International Journal of Information Systems and Supply Chain Management
Volume 17 • Issue 1

Research on Optimization of Agricultural Products Cold Chain Logistics Distribution System Based on Low Carbon Perspective

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ABSTRACT

Based on thindiscussion of the traditional agricultural product distribution model, this article establishes a low-carbon perspective of urban agricultural product co-distribution model to reduce the level of agricultural product circulation and reduce the impact of distribution activities on the environment. By comprehensively considering the factors affecting carbon emissions in the vehicle delivery process, the fuel consumption and carbon emissions estimation models of delivery vehicles are analyzed and put forward. A mathematical model for the optimization of urban agricultural product cold chain distribution routes from a low-carbon perspective is established. This article takes a logistics center as an example, selects genetic algorithm as the model solution method, optimizes the distribution route, and obtains the corresponding result, thus verifying the rationality and feasibility of the model.

KEYWORDS

Agricultural Products, Cold Chain, Genetic Algorithm, Low Carbon, Path Optimization

INTRODUCTION

Agriculture plays a crucial role in national economic development, and the well-being of the agricultural sector and its related industries is closely tied to the overall economic progress and social stability of a country (Pan, 2021). In recent years, China has made significant adjustments to its agricultural industry structure, leading to continuous advancements and transformations in the agricultural economy. As a result, China has consistently ranked among the top producers of agricultural products worldwide. Moreover, there has been a shift in the consumption patterns of agricultural goods, moving away from traditional grain-based diets towards a diversified range of fresh vegetables, fruits, and meats (Bai, 2021). This evolution in dietary preferences has also raised expectations for higher product quality.

DOI: 10.4018/IJISSCM.338220 *Corresponding Author

In the search for ways to ensure product quality and minimize losses, cold chain logistics offers distinct advantages over conventional temperature-controlled transportation methods. By effectively managing temperatures throughout the supply chain, cold chain logistics helps to maintain the integrity and freshness of perishable products (Zhu, 2021). As the importance of maintaining a robust food cold chain has been recognized, there has been an unprecedented focus on and investment in cold chain logistics (Sheng, 2021). Despite the rapid development of the cold chain logistics industry, since China has been later than other countries to develop cold chain logistics, there is still a considerable gap in this regard between China and other developed countries. On the one hand, establishing the cold chain infrastructure is a difficult project (Behzadi, et al., 2013). Cold storage refrigerated trucks are widely distributed in eastern coastal areas, but less so in inland western areas. This uneven distribution leads to functional imbalance (Chen, 2021). The current network of facilities is far from meeting market demand. On the other hand, the cold chain circulation rate is not high (Gunasekaran & Ngai, 2012). Most agricultural products are kept at room temperature throughout the entire cold chain logistics link; the links from production to transportation to sales lack systemicity and continuity, and the "broken chain" phenomenon sometimes occurs, resulting in serious loss of agricultural product quality.

Logistics and supply chain operations, often referred to as the "third source of profit" for modern enterprises, are also responsible for significant fossil fuel consumption and carbon emissions (Hao et al., 2017). According to the Stern Report, the logistics industry contributes approximately one-seventh of total global greenhouse gas emissions, primarily through the production of carbon dioxide and other greenhouse gases. Unlike regular temperature-controlled logistics, cold chain logistics requires maintaining low temperatures throughout various stages, from raw material production and processing to transportation, sales, and final consumption. Consequently, cold chain logistics consumes more energy to ensure the quality and integrity of perishable goods (De La Fuente & Ros-McDonnell., 2013).

In the United Kingdom, for example, the food processing, retail, and catering industries collectively account for 3.7% of total greenhouse gas emissions. Within this category, the greenhouse gases produced by cold chain preservation alone contribute 2.5% of the country's emissions. This number highlights the significant environmental impact of cold chain logistics caused by its high energy consumption and carbon emissions. Therefore, it has become crucial to transform cold chain logistics from a big energy consumer to a low-carbon industry in order to align with the new era of low-carbon economic development. Optimizing transportation routes offers an effective approach to reducing carbon emissions (Montanari, 2008).

Some scholars have incorporated the perishability of fresh food and transportation time into cold chain distribution route optimization models. They have utilized methods such as taboo search to find the optimal solutions to these problems (Delice et al., 2009). Furthermore, researchers have developed mixed-integer linear programming (MILP) models to design optimal cold chain logistics distribution networks for various fresh agricultural products. They have employed hybrid optimization techniques to optimize the entire distribution network (Khezrimotlagh et al., 2013).

To establish sustainable fresh produce supply chain networks, scholars have analyzed two-layer path optimization problems considering time window constraints (Jin & Edmunds, 2015). They have also designed multi-objective optimization models (Pokharel, 2008) and proposed a hybrid optimization algorithm that combines variable domain search with a multi-objective particle swarm optimization algorithm (Yeh, 2005) to achieve the desired results. These research efforts aim to improve the efficiency and sustainability of cold chain logistics, reducing energy consumption and carbon emissions in the process.

Currently, there has been significant research conducted on both agricultural cold chain logistics and low-carbon vehicle routing. However, there remains a scarcity of literature that directly focuses on the integration of these two fields; there is also a lack of quantitative analysis of carbon emission calculations (Xu et al., 2015).

This paper aims to address this gap by focusing on the cold chain distribution system for agricultural products. It establishes an optimization model for cold chain logistics distribution under low-carbon constraints. The objective is to minimize the total distribution cost while simultaneously ensuring low carbon dioxide emissions throughout the distribution process. By combining the principles of efficient cold chain logistics and environmentally friendly transportation, this research endeavors to contribute to the development of sustainable and low-carbon agricultural supply chains.

MATERIALS AND METHODS

The vehicle path problem in cold chain logistics is a critical and complex challenge. In the cold chain transportation process, in order to ensure the freshness and quality of the goods, vehicle paths need to be properly planned and optimized to minimize the transportation time and energy consumption. However, due to the special characteristics of cold chain logistics, vehicle path planning faces several challenges, such as temperature requirements, cargo capacity, and traffic congestion.

To address the vehicle path problem in cold chain logistics, researchers have actively explored various solutions. One of the common approaches is to use intelligent algorithms and optimization models for path planning. These methods can consider various factors, such as temperature requirements of goods, transportation distance, traffic conditions, etc., and find the optimal vehicle path scheme by calculating and comparing the costs and benefits of different paths.

In addition, with the development of IoT and big data technologies, vehicle path planning can also be combined with real-time monitoring and data analysis in order to more accurately grasp road conditions and cargo status. The efficiency and flexibility of cold chain logistics can be improved by real-time updating of path information and dynamic adjustment of vehicle routes.

This paper will focus on the vehicle path problem in cold chain logistics and introduce different solutions and methods. It will also discuss the application cases and future development trends of related technologies, with a view to providing a more feasible and effective vehicle path planning strategy for the cold chain logistics industry.

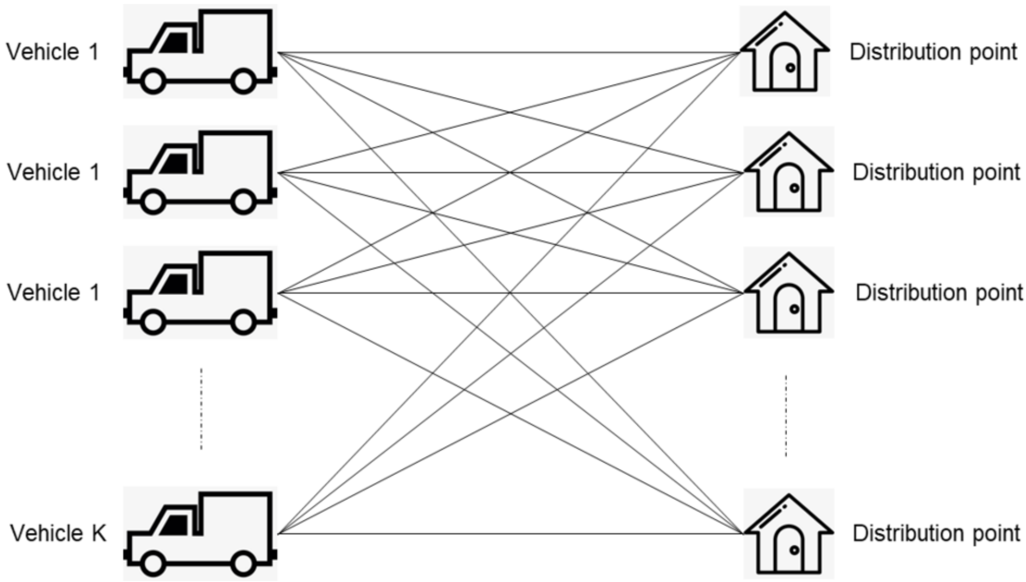
Problem Description

The optimal model for urban cold chain logistics path distribution under low-carbon constraints involves a cold chain logistics distribution center for distribution and transportation for "a demand point in the city (Smairi et al., 2016). We assume that the cold chain logistics distribution center has K vehicles of the same model and the same load capacity and that the refrigerated truck delivery vehicles have the same refrigeration equipment. Each refrigerated truck departs from the distribution center and must return to the distribution center after completing the distribution work at each distribution point. The specific distribution system is shown in Figure 1. The logistics company needs to determine the location of the point to which good are to be distributed this time, the demand at that point, the type of goods to be distributed, the distribution temperature, the humidity, and other issues. Here, it is assumed that the goods can be transported every time. Combined transportation means that the goods to be delivered each time need the same temperature and humidity conditions, and the demand for delivery point i is represented by Qt. In summary, the problem of urban cold chain logistics path optimization is essentially the study of the specific vehicle dispatching sequence. The number of dispatched vehicles, dispatch time, and distribution route minimize the total cost of the cold chain logistics distribution system.

Basic Idea of Modeling

It can be seen that the urban cold chain logistics path optimization model studied in this paper is based on a situation with multiple distribution customers in a single distribution center. All the delivery vehicles in the model have refrigeration and freezing functions. The study use the city as a unit to optimize the urban cold chain logistics distribution path. The costs considered in the model were the fixed cost of using refrigerated trucks in the distribution process, the variable costs determined by mileage, the cost caused of operating the refrigeration equipment, and the penalty cost of not

Figure 1. The distribution body of the cold chain logistics distribution center



arriving at the time required by the customer. For the low-carbon constraints involved, the carbon dioxide emissions produced by refrigerated trucks during the distribution process were converted into a carbon emission cost method, which was included in the total cost calculation. Then the minimum total cost was taken as the objective function to construct the basic model of the urban cold chain logistics path problem.

Cost Analysis

Fixed Costs and Variable Costs

In cold chain logistics and distribution, there are some costs that are not affected by time, energy consumption, etc. As long as the vehicles are deployed, these costs are fixed. For example, the wages of the drivers of the delivery vehicles or the needs of the vehicle's depreciation expense (Wang & Zhao, 2012) are fixed costs. But there is also a part of the cost that is proportional to the number of transport miles, which is called a variable cost here. Examples of variable costs are fuel consumption costs incurred in the delivery process, vehicle repairs and maintenance costs, and costs incurred in crossing roads and bridges. Both kinds of cost are represented by formula 1:

$$c_1 = \sum_{k=1}^{K} S_k \sum_{i=1}^{m} f_i + \sum_{i=0}^{n} \sum_{j=1}^{n} \sum_{k=1}^{K} c_{ijk} x_{ijk} \tag{1}$$

c_1 is the fixed cost and variable cost of the vehicle; S_k is a 0-1 variable. If the value is 1, it means the k-th car called, otherwise, it is not called. $\sum_{i=1}^{m} f_i$ means the sum of m fixed expenses, such as driver wages and vehicle depreciation expenses required when the vehicle is called. c_{ijk} is the transportation cost of the k-th car from customer point i to customer point j on the road segment. x_{ijk}

is a variable of 0-1; if the k-th car passes from customer i to customer j, it is 1, and vice versa (Zhang et al., 2019).

Cost of Carbon Emissions

In the process of urban cold chain logistics and distribution, the carbon dioxide emissions of refrigerated trucks are directly related to their energy consumption, so the carbon dioxide emissions of refrigerated trucks are relatively high, a factor which is the focus of this article. Here, carbon emissions are quantified as the corresponding cost of carbon emissions as a cost factor that affects the cost of logistics enterprises. According to the existing formula for calculating carbon dioxide emissions, the following formula is obtained:

$$c_2 = p_1 \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} E_k l_{ijk} m_{ijk} x_{ijk} \tag{2}$$

$$E_k = \sum_{i=1}^{N} G_{ki} \times F_i \tag{3}$$

c_2 is the cost of carbon emissions. p_1 is the cost of carbon emissions per unit, based on the transaction price of the carbon trading market on a given day. E_k represents the amount of carbon dioxide emitted per unit kilometer of the k-th car. l_{ijk} is the number of kilometers travelled to move the k-th car from customer i to customer j. m_{ijk} represents the load of the k-th car from customer i to customer j. x_{ijk} is a 0-1 variable, which means that the kth car passes from customer i to customer j, and vice versa is 0. G_{ki} means the amount of energy consumed by the k-th car per unit of cargo per kilometer, F_i is the emission coefficient, that is, the amount of carbon dioxide emitted per unit of energy consumption.

Refrigeration Cost

The cost of refrigeration is the cost of energy consumed by cold storage and freezing equipment. Refrigeration costs consist of two parts. One part is the refrigeration cost C_{31} caused by maintaining a low-temperature environment in the compartment during the distribution and transportation process, and one part is the refrigeration cost C_{32} generated by maintaining the temperature in the compartment during the opening of the door and the exposure of the refrigerated goods to outdoor temperatures when arriving at the distribution point for unloading, with the total refrigeration cost C_3 for the two parts being expressed as follows:

$$c_3 = c_{31} + c_{32} = \sum_{k=1}^{K} G_1 \times \left(t_{ko} - t_{ok}\right) \times p_2 + \sum_{k=1}^{K} G_2^{'} \times \left(t_{ko} - t_{ok}\right) \times p_2 \tag{4}$$

C31 is the cooling cost during the distribution process. G1 is the heat load of the car box (kcal/h). $G_2^{'}$ is the door-opening heat load (kcal/h). p_2 is the unit cooling cost. The time when the k-th car leaves the distribution center; t_{ok} is the time when the k-th vehicle arrives at the distribution center after the completion of the distribution.

Time Penalty Cost

The consumer wishes to receive the items in the agreed-upon timeframe during the actual delivery procedure, but there are a number of reasons why this may not be possible in practice, including delivery schedule issues and urban traffic congestion. Customers typically agree to a specific window of time in this situation for the delivery. For instance, if a customer orders groceries, they might accept delivery up to an hour ahead of schedule or later. The consumer has the option to reject the products if the delivery truck is early or late. However, occasionally the delivery van may arrive to the supermarket ahead of schedule and require a wait until the scheduled time because of traffic and other complicating factors. The logistics business permits this activity but applies penalties if the refrigerated van arrives at the supermarket one hour before the scheduled ceiling time. Simultaneously, the expense of refrigeration during transit is designated as a penalty expense to restrict the advancement or delay of the delivery vehicle. If delivery vehicles arrive more than one hour early or late, they will be subject to harsher fines. The time penalty cost calculation formula is:

$$c_4 = \sum_k^K \sum_i^n y_{ik} c_{42} \tag{5}$$

$$c_{42} = \begin{cases} M, tc_{ik} \left\langle ta_i^{'}, tc_{ik} \right\rangle tb_i^{'} \\ c_{31}, ta_i^{'} < tc_{ik} \leq tb_i^{'} \\ \quad 0,\ otherwise \end{cases} \tag{6}$$

y_{ik} is a 0-1 variable. If the value is 1, it means that the k-th car is responsible for the i-th customer point. c_{42} is the penalty cost of the soft time window. tb_i is the standard time set by the supermarket. tb_i and ta_i indicate the normal delivery time. If the delivery is within the time period (ta_i , $tb_i^{'}$), then the normal delivery will be given. If it arrives after the time point $ta_i^{'}$ and after ta_i , a penalty of a certain amount will be imposed. If it arrives after time $tb_i^{'}$ or before time $ta_i^{'}$, it will seriously damage the interests of cold chain logistics distributors, resulting in a higher penalty M,

Model Establishment

We constructed a model with the least total cost of distribution as the goal; that is, the model established is as follows:

$$minz = c_1 + c_2 + c_3 + c_4 \tag{7}$$

Formula 7 needs to meet the following constraints:

$$\sum_{i=1}^n y_{ik} Q_i \leq Q_k,\ \ k = 1,2,\ldots K \tag{8}$$

$$\sum_{k=1}^{K} yik = \begin{cases} 1 & i = 1, 2, \ldots n \\ K & i = 0 \end{cases} \tag{9}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{n} y_{ik} = N \tag{10}$$

$$ta_i^{'} \leq tc_i \leq tb_i^{'} \tag{11}$$

Suppose the time to the i-th customer point is tc_i, the next customer point for delivery is j, s_{ij} is the distance from the i-th customer point to the j-th customer point, and v_{ij} is the c-th customer point to the j-th customer point. T_i is the operating time for unloading and handing over at the i-th customer point. Thus:

$$ta_j^{'} \leq tc_i + \frac{s_{ij}}{v_{ij}} + T_i \leq tb_j^{'} \tag{12}$$

Among the above constraints, formula (8) indicates that the weight of the goods carried by the delivery vehicle does not exceed the maximum load capacity of the vehicle; formula (9) indicates that each customer point has only one vehicle for delivery, and the delivery vehicle must depart from the distribution center. After completing the delivery, the driver must return to the distribution center; formula (10) means that the delivery vehicle is sufficient to complete all the customer's delivery tasks; formula (11) means that the customer's delivery time requirements must be met when delivering to the customer; formula (12) means that when the delivery task for the previous customer is completed, the delivery time requirement of the next customer must be met when delivering to the next customer.

Urban Cold Chain Path Optimization Method

The vehicle routing problem is a typical NP-hard combination problem. To solve this type of problem, genetic algorithm is often the method of choice (Rao et al., 2014). Therefore, in this paper, genetic algorithm was selected to solve the problem of urban cold chain path optimization, and the programming was realized through MATLAB software.

In using genetic algorithm to solve, it is necessary to establish a chromosome coding design, fitness function design, operator design, etc. (Liu et al., 2021). Commonly used encoding methods in genetic algorithms include binary encoding, natural number encoding, integer encoding, and so on (Wang et al., 2018). The route distribution problem concerns delivery order, and the intuitive natural number coding method is often used (Zhang et al., 2019). The coding sequence of a chromosome from left to right determines the number of delivery vehicles and the delivery order of the delivery point (Wang et al., 2022). The fitness function should be selected according to different research purposes. For example, the purpose of this study is to minimize the total cost of distribution, which belongs to the global minimum problem of the objective function. For such problems, the fitness function can be selected as the reciprocal of the objective function (Wang et al., 2022).

The genetic operator design includes mainly the following:

Selection Operator

Roulette, expected value, random league selection, and other methods are commonly used selection operations in genetic algorithms. We chose random league selection here, which is also known as tournament selection strategy. The main operation process consisted of randomly selecting m individuals from the population, comparing their fitness function values, selecting the individual with the largest fitness value as the optimal individual, directly saving it to the next generation, and repeating this process. In this paper, m is selected as 2.

Crossover Operator

Crossover refers to the generation of new chromosomes by exchanging some of the genetic information in two parent individuals and recombining them. The crossover operation generally consists of two steps: the first step is to determine the chromosome region in which the crossover operation is performed; the second step is to randomly determine the crossover point location according to the probability to exchange the genetic information.

In this paper, we use a crossover algorithm similar to PMX. Specifically, the crossover region is first randomly selected, and then the region is placed at the most anterior end of the opponent's chromosome, where the part of the gene that is identical to the one placed at the anterior end is removed.

For example, if parent d = 735|241|689 and S = 52|879|463, then we randomly select the 4th and 7th positions in d and S as the crossover positions (denoted by "|"). The crossover sequence from each parent is then placed in front of the first gene of the other, yielding new chromosomes B = 879735241689 and 2 = 241528793463. Finally, the portion of the chromosome with the same gene as the one placed at the front is removed, yielding B = 879735246 and 2 = 2415287936.

To summarize, the crossover operation is able to generate new chromosomes, and the crossover operation can be achieved with an algorithm similar to PMX and generate different combinations of genes.

The Mutation Operator

The mutation operator is an operation in genetic algorithms used to introduce randomness in individual chromosomes, thereby increasing individual diversity. The mutation operator is implemented mainly by changing the gene sequences of chromosomes.

The mutation operator usually consists of the following steps:

1. Randomly select an individual for the mutation operation.
2. Randomly select one of the genes of this individual for mutation and replace it with another randomly generated gene.
3. Determine whether or not to perform the mutation operation based on a certain probability. If the probability is low, the individual is likely to be skipped.

Assumptions are made about factors such as the unit cost of vehicle travel from the logistics company to the supermarket and the fixed cost of vehicle usage, as shown in Table 1.

Model Solution Steps

Step 1: Determine the maximum number of iterations T and the population size N of the genetic algorithm.

Step 2: Generate a random and feasible initial population Po with a size of N * (n +1). Among them, n is the gene contained in a chromosome, that is, the number of distribution points. In this article, the (n+1)th gene represents the distribution center. Each gene represents a distribution center.

Table 1. Assumptions

Variables	Cost term
P: unit cooling cost	Vehicle cost(C_1):
C: time penalty cost	Fixed and variable costs
S: average surface area of the vehicle body in m^3	Carbon emission cost(P_1)
E_k: CO2 emissions per unit of cargo per kilometer for the k-th vehicle	Unit carbon emission cost (P), based on the carbon trading price of the day
M_{ijk}: the load of the k-th vehicle from customer i to customer j	Cooling cost(C_3)
G_{ki}: the amount of energy type i consumed by vehicle k per unit of cargo per kilometer	Total refrigeration cost
	Cooling cost during distribution transportation (C_{31})
	Cooling cost during door opening (C_{32})
	Time penalty cost (C_4):

Each chromosome represents a route distribution order. If a chromosome in Po is 2-3-4-5-1-6, it means that there are 5 distribution points in total, and 6 represents the distribution center. If this route is operated only by a refrigerated truck, the route should be 6-2-3-4-5-1-6. That is, the vehicle starts from the distribution center, passes through five distribution points in turn, and finally returns to the distribution center.

Step 3: Calculate the fitness value of each chromosome according to the designed fitness function, and use the partheno-genetic combination operator to operate it.

Step 4: Select operation.

Step 5: Crossover operation and mutation operation: according to the crossover probability and mutation probability, crossover and mutation operations are performed on the population to generate a new generation of population.

Step 6: Termination condition. If it is established that the number of iterations is less than the maximum number of iterations, Step 2 is repeated. Otherwise, the algorithm ends, and the optimal distribution plan for cold chain logistics distribution is output.

The procedure and implementation of the main steps are described as follows: in genetic algorithms, the mutation operator is an important operation. At the beginning, it is necessary to input the population size N and randomly generate the initial population P0. Then, the chromosome with the largest fitness function value is selected as the optimal solution Best from P0. Next, the number of evolutionary cycles LS is set, as well as the number of generations of evolution contained in each evolutionary cycle EG. In each evolutionary cycle, the operation is carried out according to the designed combinatorial operator on P0, the fitness function of the individuals before and after the use of it is compared, and a larger value is selected to continue the operation values, and select the individual with the larger value to continue the operation. At the end of one evolutionary cycle, the optimal individual is retained, and selection operations are performed according to the race selection strategy to obtain a new population newP. Then, newP is operated by the crossover operator and the variation operator, respectively, to generate new offspring newP1 and newP2. NewP1 and newP2 are merged to form P0 and enter the next evolutionary cycle. When all evolutionary cycles are over, the chromosome with the largest fitness function value is output. The variation operator plays an important role in genetic algorithms by introducing randomness, increasing diversity, avoiding precocity, and improving the global search ability of the algorithm. Therefore, the adjustment and optimization of the variation operator is of great significance in the implementation of genetic algorithms.

RESULTS

This study uses the example of a logistics company that cooperates with a supermarket in a certain city; the logistics company needs to provide distribution services to all supermarkets in this city. According to the data, it can be understood that the number of supermarkets owned by this company in this city is 17. During the distribution process, the distribution vehicles selected by the logistics company have refrigerated compartments that are 4.2 meters long, and the goods to be distributed are all agricultural products. According to the driver's experience, if the traffic conditions are good, the average speed of the delivery vehicle is about 40km/h. All supermarkets of this enterprise have a timeframe within which they can accept delivery, and within a 60-minutes deviation from the standard time, they will unconditionally accept the goods. However, if the delivery is two hours ahead of schedule, or if the delivery is postponed beyond 60 minutes, the supermarket will refuse to accept the goods.

We draw the distribution map of each supermarket in the city as shown in Figure 2. For cold chain distribution to all supermarkets in this city, the company uses 4.2-meter refrigerated trucks of the same brand, type, and parameters for transportation. We suppose that when the refrigerated truck is delivering to various supermarkets, all roadway segments through which this route passes are permitted, there are no prohibited segments, and there are no restrictions on the number of vehicles that may pass. The average driving speed during the delivery process is 40km/h.

The research platform software used in the study was MATLAB2010, which is based mainly on the steps of genetic algorithm design for programming operations. In this step, we set the population size to 150 and the maximum evolution period to 200. When selecting the crossover probability and the mutation probability, the adaptive function was selected as the crossover probability, and the mutation probability was selected as a fixed constant, which is 0.42.

In order to obtain a better distribution route plan, the designed genetic algorithm is run 10 times, and the distribution plan with the lowest distribution cost and the lowest carbon emission cost was selected as the optimal distribution plan. The results of 10 runs and the cost involved in obtaining the optimal distribution route for each run are shown in Table 2.

Figure 2. Location distribution to various supermarkets

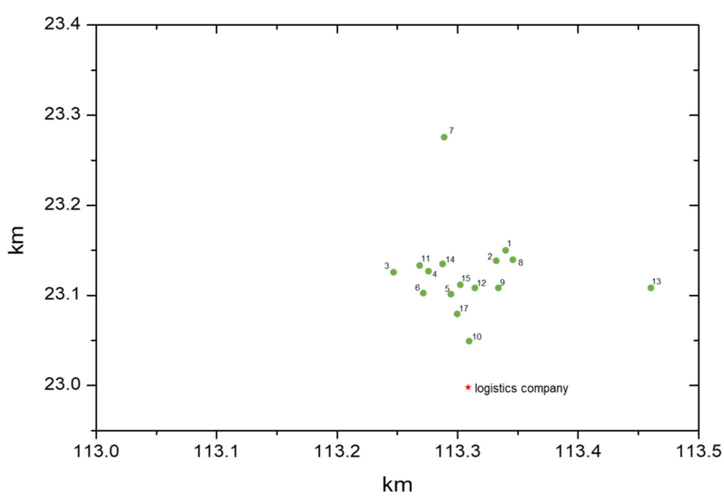


Table 2. Results of eight runs and various costs

No	Route	Cost(yuan)
1	0-16-10-0-7-4-6-0-1-8-13-0-5-15-12-0-14-2-9-0-17-11-3-0	2014.32
2	0-16-10-0-5-15-12-0-1-8-13-0-7-6-1-7-0-14-2-9-0-4-11-3-0	2016.78
3	0-16-10-0-7-11-3-0-5-15-9-0-1-8-13-0-14-4-2-0-17-12-6-0	1999.57
4	0-16-10-0-1-2-7-0-9-8-13-0-14-15-2-0-5-11-3-0-17-4-6-0	1943.72
5	0-10-0-1-8-13-0-5-15-6-0-3-11-7-0-12-9-2-0-14-4-17-0-16-0	2021.34
6	0-16-10-0-11-4-3-0-1-2-7-0-5-15-6-0-14-8-13-0-17-12-9-0	1980.818
7	0-16-10-0-11-6-15-0-14-8-13-0-9-12-5-0-1-2-7-0-17-4-3-0	2018.45
8	0-16-10-0-14-12-9-0-5-15-6-0-1-8-13-0-3-11-7-0-17-4-2-0	2008.56
9	0-16-10-0-5-15-6-0-1-2-7-0-4-11-3-0-14-8-13-0-17-12-9-0	1998.20
10	0-16-10-0-7-11-3-0-14-8-13-0-1-2-5-0-15-6-9-0-17-4-12-0	2014.09

We compared and analyzed the eight optimal distribution schemes obtained from the above eight runs. The lowest total cost is the result of the sixth run, so the optimal distribution scheme obtained from the sixth run was selected as the final distribution plan. This delivery scheme involves six refrigerated trucks for delivery, so there are six delivery routes for the refrigerated trucks, namely the following:

Route 1: Company—Supermarket 16—Supermarket 10—Company
Route 2: Company—Supermarket 11—Supermarket 4—Supermarket 3—Company
Route 3: Company—Supermarket 1—Supermarket 2—Supermarket 7—Company
Route 4: Company—Supermarket 5—Supermarket 15— Supermarket 6—Company
Route 5: Company—Supermarket 14—Supermarket 8—Supermarket 13—Company
Route 6: Company—Supermarket 17—Supermarket 12—Supermarket 9—Company

Then we used MATLAB software to draw the optimal fitness function value and the average value change graph for this running process with the abscissa as the number of iterations and the ordinate as the fitness function value. The obtained optimal value-average evolution diagram is shown in Figure 3.

The distribution costs involved in the optimal distribution route are shown in Table 3.

Figure 3. The optimal value-average evolution diagram

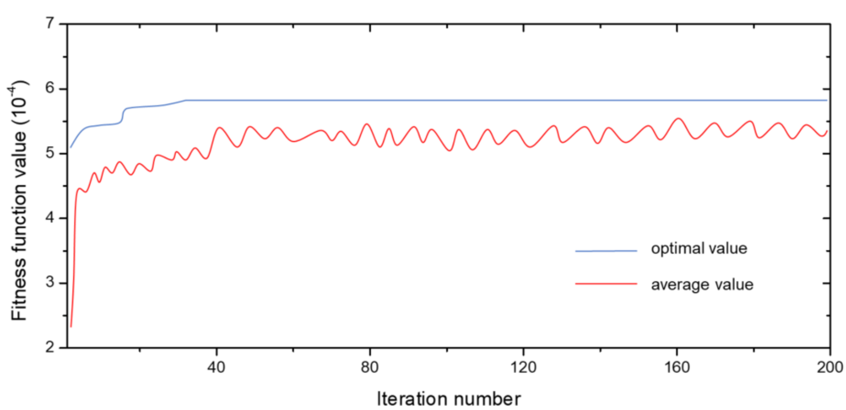


Table 3. The distribution cost of the optimal distribution route (yuan)

Total cost	Fixed cost	Variable cost	Cooling cost	Carbon emission cost	Penalty cost
1980.818	350	763.4	394.26	0.5134	472.645

If we analyze the proportion of each distribution cost in the result of eight runs, the analysis result can be concluded. In the total cost, the carbon emission cost accounts for the least proportion, which is the least cost part. In essence, quantifying carbon emissions as carbon emissions costs does not have a great impact on the total distribution costs of cold chain logistics companies.

CONCLUSION

This article focuses on the need to establish cold chain logistics in low-carbon cities. We discuss the definition of the vehicle routing problem, the division of the time window, and the components involved in solving the problem. The main objective is to develop a route optimization model for low-carbon urban cold chain logistics.

The process of building the model begins with a description of the problem to be studied and the modeling approach. The assumptions and constraints required to build the model are then presented. The model incorporates fixed costs, variable costs, cooling costs, carbon emission costs, and penalty costs into the objective function.

In order to optimize the model, an algorithmic approach is designed in this paper, including the definition of the objective function and the genetic operator. The parameters were set using genetic steps incorporating actual data provided by a logistics company. The solution was executed using MATLAB software following the defined steps. This process was repeated 10 times, and finally the distribution route with the lowest distribution cost was selected as the optimization result.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

FUNDING STATEMENT

This work was not supported by any funds.

ACKNOWLEDGMENT

The authors would like to show sincere thanks to those techniques who have contributed to this research.

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