 | 0-4-20-8-17-0 | 0-4-18-11-0 | 0-6-14-0 | 0-4-2-0 | 0-16-18-0 | 0-17-1-0 |
| 5 | 0-1-9-0 | 0-15-5-0 | 0-7-18-20-0 | 0-20-5-0 | 0-15-13-0 | 0-19-0 |
| 6 | 0-3-18-5-0 | 0-6-2-7-0 | 0-19-5-0 | 0-9-18-0 | 0-2-4-0 | 0-13-20-0 |
| 7 | 0-7-6-11-0 | 0-3-16-20-0 | 0-12-3-17-0 | 0-12-15-0 | 0-11-7-0 | 0-15-7-0 |
| 8 | — | — | 0-4-10-0 | 0-7-11-0 | 0-9-8-0 | 0-9-11-0 |
| 9 | — | — | — | 0-1-16-0 | 0-5-1-17-0 | 0-2-18-0 |
| 10 | | | | | | |

The results listed in Table 3 indicate that as the demand variance $\sigma$ increases, the number of distribution paths gradually increases. When $\sigma = 6$, the number of distribution paths is the highest, which is three more paths than that when $\sigma = 1$. The reason is probably that the greater the change in customer demand, the more distribution routes are required. By increasing the number of distribution vehicles or distribution paths, the model can only meet the changing customer

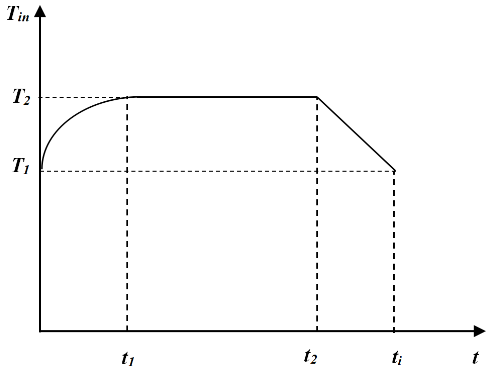


**FIGURE 2.** Temperature changes during loading and unloading.

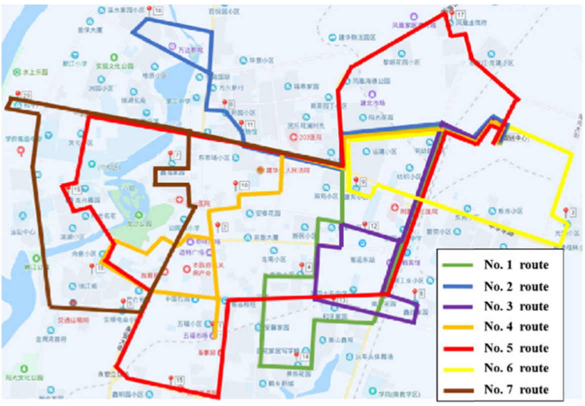


**FIGURE 3.** Distribution route ($\sigma = 1$).

demand. In addition, we find that when $\sigma = 1$ and $\sigma = 2$, the number of paths is the same. Similarly, when $\sigma = 4$ and $\sigma = 5$, the number of paths is 9. The reason is that even if customer demand is different, by optimizing the distribution path, we can obtain the optimal distribution scheme, thereby reducing the distribution cost.

### 3) DETERMINATION OF DISTRIBUTION COST

Based on the "Cold Chain Logistics Development Annual Report" of 2018, the variables of distribution cost are listed in Table 4. In addition, in this paper, we set the chromosome length $n$ to 20, population size to 1600, crossover probability $P_e$ to 90%, and number of iterations $Gen$ to 60.

As shown in Fig. 4 and Table 4, after substituting the above values into Eqs. (20)-(34), we obtained the distribution cost for each variance and the corresponding number of iterations. The results indicate that the number of iterations of the new algorithm is lower than that of the original algorithm under random demand; that is, the efficiency of the improved genetic algorithm is better than that of the original genetic algorithm. This also shows that the variety of customer demand has a negative influence on the distribution cost; that is, the greater the variety of customer demand, the higher the distribution cost.

The reason is that the variety of customer demands directly determines the planning of the distribution path and the formulation of the distribution strategy. For certain customer

**TABLE 4.** Iterative times.

| Random demand | σ=1 | σ=2 | σ=3 |
|---|---|---|---|
| Iterative times of original genetic algorithm | 78 | 38 | 55 |
| Iterative times of improved genetic algorithm | 61 | 34 | 41 |
| Random demand | σ=4 | σ=5 | σ=6 |
| Iterative times of original genetic algorithm | 62 | 63 | 38 |
| Iterative times of improved genetic algorithm | 49 | 51 | 23 |

demand, refrigerated trucks only need to carry out the transportation and distribution of fresh food regularly and quantitatively every day.

However, when customer demand changes, according to actual customer demand, the distribution strategy needs to be adjusted to meet the needs of each customer. In this case, refrigerated trucks may need to deliver to the same distribution link several times a day. This inevitably leads to an increase in the distribution cost. Moreover, the greater the distribution time, the higher the distribution cost.

Successively, we use different variances to calculate each part of the distribution cost and the total distribution cost. The calculation results are shown in Table 5.

**TABLE 5.** Distribution cost.

| Cost | $\sigma = 1$ | $\sigma = 2$ | $\sigma = 3$ |
|---|---|---|---|
| Fixed cost | 790 | 790 | 940 |
| Transportation cost | 813.8 | 839.6 | 851.2 |
| Cargo damage cost | 636.3 | 739.2 | 889.3 |
| Refrigeration cost | 3181.6 | 3495.4 | 3711.7 |
| Penalty cost | 0 | 0.8 | 0.9 |
| Shortage cost | 451.6 | 432.5 | 531.7 |
| Total cost | 5873.3 | 6297.5 | 6924.8 |
| Cost | $\sigma = 4$ | $\sigma = 5$ | $\sigma = 6$ |
| Fixed cost | 1140 | 1140 | 1280 |
| Transportation cost | 901.1 | 913.5 | 929.8 |
| Cargo damage cost | 933 | 950.1 | 963.4 |
| Refrigeration cost | 3991.3 | 4366.2 | 4672.4 |
| Penalty cost | 1.2 | 0.4 | 0.5 |
| Shortage cost | 559.5 | 621.5 | 664.1 |
| Total cost | 7526.1 | 7991.7 | 8510.2 |

The results indicate that as the customer demands increases, the cost of each part increases gradually, and the corresponding total distribution cost also increases. When $\sigma = 1$, the total cost is the lowest (¥5873.3). However, when $\sigma = 6$, the total distribution cost increases to ¥8510.2. The fixed cost increased by nearly ¥500, and the refrigeration cost increased by nearly ¥1500. The underlying reason is that with the change in customer demand, the number of refrigerated vehicles required increases; and then the fixed cost, transportation cost, and refrigeration cost also increased.

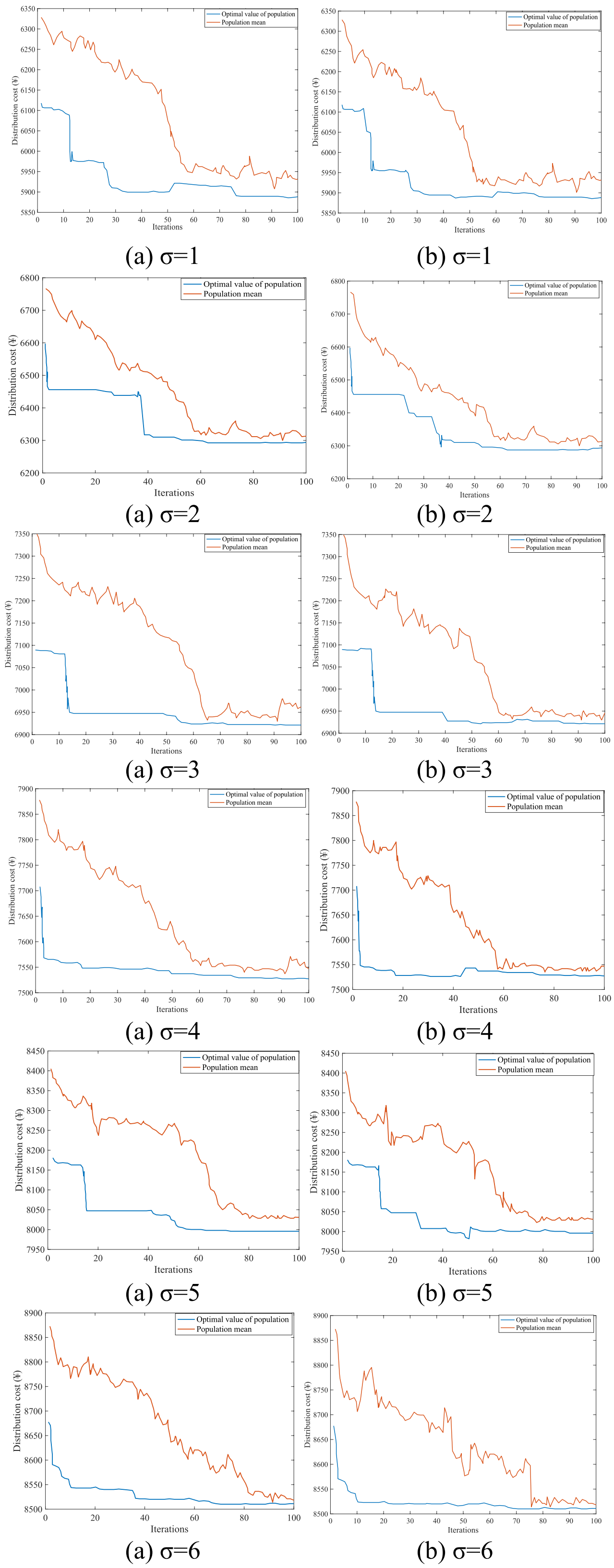


**FIGURE 4.** Changing trends of objective function calculated by (a) original algorithm and (b) improved algorithm under random demand.

At the same time, uncertain customer demand further increases the risk of shortages, so the shortage cost increases by 47.05% compared with $\sigma = 1$. In addition, across the entire distribution cost, the fluctuations of transportation cost, damage cost, shortage cost, and penalty cost are small. In this paper, we select urban and suburban traffic situations so the road conditions are relatively simple and the distribution time of refrigerated trucks is less affected by road conditions.

Conversely, the refrigeration cost accounts for a large proportion of the total distribution cost; and with an increase in customer demand, the corresponding refrigeration cost increases. In the entire cold chain logistics distribution, the longer the distribution time, the higher the refrigeration cost. Therefore, reasonable transportation path planning can effectively reduce the refrigeration cost, thereby reducing the total distribution cost.

By comparing the distribution costs under six variances, we find that when $\sigma = 1$, the distribution cost is the lowest. Therefore, we substitute the path with $\sigma = 1$ with those of other variances and calculate the corresponding total cost. The optimized distribution costs for each variance are shown in Fig. 5.

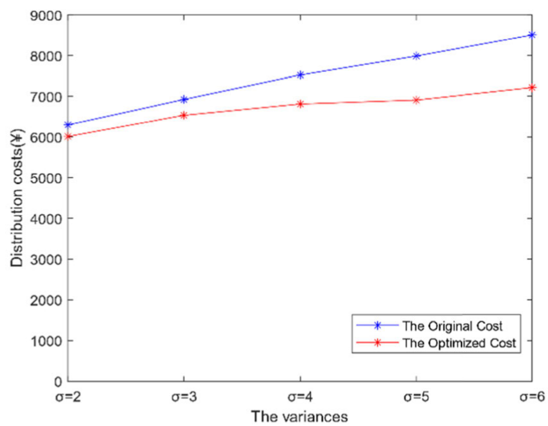


**FIGURE 5.** Optimized distribution cost.

Compared to the total distribution cost without the distribution scheme, the total distribution cost within the survey period increased, which means that the new distribution scheme has a positive effect. In a detailed comparison among the 5 variances, the results in Fig. 5 suggest that the greater the change in customer demand, the better the effect of the distribution scheme. Among them, the distribution cost with $\sigma = 6$ dropped the most, from ¥8510.2 to ¥7213.8. Similarly, the distribution cost with other variances also dropped. This indicates that after we implemented the new distribution scheme, the distribution path of refrigerated trucks was optimized. The reason is that compared with the original distribution scheme, the new distribution scheme has a more reasonable distribution path, which is beneficial for reducing the number of refrigerated trucks and distribution distance, thereby decreasing the transportation and refrigeration costs.

Conclusively, after implementation of the new distribution scheme, we found that the average distribution cost dropped 8.73%. The results of the case study indicate that by implementing the proposed distribution scheme, the distribution path was reasonably planned, decreasing the distribution distance to reduce the distribution cost.

Based on the above analysis, we provide some suggestions for the managements of companies. Through the analysis of the distribution cost under different customer demands, we found that each cost has increased with the increase of customer demands, but the increase in the cost of refrigeration is the largest. This means that we can consider the cost of refrigeration from the perspective of this. On the one hand, when the refrigerated trucks are correctly used, the transportation volume and speed of the vehicles must be increased without increasing driver fatigue and risk and overloading. Thus, the distribution cost can be reduced by reducing the time on the road. On the other hand, we should choose quality refrigerating equipment and unload quickly to reduce cargo damage, refrigeration costs and carbon emissions [21]. In addition, we should plan the distribution path through reasonable and scientific methods, so as to reduce the distribution cost.

## VII. CONCLUSION

In this paper, the influencing factors in cold chain logistics distribution, including customer demand, time demand, three-layer cargo damage cost, and distribution links, were analyzed based on the characteristics of fresh food and random customer demand. Then, a distribution cost model was established in terms of the fixed cost, transportation cost, refrigeration cost, cargo damage cost, shortage cost, and penalty cost, aiming at the minimization of distribution cost. An improved genetic algorithm was used to solve the model. The results of a case study demonstrated that by implementing the distribution scheme designed in this paper, not only was the distribution path more reasonable, but the total distribution within the survey period also decreased.

In contrast to existing studies, in the process of transportation, we took into account the actual transportation time. In addition, we took into account the cost of carbon emissions in transportation and refrigeration costs to make the model more reliable. Additionally, we considered the nonlinear deterioration rate of fresh food and the effect of temperature changes on the metamorphic reaction rate during unloading, and modeled the three-layer cargo damage cost.

Then, we analyzed the effect of temperature changes on the decay rate of fresh products during unloading, the carbon emission costs during transportation and cold storage and construct a distribution cost model in association with the actual distribution time. The results of the case study in Harbin demonstrated that after implementing the distribution scheme, each cost had a different proportion in the total cost. The results in Table 4 suggest that compared to the other costs, the refrigeration cost accounts for the largest proportion. Conversely, the proportion of penalty cost is the smallest. Conclusively, the costs related to transportation account for more than 90% of the total cost, and we can infer from the results that a reasonable distribution path is helpful to reduce the distribution cost.

This study provides theoretical references and practical insights for the effective analysis of distribution schemes and makes a methodological contribution to calculating distribution costs. By considering the comprehensive cold chain logistics and distribution influencing factors and the entire distribution process, the distribution scheme can be used for a wide range of cold chain logistics management. By optimizing the distribution path, a reduction in distribution time and an increase in the efficiency of distribution can be realized, thereby decreasing cold chain logistics distribution costs and solving the problem of distribution. Notably, consideration of the cold chain logistics distribution in this paper occurred in a city. Different cities can be considered to expand the proposed model. Moreover, the distribution pattern we considered is that a distribution center distributes to multiple demand links; thus, more comprehensive distribution patterns with multiple distribution centers can be considered in the distribution cost model.

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