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A Hybrid Genetic Based Approach for Solving Vehicle Routing Problem in Cold Chain Logistics Distribution

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Abstract. In order to solve the problems of slow convergence speed, high total distribution cost, long total distance, large number of vehicles used and long algorithm running time in the process of solving the cold chain logistics distribution vehicle routing problem by genetic algorithm, the hybrid genetic algorithm is used to study the cold chain logistics distribution vehicle routing problem. By establishing the distribution vehicle routing problem model under the dynamic network and introducing the time window to optimize the model, the distribution vehicle routing problem model under the dynamic network of cold chain logistics with time window is constructed. Therefore, the mountain climbing algorithm optimizes the genetic algorithm and obtains the hybrid genetic algorithm. The hybrid genetic algorithm is used to solve the constructed model, and the relevant analysis results are obtained. The experimental results show that the hybrid genetic algorithm is superior to the genetic algorithm in terms of speed and accuracy. The total distribution cost is low, the total distance is short, the number of vehicles used is small, and the operation time of the algorithm is short. The analysis results are more in line with the actual needs of logistics distribution, and have important contributions to the development of logistics enterprises. It can effectively control logistics costs and improve customer satisfaction.

Keywords: Cold chain logistics; Vehicle routing problem; Dynamic network; Genetic algorithm; Mountain climbing algorithm.

1. Introduction

The report of the 19th National Congress of the Communist Party of China pointed out that the main contradiction in China at present is the contradiction between the people's growing need for a better life and unbalanced and inadequate development. With the acceleration of urbanization, the urban population has surpassed the rural population, and the vast majority is concentrated in cities and towns. Population concentration is conducive to the growth of the urban economy. However, it also challenges urban management, such as treating urban sewage and garbage and the supply of daily necessities for urban residents. The main goal of urban management is to better meet people's needs for a better life. As a necessity of daily life, fresh agricultural products are also the basic link to meet people's better life. Ensuring the effective supply of fresh agricultural products is conducive to the cost control of logistics enterprises and to improving the quality of life of urban residents. The distribution link is the key to the supply of fresh agricultural products. Compared with traditional logistics, because the fresh-keeping period of fresh agricultural products is generally shorter, to better preserve its nutritional value and prevent the occurrence of rot and deterioration, its storage, transportation, and sales must be carried out in a cold storage environment with strict requirements.

Since the VRP problem was put forward, it has become the key research object of scholars at home and abroad. Balinski[1] and others first established the VRP model and proposed the method of cluster segmentation to deal with the VRP problem; Li Shan [2] constructed a minimum-cost distribution model including vehicle assignment, transportation, overtime, and cargo damage according to the current actual road network vehicle transportation situation, and optimized the driving route and departure order of the distribution vehicles; Liu Xinmeng [14] and others proposed to solve VRP problem with time window by multi-agent co-evolution algorithm, and constructed a double-objective constraint model with the vehicle carrying capacity and service time window as constraints; Ren Xiaozhi [3] solved the problem by using a clustering algorithm, and optimized the logistics distribution route of domestic tobacco companies, taking the idea of studying the regional problem first and then the routing problem. The solution goal is to reduce the workload in the optimization process, thus effectively improving the logistics distribution efficiency of tobacco companies; Zhang Ting [4] and others studied the vehicle routing problem in urban distribution. Through analyzing the influence of real-time information on the whole process of distribution, the dynamic change data of information in the distribution process was obtained, and then a dynamic vehicle path problem analysis model was constructed, and the hybrid genetic algorithm was used to solve the model; Hsu[5] comprehensively considers the factors such as food damage during transportation, random congestion in traffic conditions, and delivery time window, to build SVRPTW model by adding random constraints in-vehicle road network distribution. The model's objective function includes transportation, fixed, and time penalty costs. Real-life examples verify the correctness and feasibility of the model, and the model is compared with the traditional VRPTW model. Qi C. [6] solved the vehicle routing problem with capacity constraints by using the improved particle swarm optimization algorithm and ensure the accuracy and feasibility of the method through a comparative analysis of examples. Border G. [7] built a model aiming at the shortest distribution distance by studying the VRPPD of drinking water products and solved the above model with three algorithms: genetic algorithm, tabu search algorithm, and hybrid strategy. S.Jung [8] studied the vehicle routing problem (TDVRP) under time-varying conditions and solved and analyzed the above model by improving the optimized genetic algorithm.

Yang Wei [9] set up the cold chain logistics path model of agricultural products with the shortest distance of vehicles as the goal and solved the problem using a particle swarm optimization algorithm. The solution results are consistent with the actual logistics distribution path, which verifies the effectiveness of the model and algorithm. However, this method has the problem of slow convergence, and the actual application effect is not good; Yang Dating [10] built a cold chain logistics distribution model whose objective function includes transportation cost, fixed cost and time penalty cost, and solved it with improved genetic algorithm and C-W saving algorithm. However, this method has the problems of high total distribution cost and long total distance, and there is still a certain gap with the ideal application effect; Chen Meng [11] solved the routing problem by constructing an optimal scheduling model with the lowest sum of three costs: the cost of vehicles in transportation, the overtime cost not delivered at the specified time and the refrigeration cost of refrigerated vehicles in transportation, and obtained the optimal solution reflecting the uniqueness of cold chain logistics. However, in practical application, it is found that this method has many problems such as the number of vehicles used and the long running time of the algorithm, and it is difficult to apply it to the actual process on a large scale. The model built by Han Yin and Shi Pan [12] is composed of goods loss cost, transportation cost, time penalty cost, and refrigeration cost. Based on considering the dynamic changes of the existing road network, the algorithm of saving value is selected, and the feasibility and accuracy of the model and algorithm are determined according to the analysis and verification of an example. However, in the actual test process, it was found that this method had the problems of high total distribution cost and large number of vehicles used, and did not achieve the expected goal. Yu Kun [13] analyzed the path optimization problem of simultaneous delivery and pickup in cold chain logistics distribution. According to the unique characteristics of urban cold chain logistics distribution, the delivery mode is not simply pickup, and the objective function is the least cost, and then the genetic algorithm is used to solve the above model. However, this method has slow convergence speed and long running time, and the actual application effect is not good; Pan Dongjing [14] built the vehicle scheduling model with the lowest total cost under the fuzzy demand of customers based on the actual vehicle transportation situation, and analyzed and solved the fuzzy demand of each retail outlet by using the hybrid intelligent algorithm, which proved the correctness of the model and the feasibility of the algorithm. However, in the follow-up test, it was found that there were many problems in this method, such as the number of vehicles used and the long running time of the algorithm. There was still a certain gap between this method and the expected goal; Wang Xiaoning [15] et al., through observing and analyzing the low-carbon energy-saving perspective, studied the vehicle distribution path of cold chain logistics in low-carbon mode, solved the constructed model by using genetic algorithm, and verified the feasibility and correctness of the algorithm through actual case analysis. However, the solution process of this method is relatively complex, and there are problems of slow convergence speed and long running time of the algorithm; Osvald A and Stirn L Z[16] put forward that the efficiency of fresh food transportation and distribution is determined by transportation time, and the factors such as damage during food transportation, random traffic congestion and distribution time window are considered comprehensively, so random constraints are added to the vehicle road network distribution to build a model and then build a model, and the tabu search algorithm is used to solve the case, which verifies the correctness and feasibility of the algorithm. However, in the actual test process, it is found that this method has many problems such as high total distribution cost, long total distance and large number of vehicles; Zou Y and Xie R[17] systematically expounded and analyzed the current development of food cold chain logistics in China, mainly from the factor of ensuring food safety and reliability, and constructed the total cost including goods damage cost and transportation cost, and solved the actual case by ant colony algorithm, thus verifying the correctness and feasibility of the model. However, in the actual test process, it is found that this method has the problems of slow convergence, high total distribution cost and long total distance, and there is still a certain gap with the expected goal; Jiang W X[18] analyzes the related costs that may arise in the process of supply chain transportation, establishes an optimized cold chain logistics network model, and proves its feasibility and accuracy by adopting a hybrid intelligent algorithm. However, the solution process of this method is relatively complex, and there are problems such as slow convergence speed, high total distribution cost and long algorithm running time, which are difficult to achieve the desired goal.

Currently, the research on cold chain logistics distribution of fresh agricultural products tends to be static analysis. It is considered that the driving time from the distribution center to each point of sale is only related to distance, or the vehicle driving speed is uniform. In contrast, other related factors are not considered. In addition, different scholars have built models for the distribution vehicle routing problem from different angles, and the established models need to be more generality. To solve the problems of slow convergence speed, high total distribution cost, long total distance, large number of vehicles used and long algorithm running time in the above methods, this paper comprehensively considers the factors affecting the cold chain logistics distribution, establishes a mathematical model to simulate the distribution process of fresh agricultural products, and designs an algorithm to solve the model to obtain the best distribution route. According to the research results of this paper, cold chain logistics distribution is beneficial to enterprises to control logistics costs, improve customer satisfaction, and make outstanding contributions to the further development of logistics.

2. Research model

2.1 Model of distribution vehicle routing problem under dynamic network

2.1.1 Problem description

When the distribution vehicles are distributed in a certain road section of the road network, the driving time of the vehicles will change according to a certain probability distribution. The distribution vehicles start from the distribution center to several sales points and return to the distribution center after completing the service. The distribution vehicles are all of the same types. Given the loading and unloading time and maximum load of distribution vehicles at sales points, the specific location and goods demand of each sales point are clear, and the distance between the distribution center and each sales point is determined, so it is necessary to arrange the driving route reasonably to minimize the total cost of distribution services.

2.1.2 Assumed condition

In order to build a better model to solve the problem, the related variables involved in the model are assumed as follows:

(1)The distribution process is one-way; that is, the customer only serves once;

(2) The vehicles for distribution and transportation are of the same model and have the same load:

(3) The customer demand is less than the maximum load capacity of the delivery vehicle;

(4) When distributing goods, each point of sale can only be delivered by one car and meet customer demand;

(5) Each transport vehicle needs to start from the distribution center and then return to the distribution center after the distribution is completed;

(6) The demand for goods at each point of sale can be known in advance, and the position of the point of sale remains unchanged;
(7) The travel time between the distribution center and point of sale, and between the point of sale and point of sale obeys normal distribution;
(8) The distribution cost of vehicles is related to the distribution distance and travel time;

2.1.3 Symbol Description

K: The number of vehicles required by the distribution center;
Q: The approved weight of the distribution vehicle;
q_i: The demand for the I the sale;
n: Represents the number of sales points ($i, j \in \{1,2,\cdots,n\}, I \neq j$, distribution center number is 0);
t_{kj}; A time when the vehicle k leaves the point of sale j;
$t_{ijk}(t_{ki})$: represents the time when the vehicle k travels from the point of sale i to the point of sale j at time t_{ki}, and the travel time obeys the normal distribution, that is, $t_{ick}(t_{ki}) \in N\left(\mu_{ijk}(t_{ki}), \delta_{ijk}(t_{ki})\right)$;
S_i: Unloading time of point of sale i;
d_{ij}: Indicates the delivery distance from the point of sale i to the point of sale j;
FK: Fixed cost of vehicle k distribution;
C_l: Operating cost per unit distance;
C_t: Operating cost per unit time;

2.1.4 Objective function

$$P_1 = \sum_{k=1}^{K} f_k \tag{2-1}$$

$$P_2 = C_l \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} d_{ij}\, x_{ijk} \tag{2-2}$$

$$P_2 = C_t \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} t_{ijk}(t_{ki})\, x_{ijk} \tag{2-3}$$

$$\min P = \sum_{k}^{K} f_k + C_l \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} d_{ij} x_{ijk} + C_t \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} t_{ijk}(t_{ki}) x_{ijk} \tag{2-4}$$

$$\mathrm{s.t.} \sum_{i=0}^{n} \sum_{j=0}^{n} q_i\, x_{ijk} \leq Q, k \in (1,2,\cdots,K), i \neq j \tag{2-5}$$

$$\sum_{k=1}^{K} \sum_{i=0}^{n} x_{ijk} = 1, j \in (1,2,\cdots,n), i \neq j \tag{2-6}$$

$$\sum_{k=1}^{K} \sum_{j=0}^{n} x_{ijk} = 1, i \in (1,2,\cdots,n), i \neq j \tag{2-7}$$

$$\sum_{i=0}^{n} \sum_{j=1}^{n} x_{ijk} = n, k \in (1,2,\cdots,K), i \neq j \tag{2-8}$$

$$\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{jik} \leq 1, i = 0, k \in \{1,2,\cdots,K\} \tag{2-9}$$

$$t_{kj} = \sum_{i=0}^{n} x_{ijk}\,(t_{ki} + t_{ijk}(t_{ki}) + S_j), j \in (1,2,\cdots,n) \tag{2-10}$$

$$x_{ijk} = \begin{cases} 1 & \text{Vehicle } k \text{ is delivered from customer } i \text{ to customer } j \\ 0 & \end{cases} \quad i \neq j \quad (2\text{-}11)$$

Formula (2-1) is the fixed cost of distribution, and formula (2-2) is the cost of distribution distance in the distribution process; Formula (2-3) is the time cost caused by route congestion in the distribution process; Formula (2-4) is the objective function, which mainly consists of the fixed cost of vehicles and the transportation cost of vehicles. Formula (2-5) is that the total demand of all customers on the same distribution route is less than or equal to the maximum load of a single vehicle; Formulas (2-6) and (2-7) show that each point of sale can only be served once; The formula (2-8) is that every point of sale can be served; The formula (2-9) is starting from the distribution center and returning to the starting point; The formula (2-10) is as follows: on each distribution route, when the distribution vehicle leaves the point of sale, the current time is equal to the time when the distribution vehicle leaves the previous point of sale plus the vehicle traveling time from the point of sale to the point of sale and the unloading time of the vehicle at the point of sale ; (2-11) is a variable where the decision variable is limited to 0-1.

2.2 Vehicle routing problem model for dynamic network distribution with time windows

In the actual distribution process, customers have certain requirements for the delivery time of goods. However, due to various objective factors, such as road traffic conditions, weather conditions, and traffic control, delivery vehicles will arrive at the point of the sale earlier or later. Combined with the needs of the actual delivery process, this paper adopts a soft time window, which means that customers allow delivery vehicles to advance or delay the delivery of goods [19]. However, because suppliers fail to deliver goods according to the agreed time, certain penalty costs will be incurred, and the penalty situation of the soft time window is shown in Figure 1.

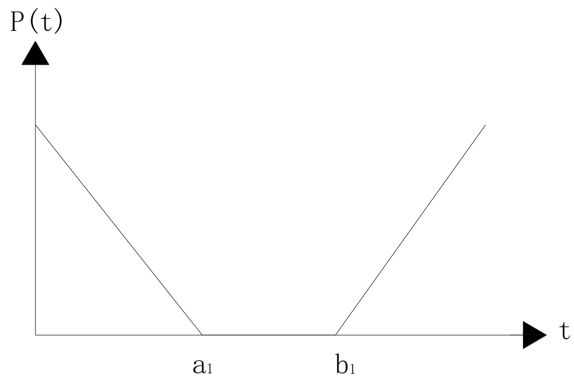

Fig.1: Schematic diagram of soft time window punishment

2.2.1 Problem description

It is assumed that the distribution vehicles start from the distribution center and provide distribution services to each point of sale. All the distribution vehicles are of the same type. When returning to the distribution center after the distribution is completed, the service time and maximum load of the distribution vehicle at the point of sale are known, and the goods required by each point of sale and their location are known, so the distribution time belongs to the soft time window. If vehicles arrive at the point of sale early or late, there will be a certain penalty cost. The shortest distance between the distribution center and the point of sale and between the point of sale and the point of sale is known and fixed. The travel time of vehicle transportation obeys the normal distribution of a certain probability [20] and satisfies the same assumptions as the distribution vehicle routing problem model under a dynamic network. The distribution route and travel time are optimized to minimize the total distribution cost.

2.2.2 Symbol Description

The main symbols of the formula in this section are consistent with the symbols in the vehicle routing problem model under dynamic network, but some of them are inconsistent, which will be described in detail below;

(1) $[a_i, b_i]$: Represents the time range, a_i represents the earliest arrival time, and b_i represents the latest arrival time, that is, the arrival time window of the delivered goods required by the point of sale i, which is a soft time window;

(2) θ_1: When the goods arrive early, the waiting cost per unit time;

(3) θ_2: Penalty cost per unit time for delayed delivery of goods;

2.2.3 Model building

$$\min P = \sum_{k=1}^{K} f_k + C_l \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} d_{ij}x_{ijk} + C_t \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} t_{ijk}(t_{ki})x_{ijk}$$

$$+ \sum_{k=1}^{K}\sum_{i=1}^{n} \theta_1 \max[a_i - t_{ki}, 0] + \sum_{k=1}^{K}\sum_{i=1}^{n} \theta_2 \max[0, t_{ki} - S_i - b_i] \qquad (2\text{-}12)$$

$$\text{s.t.} \quad \sum_{i=0}^{n}\sum_{j=0}^{n} q_i x_{ijk} \le Q \qquad k \in (1,2,\cdots,K), i \neq j \qquad (2\text{-}13)$$

$$\sum_{k=1}^{K}\sum_{i=0}^{n} x_{ijk} = 1 \qquad j \in (1,2,\cdots,n), i \neq j \qquad (2\text{-}14)$$

$$\sum_{k=1}^{K}\sum_{j=0}^{n} x_{ijk} = 1 \qquad i \in (1,2,\cdots,n), i \neq j \qquad (2\text{-}15)$$

$$\sum_{i=0}^{n}\sum_{j=1}^{n} x_{ijk} = n \qquad k \in (1,2,\cdots,K), i \neq j \qquad (2\text{-}16)$$

$$\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{jik} \le 1, \quad i = 0; k \in \{1,2,\cdots,K\} \qquad (2\text{-}17)$$

$$t_{kj} = \sum_{i=0}^{n} x_{ijk} (t_{kj} + t_{ijk}(t_{ki}) + S_i) \qquad j \in (1,2,\cdots,n) \qquad (2\text{-}18)$$

$$x_{ijk}=\begin{cases}1 & \text{Vehicle } k \text{ is delivered from customer } i \text{ to customer } j\\ 0 & \end{cases} \quad i\neq j \quad (2\text{-}19)$$

Formula (2-12) is the objective function, which is divided into five parts: Part 1 is the fixed cost of distribution vehicles; The second part is the related expenses caused by the distribution distance; The third part is the time cost in the event of traffic congestion. The fourth part is the waiting cost caused by early delivery; The fifth part is the penalty cost caused by delayed delivery; The meanings of formulas (2-13) to (2-19) are consistent with those of (2-5) to (2-11) in the vehicle routing problem model under dynamic network.

2.3 Distribution vehicle routing problem model in cold chain logistics dynamic network with time window

According to the distribution vehicle routing problem model under a dynamic network with time windows, this paper will continue to add the related constraints of cold chain logistics to the model. When the fresh agricultural products rot and deteriorate due to the temperature and humidity of the distribution vehicles in the distribution process, the cost of goods damage will be generated, which is mainly divided into two parts [21]: One is the wilting cost caused by the increase of time, and the other is in the process of distribution and handling. Due to the change of temperature and humidity due to non-standard operation or other reasons, the cost of goods damage during the distribution of fresh agricultural products is divided into two parts, namely, the cost of goods damage caused by long distribution distance or time, and the cost of goods damage caused during handling. The calculation method of goods damage cost P_5 is as follows:

$$P_5=C_0\sum_{k=1}^{K}\sum_{j=1}^{n}t_{0jk}(t_{k0})\alpha_1 x_{0jk}q_j+C_0\sum_{j=1}^{n}\alpha_2 q_j \quad (2\text{-}20)$$

C_0 stands for the average unit price of fresh agricultural products, and AA stands for the loss ratio of goods per unit time, indicating the loss ratio of fresh agricultural products when the delivery time increases gradually; $\alpha_2$is the loss ratio of goods per unit weight, which indicates the loss generated in the process of transporting and unloading goods. The assumptions and main symbols of the optimal dispatching model of distribution vehicles under the dynamic network of cold chain logistics with time windows are the same as those of the model (2-12). The model is constructed as follows:

$$\min P=\sum_{k=1}^{K}f_k+C_l\sum_{k=1}^{K}\sum_{i,j=0,i\neq j}^{n}d_{ij}x_{ijk}+C_t\sum_{k=1}^{K}\sum_{i,j=0,i\neq j}^{n}t_{ijk}(t_{ki})x_{ijk}$$
$$+\sum_{k=1}^{K}\sum_{i=1}^{n}\theta_1\max[a_i-t_{ki},0]+\sum_{k=1}^{K}\sum_{i=1}^{n}\theta_2\max[0,t_{ki}-S_i-b_i]+$$
$$C_0\sum_{k=1}^{K}\sum_{j=1}^{n}t_{0jk}(t_{k0})\,\alpha_1 x_{0jk}q_j+C_0\sum_{j=1}^{n}\alpha_2 q_j \quad (2\text{-}21)$$

$$\text{s.t.}\quad \sum_{i=0}^{n}\sum_{j=0}^{n}q_i\,x_{ijk}\leq Q \qquad k\in(1,2,\cdots,K),\, i\neq j \quad (2\text{-}22)$$

$$\sum_{k=1}^{K}\sum_{i=0}^{n} x_{ijk} = 1 \qquad j \in (1,2,\cdots,n), i \neq j \tag{2-23}$$

$$\sum_{k=1}^{K}\sum_{j=0}^{n} x_{ijk} = 1 \qquad i \in (1,2,\cdots,n), i \neq j \tag{2-24}$$

$$\sum_{i=0}^{n}\sum_{j=1}^{n} x_{ijk} = n \qquad k \in (1,2,\cdots,K), i \neq j \tag{2-25}$$

$$\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{jik} \leq 1, \quad i = 0; \quad k \in \{1,2,\cdots,K\} \tag{2-26}$$

$$t_{kj} = \sum_{i=0}^{n} x_{ijk}\left(t_{kj} + t_{ijk}(t_{ki}) + S_i\right) \qquad j \in (1,2,\cdots,n) \tag{2-27}$$

$$x_{ijk} = \begin{cases} 1 & \text{Vehicle } k \text{ is delivered from customer } i \text{ to customer } j \\ 0 & \end{cases} \qquad i \neq j \tag{2-28}$$

Formula (2-21) is the objective function of the minimum total cost of distribution, which consists of six parts: the first part is the fixed cost generated by the transport vehicle itself; The second part is the related expenses caused by the distribution distance; The third part is the time cost in the event of traffic congestion. The fourth part is the waiting cost caused by early delivery; The fifth part is the penalty cost caused by delayed delivery; Part 6 represents the cost of goods damage of transport vehicles; The specific meanings of formulas (2-22)~(2-28) are generally consistent with those marked in the vehicle routing model under dynamic network with time windows. See formulas (2-5)~(2-11) for details.

3. Solution idea and algorithm design

3.1 Overview of genetic algorithm

A genetic algorithm is a random search algorithm based on biological phenomena, such as natural evolution, crossover, and mutation. It uses mathematical modeling based on a genetic mechanism to search randomly to find the optimal solution to practical problems. The genetic algorithm is composed mainly of six parts [22]: coding, initial population generation, fitness evaluation, selection, crossover, and mutation. The flow chart of the genetic algorithm is shown in Figure 2.

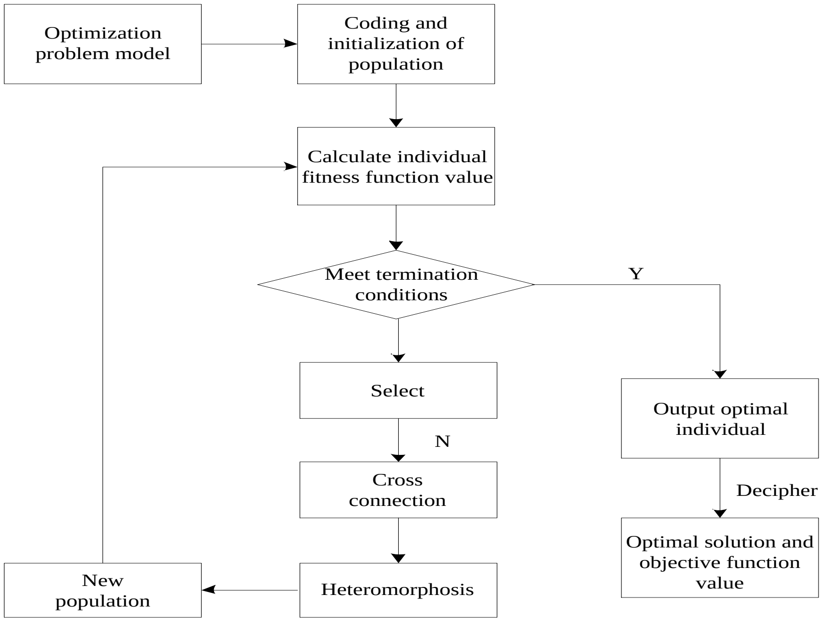

Fig.2: Flow chart of genetic algorithm

3.2 Improvement of genetic algorithm

The mountain climbing algorithm is a simple greedy search algorithm, which selects an optimal solution from the adjacent solution space of the current solution as the current solution until it reaches a locally optimal solution. The algorithm has strong local search ability; because of this, the main disadvantage is that it will fall into the optimal local solution and may not be able to search for the optimal global solution. Complementing the genetic algorithm, it combines the global search ability of the genetic algorithm with the hill-climbing algorithm's local search ability to enhance the hybrid algorithm's searchability. It approaches a better direction through local search [23], as shown in Figure 3 below.

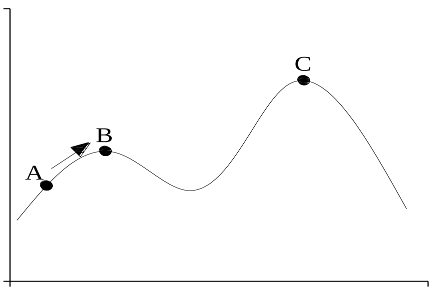

Fig.3: Demonstration diagram of mountain climbing algorithm limitations

3.3 Design of hybrid genetic algorithm

3.3.1 Coding and decoding of chromosomes

In the traditional genetic algorithm, there are two transformations: phenotype and genotype [24]. Common coding techniques are [25] natural number, binary, and diploid coding. In this paper, natural number coding is chosen as the coding method. When the number of delivery vehicles K is known, the composition of the chromosome is made up of natural number coding. For example, chromosome (01304602570) indicates that three transport vehicles serve seven customers, which can better deal with the problem. Then the code of an individual can be expressed by the following formula:

$$K: b_{\lambda} b_{\lambda-1} b_{\lambda-2} \ldots b_2 b_1 \tag{3-1}$$

Where, b_{λ} represents the encoding result of the λ-th individual, λ indicates the encoding length..

Its corresponding decoding formula is expressed by the following formula:

$$K = U_{min} + \left(\sum_{i=1}^{\lambda} b_i \times 2^{i-1}\right) \times \frac{U_{max}-U_{min}}{2^{\lambda}-1} \tag{3-2}$$

Where, U_{max} and U_{min} represent the maximum and minimum values of coding respectively

3.3.2 Generation of the initial population

To ensure chromosome diversity, we should also pay attention to the moderate population size; too large or too small will impact the solution. In order to achieve the balance between the two, the population size is 20-200, and the initial population is generated by random method.

3.3.3 Design of fitness function

Fitness function is used to evaluate the individual's excellent degree in genetic algorithm. The objective function of practical problems is defined as the fitness function in the algorithm. The higher the fitness, the easier it is to survive. The fitness function constructed in this paper is as follows, P is the objective function, and f_i is the fitness function.

$$P = \sum_{k=1}^{K} f_k + C_l \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} d_{ij} x_{ijk} + C_t \sum_{k=1}^{K} \sum_{i,j=0,i\neq j}^{n} t_{ijk}(t_{ki}) x_{ijk} + \sum_{k=1}^{K} \sum_{i=1}^{n} \theta_1 \max[(a_{ki} - t_{ki}), 0] + \sum_{k=1}^{K} \sum_{i=1}^{n} \theta_2 \max[0, t_{ki} - S_i - b_i] + C_0 \sum_{k=1}^{K} \sum_{j=1}^{n} t_{0jk}(t_{k0}) \alpha_1 x_{0jk} q_j + C_0 \sum_{j=1}^{n} \alpha_2 q_j \tag{3-3}$$

$$f_i = \frac{1}{P} \tag{3-4}$$

3.3.4 Design of selection operator

In order to make the whole population continue better, it is necessary to pass on the genes of individuals with high fitness in the current population to the next generation, and the selection operation is based on fitness. The greater the fitness value, the higher the survival probability of individuals. This is the natural law of survival and survival of the fittest. Currently, the commonly used selection operators are [26]: Expected value method, proportional selection method, league selection method, elite selection method, ranking selection method, etc. The selection operator in this paper adopts the proportional selection method, also called roulette or Monte Carlo simulation. The principle of the proportional selection method is to select according to the proportion of individual fitness to the fitness of the whole population. The higher the fitness value, the greater the probability of being selected.

3.3.5 Design of crossover operator

The design idea of the crossover operator is to find a cycle from two parent chromosomes based on the crossover probability, and form a new offspring by copying the genes at the cycle position to the offspring chromosomes. The calculation formula of cross probability is as follows:

$$P_c = \frac{M_c}{M} \times 100\% \tag{3-5}$$

Where, M represents the number of individuals in the population, and M_c represents the number of individuals exchanged in the population.

(1)Randomly select a gene on a certain parent, then find the gene number in the corresponding position of another parent, then go back to the position where the first parent found the gene with the same number, and repeat the previous work until a ring is formed, and the positions of all genes in the ring are the last selected positions;

(2) Generate offspring with the selected gene in parent 1, and ensure the position correspondence;

(3) The remaining genes in parent two are put into the offspring generated by parent 1. Similarly, the remaining genes in parent one are put into the offspring generated by parent 2.

3.3.6 Design of mutation operator

Because each individual has different coding methods, the mutation can be divided into two types: binary mutation and real-value metamorphism. This paper uses the exchange mutation in real-value mutation to select the mutated individual according to the mutation probability. The genes at any two positions are exchanged to form a new individual. Finally, the mutation operation is completed. The calculation formula of variation probability is as follows:

$$P_M = \frac{B}{M \times \lambda} \times 100\% \tag{3-6}$$

Where, B represents the number of genes with variation in each generation.

3.3.7 Mountain climbing operation

In order to select the best chromosome individual in the new population generated by genetic operation, the introduction of a hill climbing algorithm can search the current state constantly to change to the better direction and select the most promising point in the solution space to search. The implementation steps are as follows:

(1)Randomly exchange two genes in an individual;

(2)After gene exchange, check whether the adaptability to the environment is enhanced. If it is enhanced, choose the improved individual. If it is not better, continue to search for a better direction and stop running when it reaches the maximum exchange times set by the algorithm.

3.3.8 Algorithm termination rule design

The selection of crossover and mutation rates in the genetic algorithm significantly impacts the algorithm's solution effect. This paper uses the self-adaptive strategy for probability calculation instead of a fixed value to ensure the diversity of individuals in the population [27]. In which p_c and p_m represent crossover rate and mutation rate, respectively, the maximum fitness in the population is f_{max}, the average fitness is represented by $\overline{f}$, f represents the fitness value of individuals who perform mutation operation, and k_1, k_2, k_3, k_4 is an arbitrary constant between 0 and 1. If the chromosome fitness is closer to the optimal fitness, the crossover mutation rate will be lower, and its calculation formula is as follows:

$$P_c = \begin{cases} k_1(f_{max} - f')/\left(f_{max} - \overline{f}\right), f' \geq \overline{f} \\ k_2, f' < \overline{f} \end{cases} \tag{3-7}$$

$$P_m = \begin{cases} k_3(f_{max} - f')/\left(f_{max} - \overline{f}\right), f' \geq \overline{f} \\ k_4, f < \overline{f} \end{cases} \tag{3-8}$$

In this paper, the algorithm is terminated by setting the maximum number of iterations (the loop is terminated when there is no change in successive iterations of the genetic algorithm), which can effectively limit the running time of the algorithm and avoid repeated invalid iterations, which also improves the running efficiency of the algorithm to a certain extent. The flow chart of the hybrid genetic algorithm is shown in Figure 4.

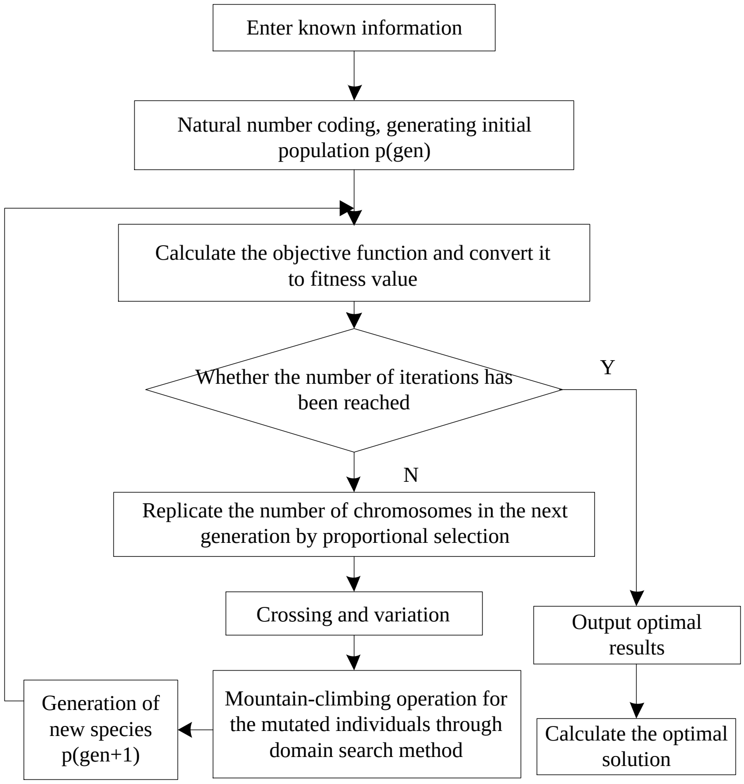

Fig.4: Flow chart of hybrid genetic algorithm

4. Empirical analysis

The distribution path is optimized based on the model and algorithm constructed above, combined with the actual situation of H company's cold chain logistics distribution. Through the analysis of the solution results, it can be seen that the new distribution scheme has significantly improved both the distribution cost and the distribution time, and the effectiveness of the model and algorithm is verified.

4.1 Case background

Company h mainly deals in the distribution service of fresh agricultural products in Datong city and is a large agricultural product distribution company in Shanxi province in terms of scale and function. Its cold chain logistics industry facilities are complete, including cold storage warehouse, basement with thermal insulation performance, wind-proof and rain-proof greenhouse and mobile scale, etc. Currently, H Company provides agricultural product distribution services for Pingcheng District, Yungang District, Xinrong District, and Yunzhou District. The distribution centers and sales points are shown in Figure 5.

Fig.5: Schematic diagram of locations of sales points and distribution centers

4.2 Basic data

Taking the distribution data of H Company at a certain stage as the basic data, more than 200 pieces of distribution information were collected, including distribution center location, sales point location, customer demand, and vehicle driving time. The specific data are shown in Tables 1 to 6. Get the latitude and longitude of each distribution point and distribution center through the Baidu map open platform, and then mark the actual location of each sales point in batches on the map without worry, as shown in Figure 5.1. As the above coordinates are encrypted by Baidu Company and cannot be directly used in the calculation example, the coordinates are decrypted through the open interface provided by Baidu Company and then converted into rectangular coordinates by using Gaussian coordinates, using Xi 'an 80 coordinate system and distribution center coordinates (696213.6832, 4438509.44). The specific data of H Company are shown in Tables 1 and 2 below.

Table 1 Point of sale information table

Point of sale number	x coordinate （m）	Y coordinate （m）	Demand (tons)	Prescribed time window	Service time （min）
Point of sale 1	693681.216	4442091.11	0.21	4:30-5:30	10
Point of sale 2	689996.177	4441550.28	0.19	4:30-5:30	10
Point of sale 3	686461.442	4441056.29	0.3	5:00-6:00	15
Point of sale 4	687954.97	4439947.59	0.35	5:00-6:30	20
Point of sale 5	691077.524	4439819.61	0.15	6:00-6:30	8

Point of sale 6	690107.395	4436329.4	0.25	4:30-5:30	12
Point of sale 7	688242.856	4435337.27	0.22	5:00-6:00	10
Point of sale 8	690624.181	4434348.82	0.3	5:10-6:10	15
Point of sale 9	693498.942	4434903.15	0.4	6:00-7:00	25
Point of sale 10	695061.475	4437218.44	0.35	6:10-7:10	20
Point of sale 11	700914.653	4440670.34	0.2	5:00-6:00	10
Point of sale 12	698036.666	4440005.65	0.2	5:00-5:30	10
Point of sale 13	704876.832	4441769.86	0.25	6:00-7:00	12
Point of sale 14	697200.776	4434669.26	0.3	4:30-5:30	15
Point of sale 15	698912.644	4433708.52	0.35	5:00-6:30	20
Point of sale 16	700572.804	4432203.47	0.25	5:10-6:10	12
Point of sale 17	702730.294	4432832.24	0.2	6:00-7:00	10
Point of sale 18	700783.771	4434539.65	0.3	6:00-7:00	15

Table 2 Distance between sales points and distance from distribution center to sales points(km)

d_{ij}	0	1	2	3	4	5	...	14	15	16	17	18
0	0	4.39	6.92	10.08	8.38	5.3	...	3.97	5.51	7.67	8.64	6.05
1	4.39	0	3.72	7.29	6.11	3.46	...	8.21	9.88	12.05	12.95	10.37
2	6.92	3.72	0	3.57	2.6	2.04	...	9.96	11.87	14.11	15.43	12.87
3	10.08	7.29	3.57	0	1.86	4.78	...	12.5	14.46	16.66	18.23	15.74
4	8.38	6.11	2.6	1.86	0	3.13	...	10.65	12.61	14.8	16.4	13.92
5	5.3	3.46	2.04	4.78	3.13	0	...	8	9.94	12.17	13.59	11.05
6	6.48	6.78	5.22	5.97	4.21	3.62	...	7.29	9.19	11.25	13.1	10.83
7	8.58	8.67	6.46	5.99	4.62	5.3	...	8.98	10.79	12.72	14.7	12.57
8	6.97	8.32	7.23	7.89	6.2	5.49	...	6.58	8.31	10.18	12.2	10.16
9	4.51	7.19	7.51	9.35	7.5	5.48	...	3.71	5.54	7.57	9.46	7.29
10	1.73	5.06	6.66	9.42	7.61	4.76	...	3.33	5.21	7.45	8.83	6.32
11	5.17	7.37	10.95	14.46	12.98	9.87	...	7.06	7.24	8.47	8.05	6.13
12	2.36	4.83	8.19	11.62	10.08	6.96	...	5.4	6.36	8.2	8.57	6.12

13	9.26	11.2	14.88	18.43	17.02	13.94	...	10.46	10.03	10.49	9.19	8.31
14	3.97	8.21	9.96	12.5	10.65	8	...	0	1.96	4.18	5.83	3.59
15	5.51	9.88	11.87	14.46	12.61	9.94	...	1.96	0	2.24	3.92	2.05
16	7.67	12.05	14.11	16.66	14.8	12.17	...	4.18	2.24	0	2.25	2.35
17	8.64	12.95	15.43	18.23	16.4	13.59	...	5.83	3.92	2.25	0	2.59
18	6.05	10.37	12.87	15.74	13.92	11.05	...	3.59	2.05	2.35	2.59	0

In the actual distribution process of road networks, all kinds of unexpected events caused the distribution time of vehicles to change dynamically. In order to get the driving time of vehicles more accurately, by fitting the distribution between the historical driving time of vehicles distributed by H Company and the driving time predicted by the Gaode map, it is found that the driving time of vehicles obeys the normal distribution. Taking sales points 16 and 17 as examples, the distribution of historical travel time is N (0.13,0.19), the probability distribution diagram is shown in Figure 6, and the partial probability distribution data of travel time between distribution points are shown in Table 3.

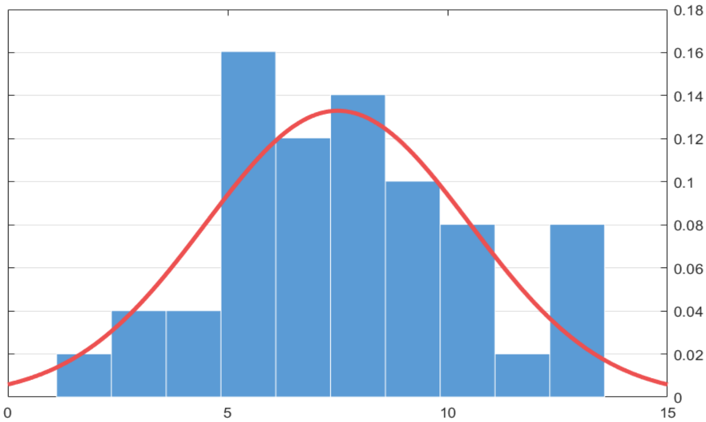

Fig.6: Probability distribution diagram of vehicle travel time from the point of sale 16 to the point of sale 17

Table 3 Probability distribution of travel time between points (partial)

	0	1	2	3	4	5
0	0	N(0.32,0.06)	N(0.47,0.02)	N(0.38,0.15)	N(0.26,0.1)	N(0.67,0.26)
1	N(0.32,0.05)	0	N(0.28,0.23)	N(0.19,0.09)	N(0.14,0.21)	N(0.36,0.28)
2	N(0.51,0.01)	N(0.32,0.22)	0	N(0.32,0.26)	N(0.33,0.33)	N(0.51,0.06)
3	N(0.37,0.13)	N(0.18,0.08)	N(0.29,0.26)	0	N(0.18,0.05)	N(0.34,0.08)
4	N(0.32,0.08)	N(0.2,0.21)	N(0.38,0.33)	N(0.26,0.03)	0	N(0.23,0.03)
5	N(0.59,0.26)	N(0.36,0.28)	N(0.4,0.06)	N(0.28,0.07)	N(0.26,0.02)	0

The algorithm parameters and models are detailed in Table 4 and Table 5.

Table 4 Genetic algorithm parameters

Algorithm parameter name	Parameter value
Species size	100
Cross rate	Adaptive strategy adjustment
Variation rate	Adaptive strategy adjustment
Maximal algebra	200
Number of hill climbing operations	5

Table 5 Model design parameters

Parameter	Parameter involves meaning	Parameter value
FK	Vehicle fixed cost	200 yuan
Q	Approved weight of a refrigerated truck	2 tons
C_0	The unit price of fresh agricultural products	1000 yuan/ton
θ_1	Waiting cost	1 yuan/min
θ_2	Penalty cost	0.2 yuan/min
C_l	Operating cost per unit distance	4 yuan/km
C_t	Operating cost per unit of time	0.6 yuan /min
α_1	The loss rate of goods during transportation	0.02
α_2	Cargo damage rate during loading and unloading	0.03

4.3 Case solving

4.3.1 Genetic algorithm solution

MATLAB is used to solve the model established above many times. It is assumed that the population size is 100, the maximum number of iterations is 200, and the adaptive strategy adjusts the crossover and mutation probabilities. By running the program, better results are obtained. The distribution path and iterative convergence diagram are shown in Table 6 and Figure 7.

Table 6 Genetic algorithm results

Vehicle serial number	Distribution path	Cost/yuan	Total time/min	Driving distance/km
1	0-3-8-9-0	517.2	237	25.41
2	0-6-11-12-17-0	567.2	232	38.29
3	0-14-15-16-18-13-0	604.9	257	28.09
4	0-4-7-10-0	499.5	225	21.8
5	0-1-2-5-0	448.2	207.6	15.45

According to table 6, the total cost of distribution calculated by the genetic algorithm is 2637 yuan, and five refrigerated trucks are needed for distribution. The driving distance is 25.41km, 38.29km, 28.09km, 21.8km, and 15.45km, respectively, and the total distance is 129.04km, and the required time is 237min, 232min, 257min, 225min and 207 respectively.

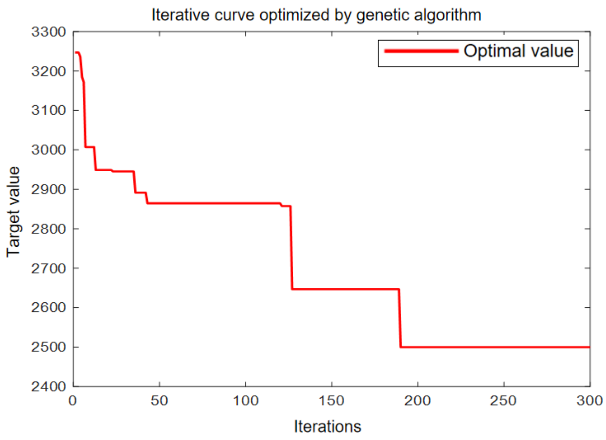

Fig.7: Iterative graph of genetic algorithm

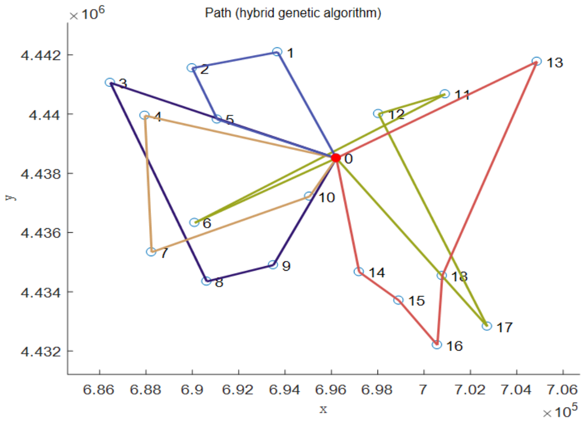

Fig.8: Path map of genetic algorithm

It can be seen from Figure 7 that the initial population is randomly generated, so it shows a downward trend in the initial stage of optimization. With the increased iteration times, its fitness curve tends to be flat. Figure 8 is the vehicle distribution route diagram.

4.3.2 Hybrid genetic algorithm for solving

Because this paper discusses the distribution path planning problem of Datong H fresh agricultural products cold chain logistics distribution company, aiming at the deficiency of the genetic algorithm, this paper introduces the mountain climbing algorithm to enhance the local search ability of the genetic algorithm, and finally designs hybrid genetic algorithm to solve the case. Assuming the population size is 100, the maximum genetic evolution is 50. The crossover and mutation probabilities are 0.8 and 0.15, respectively. In order to compare with the genetic algorithm, this paper sets the maximum iteration algebra 200, uses MATLAB to solve the model established above many times and runs the program to get better results. The distribution path and iterative convergence diagram are shown in Table 7 and Figure 9.

Table 7 Hybrid genetic algorithm results

Vehicle serial number	Distribution path	Cost/yuan	total time/min	Driving distance/km
1	0-2-3-4-5-0	490	213	20.78
2	0-6-7-8-9-10-0	581	247.2	18.62
3	0-14-15-16-17-18-0	554	233.4	19.06
4	0-1-12-11-13-0	515	216.6	25.54

It can be seen from Table 7 that the total cost of distribution calculated by the hybrid genetic algorithm is 2139.73 yuan, which requires four refrigerated trucks for distribution, saving one refrigerated truck compared with the traditional genetic algorithm. The distribution distances are 20.78km, 18.62km, 19.06km, and 25.54km, respectively, and the required time is 213min, 247.2min, 233.4min and 216.6min respectively

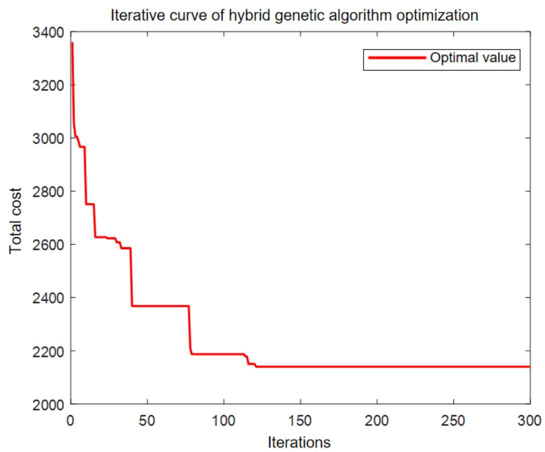

Fig.9: Iterative graph of hybrid genetic algorithm

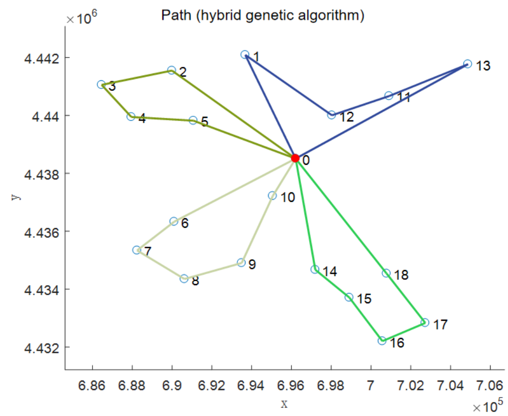

Fig.10: Path map of hybrid genetic algorithm

4.4 Result analysis

By comparing the solution results of the genetic algorithm and hybrid genetic algorithm, the population evolution process is shown in Figure 11.

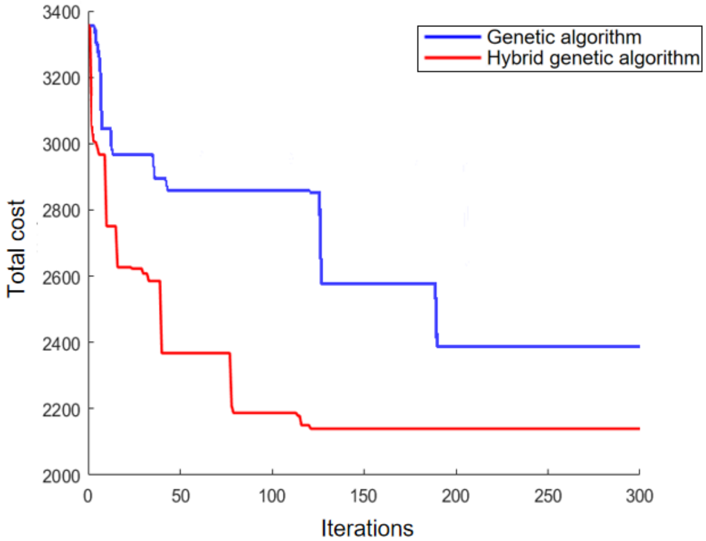

Fig.11: Iterative comparison diagram of two algorithms

By analyzing the results in Figure 11, it can be seen that with the increasing number of iterations, the total cost of genetic algorithm and hybrid genetic algorithm both show a downward trend. When the number of iterations reaches 190, the genetic algorithm achieves convergence, and the target cost is 2400 yuan. When the number of iterations reaches 121, the hybrid genetic algorithm achieves convergence. At this time, the target cost is 2150 yuan, which is far lower than the genetic algorithm, indicating that the convergence speed of the hybrid genetic algorithm is far higher than the genetic algorithm, and the optimal objective function value can be obtained at this time. In the process of evolution, it can be seen that the convergence speed of the hybrid genetic algorithm is higher than that of the traditional genetic algorithm, which indicates that the final design of the hybrid genetic algorithm has a good comprehensive performance. The main reason is that this paper uses the mountain climbing algorithm to improve the traditional genetic algorithm and get the hybrid genetic algorithm. The hybrid genetic algorithm is used to solve the constructed model, and the relevant analysis results are obtained, which shows that the hybrid genetic algorithm can fully overcome the shortcomings of the traditional genetic algorithm, improve the local search ability, and will not fall into the local optimum, so the hybrid genetic algorithm has better solution effect.

Table 8 Comparison before and after optimization

	Genetic algorithm solution	Hybrid genetic algorithm for solving
Total distribution cost/yuan	2637.07	2139.73
Total distribution distance/km	129.04	84.03
Number of delivery vehicles	5	4
Calculation time/second	30.94	33.57

According to the results in Table 8, the total distribution cost under the application of genetic algorithm is 2637.07 yuan, the total distribution distance is 129.04km, the number of vehicles delivered is 5, and the calculation time is 30.94s; The total distribution cost under the application of hybrid genetic algorithm is 2139.73 yuan, the total distribution distance is 84.03km, the number of vehicles delivered is 4, and the calculation time is 33.57s; In general, compared with genetic algorithm, hybrid genetic algorithm saves 19% of the total cost and 35% of the distribution vehicle mileage, has a higher vehicle utilization rate, reduces the number of distribution vehicles by one, and has a shorter operation time, which shows that the hybrid genetic algorithm has a better solution effect. The reason is that this paper optimizes the model by introducing a time window to build the distribution vehicle routing problem model under the dynamic network of cold chain logistics with time window. Therefore, the mountain climbing algorithm optimizes the genetic algorithm and obtains the hybrid genetic algorithm. The hybrid genetic algorithm is used to solve the constructed model and obtain the relevant analysis results. Therefore, the hybrid genetic algorithm has lower total distribution cost, shorter total distance, fewer vehicles used and shorter running time, and better practical application effect.

5. Conclusion

According to the actual situation of H company's cold chain logistics distribution, a genetic algorithm and a hybrid algorithm are designed, and the model is solved by combining the mountain climbing algorithm. The experimental results show that the hybrid genetic algorithm is superior to the genetic algorithm in speed and accuracy. The total distribution cost is low, the total distance is short, the number of vehicles used is small, and the algorithm running time is short. The analysis results are more in line with the actual needs of logistics distribution. This method can reduce distribution time and mileage, improve distribution efficiency, increase vehicle utilization and reduce distribution costs; It can speed up logistics, deliver goods to customers on time and quickly, and improve customer satisfaction; Rationalize the distribution operation arrangement and improve the operation efficiency of enterprises, which is conducive to improving the competitiveness and efficiency of enterprises, and has a prominent contribution to building an efficient and low-cost modern logistics system. However, this method still has some defects, that is, the amount of data used in the experiment is too small, which leads to a slight decline in the scientific and credibility of the research results. Therefore, in the future research, more data need to be used to thoroughly test the application effect of the hybrid genetic algorithm, so as to optimize the comprehensive performance of the algorithm and promote the further development of the modern logistics industry.

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