# Blockchain Assisted Multi-Objective Multi Time Window Cold Chain Intelligent Logistics Path Optimization

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## Abstract

Aiming at the dynamic demand path optimization problem of cold chain distribution, this paper combines the technical advantages of blockchain with the characteristics of cold chain path optimization problem on the basis of existing literature research. A multi-objective path optimization model with time window considering customer satisfaction is established, and then an example is designed and genetic algorithm (GA) is used to solve the above model. By comparing the indicators before and after optimization, it is concluded that the distribution cost of the distribution optimization scheme is low. Therefore, the combination of blockchain technology and cold chain distribution can effectively improve distribution efficiency, thereby reducing transportation costs and improving customer satisfaction. Finally, we completed the following work: 1) Summarized the research literature on vehicle routing problem (VRP) and cold chain logistics, and pointed out the current research trend. 2) The mathematical modeling of the actual logistics distribution problem is studied. Through the study of vehicle routing problem with time window (VRPTW) modeling method and multi-objective optimization theory, a multi-objective function is established and unified into cost objectives. The modeling elements are determined, and the multi-objective vehicle routing optimization model with time window is established by combining the objective function. Then the GA is determined as the algorithm for solving the model in this paper, and the algorithm flow is designed. 3) The algorithm parameters are set according to the actual distribution data of an enterprise, and then the effectiveness and optimization of the algorithm are tested to check the mutual constraints between the constraints of the model, as well as the optimization of the target value of the algorithm to solve the problem. The obtained path optimization scheme has more advantages than the original scheme.

**Keywords:** Cold chain, Path optimization, Blockchain technology, Time window

## 1 Introduction

China's meat export trade stimulated cold chain logistics. Only 40% of seafood is transported in a temperature-controlled environment, 15% of produce, and 30% of processed meat. The high damage and high wave rate caused by poor traceability and improper operation in the whole cold chain process is as high as 20% to 30% [1]. However, there are too many cold storages in some first tier and second tier cities [2]. According to the data of China Food Industry Association, about 12 million tons of fruits and 130 million tons of vegetables are wasted annually in cold chain logistics in China, with a total value of 10 billion dollars. At present, the number of refrigerated vehicles in China only accounts for 0.3% of road freight vehicles, and there is one refrigerated vehicle for every 30000 people in China. In the USA, there is one refrigerator car for every 500 people [3]. With the continuous development of urbanization in China, per capita income can meet the conditions for the outbreak of cold chain food in developed countries. By 2025, considering the potential for future development, it is expected that the market size of China's cold chain logistics industry will further grow to 897 billion yuan [4]. Especially in recent years, with the gradual popularization of cold chain e-commerce, this is due to three primary factors [5]. As a result, people are becoming increasingly comfortable consuming a wide variety of canned, boxed, and frozen foods because they know the quality is assured [6-8]. With the rapid growth of all kinds of fresh frozen and refrigerated food processing industry, cold chain product transportation is a key issue, putting huge pressure on cold chain logistics enterprises [9]. On the one hand, an economical and effective distribution route can reduce the number of vehicles used, reduce the distribution time, and reduce the loss of cold chain products caused by transportation [10]. It cannot only ease public transport congestion, but also improve the circulation rate of cold chain and prevent the possibility of chain breakage [11]. When there is a dynamic demand in the distribution process, it is convenient to find a backup distribution center to replenish goods along the way [12-13]. Thus, while ensuring food safety, supporting the reasonable and

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healthy high-speed development of the cold chain logistics industry to reduce costs, improve efficiency, low-carbon, and environmental protection is a pressing issue [14].

With this context in mind, this study presents blockchain technology as a means to effectively coordinate and control the whole distribution process, hence increasing product dissemination and decreasing the decay rate of new distribution. To successfully connect the growth of cold chain logistics with the building of an ecological society, researchers have developed a framework for optimizing the distribution route of intelligent logistics with multiple goals and different time frames in a blockchain environment.

## 2 Related Work

The supply chain system's cold storage project ensures food quality, prevents spoilage, and reduces waste. In order to cut down on cold chain logistics expenses, a pricing quantity model has been devised [15]. Reference [16] considers that cold chain products need to be transported at a lower temperature. Reference [17] studied the trading mode of perishables in the production and distribution system. The variables in the decision model are controlled to ensure rapid delivery and avoid product deterioration. Reference [18] proposed the green and low-carbon location-routing problem (LRP) model in cold chain logistics with the minimum total costs as the objective function, which includes carbon emission costs. A hybrid genetic algorithm with heuristic rules is designed to solve the model. Reference [19] points out that VRPTW is a NP hard problem, and it is difficult for traditional algorithms to find the optimal solution. Since some initial algorithms, including two-stage algorithms, transform the VRPTW problem into a single objective optimization function with penalty terms. Reference [20] uses dynamic programming method and column generation method to solve VRPTW respectively. Reference [21] analyzed the worst case of heuristic and proposed a heuristic algorithm under time constraints. Reference [22] applies GA to VRPTW for the first time, and adopts the method of arranging routes after grouping. Reference [23] proposes a neighborhood structure based on the tabu search algorithm, takes a vertex from the line containing the nearest neighbor solution and places it in another line to construct a new line or eliminate the original line. Reference [24] uses multiple colonies to optimize VRPTW, and uses ant colony algorithm to optimize the total driving route and the total number of vehicles used. Extensive study of the third-generation AI algorithm may be found in reference [25]. Reference [26] proposes a parallel simulated annealing method, and verifies the effectiveness of this algorithm. Reference [27] popularizes the standard VRP by allowing soft time windows and limiting soft travel time. Reference [28] constructed two generations of ant colony algorithm for multi-objective VRP with soft time window. Reference [29] studied the VRP with time windows under fuzzy demand. Reference [30] designed cultural gene algorithm for VRPTW model. Reference [31] established a trans-shipment alliance model between enterprises based on the fuzzy time window. Reference [32] proposed a hybrid multi-objective evolutionary algorithm to solve VRPTW. Reference [33] optimizes the number of vehicles and the total distance simultaneously by using the non-dominated sorting technology in GA and the optimal path crossover operator.

## 3 Method

### 3.1 Multi Objective Vehicle Routing Optimization Model with Time Window

#### 3.1.1 Vehicle Routing Problem

VRP means that the distribution center has a certain number of customers, and the logistics enterprise arranges a certain number of vehicles and organizes a driving route according to the number of customers and the demand for goods to complete the distribution task and meet customer needs. The optimization research on VRP is mainly based on certain constraints to optimize the vehicle distribution route reasonably.

#### 3.1.2 Vehicle Routing Problem with Time Window

1) VRPTW theory. The time window represents a specific time interval. The upper and lower bounds of this interval are composed of the earliest start time and the latest start time of the distribution service.

2) Classification of time windows. The types of time windows in VRPTW are also different, and they are generally divided according to several methods in Table 1.

**Table 1.** Types of time windows

| Classification method | Type of time window |
|---|---|
| By definition | Definitive time window/ Uncertain time window |
| By form | Unilateral time window/ Bilateral time window |
| By customer satisfaction | Hard / Soft / Mixing time window |

#### 3.1.3 Multi Objective Optimization

1) Multi-objective optimization problem (MOP). MOP refers to the comprehensive consideration of the weight of multiple indicators under certain constraints in the management and design of a problem, so that multiple objectives can find a balance point to a certain extent to achieve the overall optimization. The mathematical form of MOP is described as follows:

$$\min Z = z(x)[z_1(x), z_2(x), ..., z_n(x)] \quad (n = 1, 2, ..., N) \tag{1}$$

$$a_i(x) \leq 0 \quad i = 1, 2, ..., k \tag{2}$$

$$b_j(x) = 0 \quad i = 1, 2, ..., l \tag{3}$$

$$x = [x_1, x_2, ..., x_d, ..., x_D] \tag{4}$$

$$x_{d-\min} \le x_d \le x_{d-\max} \quad d = 1, 2, ...D \tag{5}$$

where equation (1) represents that the total objective is determined by n optimization objectives, and $z_1(x)$ is the nth objective function. $x$ is the $D$ dimension decision vector, $z$ is the objective vector, $Z$ is the objective space formed by the objective vector, and $N$ is the total number of optimization objectives.

2) MOP solution. MOP is a kind of problem that is difficult to solve in various fields. After processing or mathematical transformation, MOP method converts sub objective functions into single objective functions.

Hierarchical sequence method: First, the first objective is optimized, and the set of all optimal solutions is found to be $R_0$. Then, find the optimal solution of the second objective in $R_0$. Remember that the optimal solution set at this time is $R_1$, and so on until the optimal solution of the m-th objective is found. The premise of this method is that $R_0$, $R_1$, …, $R_{m-1}$ are not empty, and $R_0$, $R_1$, …, $R_{m-2}$ cannot have only one element, otherwise it is difficult to proceed.

Evaluation function method: The heart of this technique is an assessment function that simplifies competing goals into a single, more manageable target.

### 3.2 Analysis of Modeling Elements of the Model

#### 3.2.1 Modeling Assumptions

Modeling unstable distribution components requires appropriate assumptions. 1) The distribution center-to-target customer route will not be blocked. 2) Distribution and rental vehicle distribution will not be delayed due to distribution center vehicles failure. 3) Each vehicle's carrying capacity is much greater than a single customer's demand volume, so dividing the order is unnecessary. 4) The distribution center has enough goods to meet customer demand. 5) The enterprise knows the number, coordinate position, and distance between any two target customers. 6) The target customer's goods demand will not change during vehicle distribution.

#### 3.2.2 Model Constraints

This paper restricts vehicle mileage to reduce traffic accidents. 1) Distribution cannot exceed facility capacity. 2) Only the distribution center's full fleet of cars can be used for distribution. 3) Vehicles cannot be overloaded. 4) Each vehicle has one route and serves multiple target customers. 5) Only one vehicle can deliver each target customer's goods demand at a time. Reducing or repeating deliveries is restricted. The distribution facility is the vehicle's origin and destination. 7) Vehicles arriving and leaving each customer point should match. 8) After reaching the next customer point, goods cannot return to the previous customer point. 9) The following customer must be served later. 10) Vehicle mileage cannot exceed the maximum.

### 3.3 Construction of Cold Chain Logistics Distribution Optimization Model

#### 3.3.1 Multi-Objective VRPTW Model Objective Function Analysis

1) Total number of vehicles used. In this model, the total number of distribution vehicles is the total number of vehicles that the distribution center provides distribution services for customers. Therefore, the objective function of the minimum number of vehicles is as follows.

$$\min Z_0 = \Sigma_{k=1}^{u} \Sigma_{j=1}^{n} x_{0jk} \tag{6}$$

2) Total delivery mileage. According to the enterprise logistics operation process, the last step of cold chain products before loading and distribution is that the staff needs to carry out standard inspection, and the products can be packaged and loaded for delivery only after they pass the quality inspection. Therefore, the objective function of the shortest total distribution mileage of vehicles is as follows.

$$\min Z_1 = \Sigma_{k=1}^{u} \Sigma_{i=0}^{n} \Sigma_{j=0}^{n} d_{ij} x_{ijk} \tag{7}$$

3) Time penalty cost. Due to market demands for cold chain product quality, customers are becoming more demanding of logistics distribution timeliness. Delay penalty coefficients reflect customer satisfaction loss and product deterioration risk. The objective function of the minimum time penalty cost is as follows:

$$\begin{aligned} \min Z_2 = \Sigma_{i=1}^{n} \Sigma_{k=1}^{u} \{ &\max[(et_i - t_{ik}), 0] \times \\ M_e + &\max[(t_{ik} - lt_i), 0] \times M_l \} \end{aligned} \tag{8}$$

#### 3.3.2 Conversion of Objective Function

VRPTW develops two optimization models. Emergency logistics transportation path planning requires a single-objective mathematical model to minimize distribution time. Second, model multiple objectives mathematically, convert some into cost objectives, and use the sum of time costs as the optimization objective.

1) Number of vehicles used and fixed cost. Fixed cost refers to the fixed cost paid by the distribution center. Use $C_0$ to represent the fixed cost of a single distribution vehicle. The minimum fixed cost is:

$$\min Z_0' = C_0 \times \Sigma_{k=1}^{u} \Sigma_{j=1}^{n} x_{0jk} \tag{9}$$

2) Total vehicle distribution mileage and transportation consumption cost. The cost of vehicle transportation is mainly composed of fuel consumption cost and tire loss cost. If $C_1$ is used to represent the transportation consumption cost incurred by the vehicle per kilometer, the minimum transportation cost is:

$$\min Z_1' = C_1 \times \Sigma_{k=1}^{u} \Sigma_{i=0}^{n} \Sigma_{j=0}^{n} d_{ij} x_{ijk} \tag{10}$$

The final objective function of the model is:

$$\min Z = \min Z_0' + \min Z_1' + \min Z_2 \tag{11}$$

### 3.3.3 Establishment of Distribution Model

Combined with problem demand and actual constraints, the distribution model established in this paper is:

$$\begin{aligned} \min Z = {} & C_0 \times \Sigma_{k=1}^{u} \Sigma_{j=1}^{n} x_{0jk} \\ & + C_1 \times \Sigma_{k=1}^{u} \Sigma_{i=0}^{n} \Sigma_{j=0}^{n} d_{ij} x_{ijk} \\ & + \Sigma_{i=1}^{n} \Sigma_{k=1}^{u} \{\max[(et_i - t_{ik}), 0] \\ & \times M_e + \max[(t_{ik} - lt_i), 0] \times M_l\} \end{aligned} \tag{12}$$

$$\Sigma_{i=0}^{n} \Sigma_{j=0}^{n} d_{ij} x_{ijk} \le D, k \in K \tag{13}$$

$$\Sigma_{i=1}^{n} q_i y_{ik} \le Q, \quad k \in K \tag{14}$$

$$\Sigma_{k=1}^{u} u_k \le K \tag{15}$$

$$\Sigma_{k=1}^{u} y_{ik} = 1, \quad i \in N \tag{16}$$

$$\Sigma_{j=1}^{n} x_{ijk} = y_{ik}, \quad i \in N \tag{17}$$

$$\Sigma_{i=1}^{n} x_{ijk} = y_{ik}, \quad j \in N \tag{18}$$

$$\Sigma_{j=1}^{n} x_{0jk} = \Sigma_{i=1}^{n} x_{i0k} = u_k, \quad k \in K \tag{19}$$

$$\Sigma_{j=0}^{n} x_{jik} = \Sigma_{j=0}^{n} x_{ijk}, i \ne j, i \in N, \quad k \in K \tag{20}$$

$$x_{ijk} + x_{jik} \le 1 \tag{21}$$

$$t_{jk} = t_{ik} + s_{ik} + \frac{d_{ij}}{V}, j \in N, i \in N, k \in K \tag{22}$$

$$x_{ijk}(1 - x_{ijk}) = 0, j \in N, i \in N, k \in K \tag{23}$$

$$y_{ik}(1 - y_{ik}) = 0, i \in N, k \in K \tag{24}$$

$$u_k(1 - u_k) = 0, k \in K \tag{25}$$

where equation (12) is the objective function of the model, equation (13) is the maximum distribution mileage limit of a single vehicle, equation (14) is the vehicle load limit, and the total load of goods delivered by vehicle k cannot exceed the maximum load of vehicle k. Equation (15) means that the total number of vehicles used does not exceed the total number of vehicles owned by the distribution center. Eq. (16), Eq. (17) and Eq. (18) indicate that the demand of a single target customer cannot be split, and each customer can and can only be delivered by one vehicle. Equation (19) means that each used vehicle must depart from the distribution center and return to the distribution center eventually. Equation (20) is the balance of the number of vehicles in and out, and the number of arriving vehicles at customer point is consistent with the number of departing vehicles at customer point. Equation (21) indicates that vehicle k cannot return to the previous customer after arriving at the next customer. Equation (22) indicates that the time of the vehicle arriving at the next customer is determined by the time of arriving at the previous customer, the unloading time, the distance between two customers and the driving speed. Eq. (23), Eq. (24) and Eq. (25) indicate the value range of decision variables.

## 3.4 Principle of Genetic Algorithm

VRPTW is a complex combinatorial optimization problem, and GA is very suitable for dealing with complex nonlinear problems. The GA has the following advantages: 1) The initial solution of the GA is set as a population, which is not a single point search. 2) GA does not need other information to assist operations. 3) GA is a parallel algorithm. 4) GA has a strong intelligence advantage, which can be used to solve more complex unstructured problems.

The principles of chromosome coding, selection operator, crossover operator and mutation operator in GA are as follows.

1) Chromosome coding. The coding process refers to a specific compilation method for the potential feasible solution of the problem. GA does not act on the solution itself, but operates on all individuals in the coded population.

2) Select an operator. In the initial population, according to the law of survival of the fittest and survival of the fittest in nature, the proportion of excellent genes in the population is increased through selection operation, and high-quality chromosomes are screened for inheritance. Common selection operators are as follows.

Sorting selection method: all individuals are sorted according to their fitness after calculating their fitness values. According to the probability table designed in advance, they are allocated to individuals in order as their selection probabilities.

3) Crossing operator. Since the roulette method was used to select the population, only the average fitness value of the population was improved, and no new individuals were generated.

4) Mutation operator. After selection and crossover operations, mutation operations are performed on individuals to expand the population size and search scope of the algorithm and reduce premature convergence. Generally, the default mutation probability is 0.001~0.1.

Combined with the VRPTW mathematical model and algorithm operation design, the operation flow of the GA designed in this paper is shown in Figure 1.

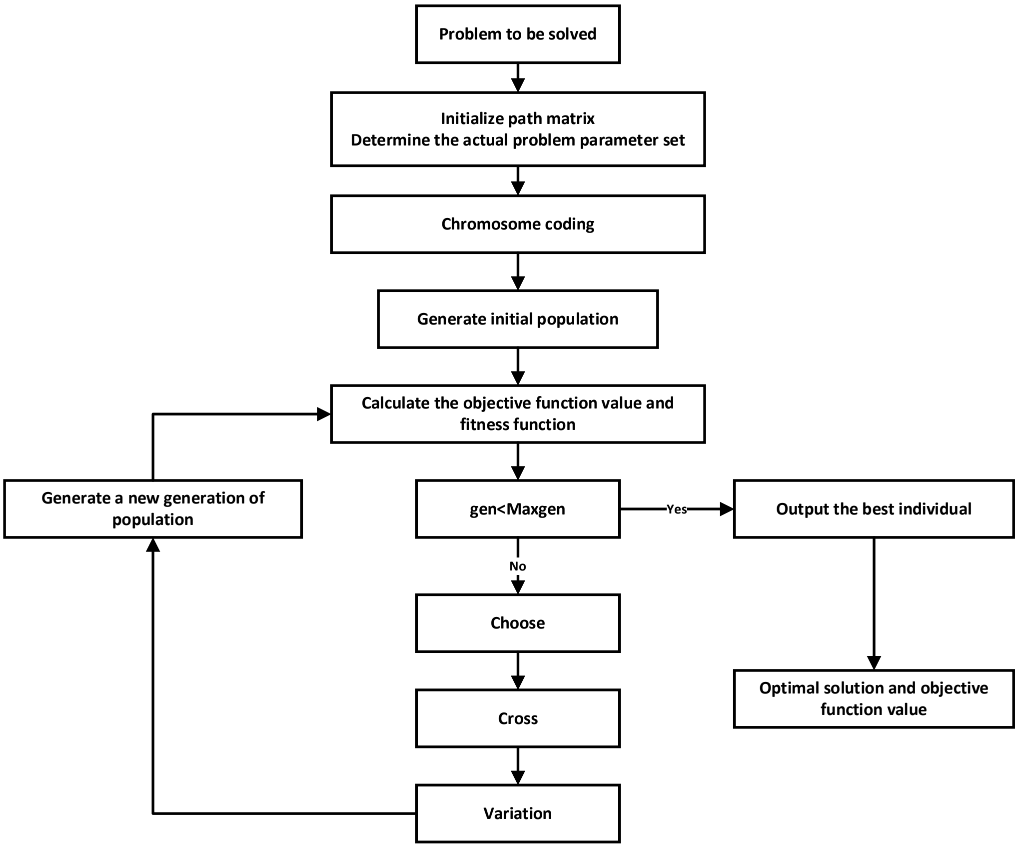


**Figure 1.** GA flow chart of logistics VRP with time window

## 4 Experiment and Analysis

### 4.1 Logistics Distribution Data and Parameters

Cold chain logistics company with 30 customers and 1 distribution center provides distribution data. 0, distribution center; 1-30, customer. Distribution center coordinates (12, 10.5) are km.

The distance between any two points can be expressed as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{26}$$

### 4.2 Simulation Test of Algorithm Effectiveness and Optimization

#### 4.2.1 Algorithm Effectiveness Simulation Test

The efficacy of the algorithm on the model and the optimization is tested in four ways: with no constraints, with the vehicle's maximum load, with the vehicle's maximum distance, and with the customer's time requirements.

1) There are no three conditions. Maximum vehicle load capacity, customer time window range, and maximum mileage prevent the algorithm from being affected. At this time, without three conditions, the algorithm iteration diagram is shown in Figure 2.

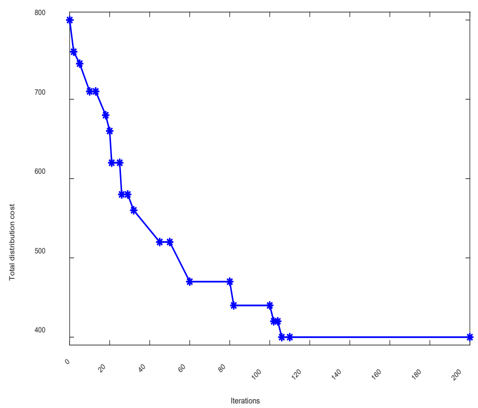


**Figure 2.** Iterative graph without restrictions

The running results show that the target value starts to converge in about 120 iterations without the restriction of the three.

2) Only the maximum load capacity of the vehicle is limited. Set the customer time window range and maximum mileage as a maximum value to ensure that they cannot affect the model during algorithm operation is shown in Figure 3.

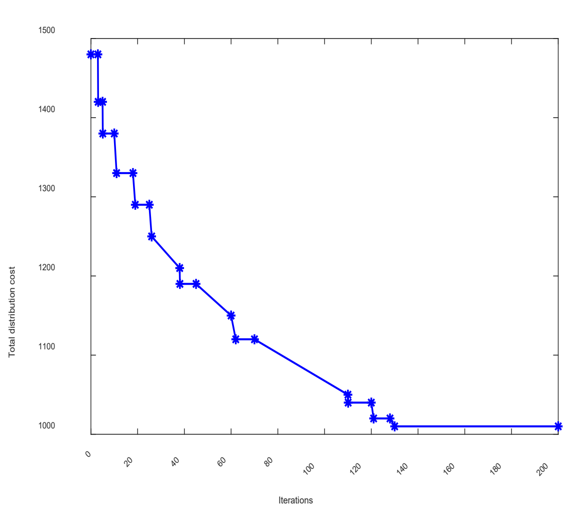


**Figure 3.** Iteration diagram with maximum load capacity limit

It can be seen that the target value starts to converge after about 140 iterations. After further testing, the enterprise discovered that one vehicle with the maximum load capacity could not distribute 30 customers. On the premise of minimizing the distribution cost, the enterprise uses 8 vehicles to complete the distribution task of 30 customer points and complete the distribution task.

3) Only customer time window requirements. The maximum load capacity and maximum mileage of the vehicle are set as a maximum value to ensure that they cannot affect the model during the algorithm operation is shown in Figure 4.

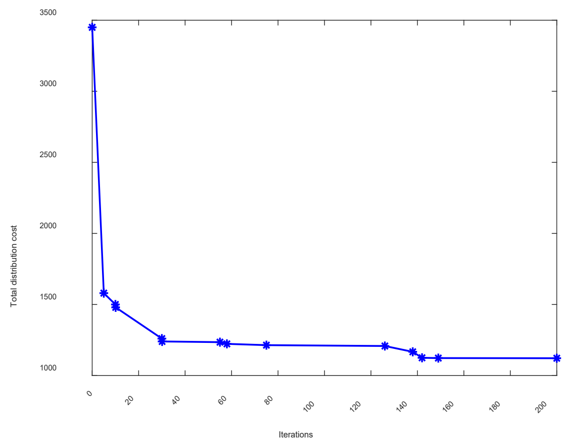


**Figure 4.** Iteration diagram with time window requirements

It can be seen that the objective value starts to converge between 150-160 iterations. On the premise of minimizing the distribution cost, the enterprise uses 4 vehicles to complete the distribution task of 30 customer points.

4) Only the maximum mileage limit. Set the maximum load capacity of the vehicle and the range of the customer time window as a maximum value to ensure that they cannot affect the model during the algorithm operation is shown in Figure 5.

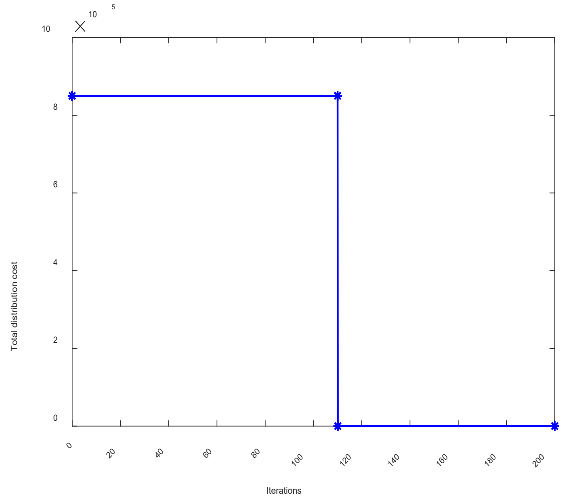


**Figure 5.** Iterative graph with maximum mileage limit

It can be seen that the target value starts to converge after about 120 iterations. A company can't fulfill the distribution needs of 30 consumers with a single vehicle if that vehicle has reached its maximum mileage.

### 4.2.2 Optimization Simulation Test of Algorithm for Target

The parameter setting of GA has a great impact on the objective function in the solution process, in which the population size and the maximum number of iterations will limit the search scope and search times of the algorithm.

1) The influence of population size on model solution. Four different population sizes, namely 50, 100, 150 and 200, were selected in the experiment, and the four population sizes were tested for ten times respectively are shown in Figure 6.

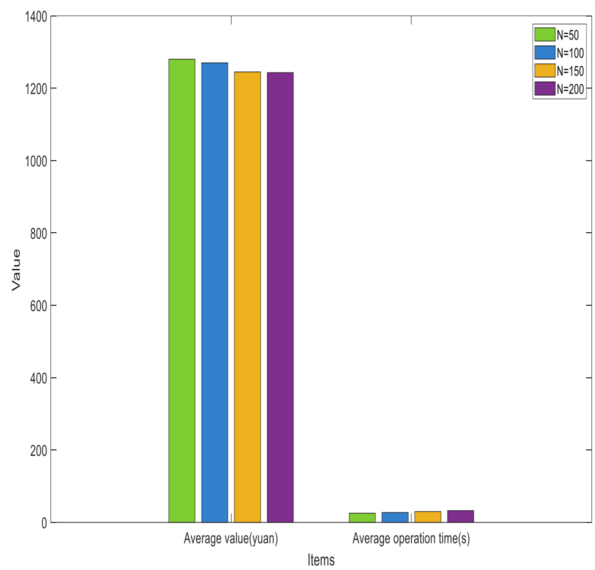


**Figure 6.** Operation results at different population sizes

The results show that when the population size is small, the search space is small and the operation time is short. When the population size is 150, compared with the average target value of 200, the difference is only 0.85, and the operation time is much shorter.

2) To improve GA's VRPTW solution, this paper must set the algorithm's termination criteria (maximum iterations) reasonably. The maximum algorithm iterations are 50, 100, 200, and 300, which are run 10 times to calculate the average objective function value of the ten tests under each value (Figure 7).

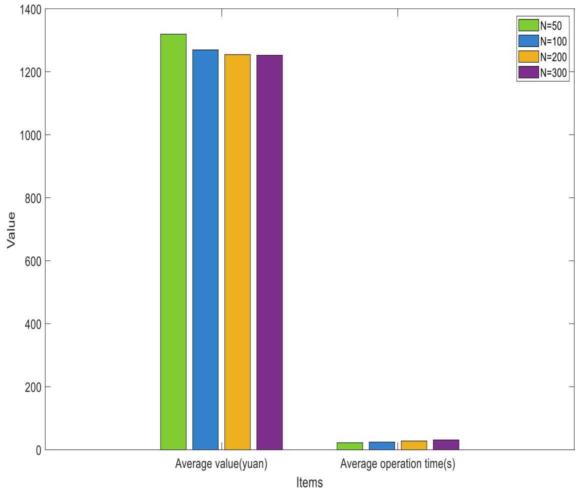


**Figure 7.** Operation results of different iterations

It can be seen from the data that the maximum number of iterations in Figure 7 increases from 200 to 300 that the algorithm can ensure the optimization of the algorithm when it runs 200 times. Therefore, this paper sets the maximum number of iterations to 200.

### 4.3 Optimize Data Analysis

The number of distribution vehicles used in the optimized distribution path is 10 in total, and the total distribution cost is 1198.55 yuan. The comparative analysis of various data before and after optimization is shown in Table 2.

**Table 2.** Data comparison before and after optimization

| Data comparison | Number of vehicles | Delivery mileage | Delivery cost |
|---|---|---|---|
| Before optimization | 12 | 228.56 | 1512.87 |
| After optimization | 10 | 201.76 | 1198.55 |

## 5 Conclusion

In this study, we integrate the technological benefits of blockchain technology with the features of the cold chain route optimization issue in an effort to solve the dynamic demand path optimization problem in cold chain distribution. Finally, we completed the following work: 1) Summarized the research literature on VRP and cold chain logistics, and pointed out the current research trend. 2) The mathematical modeling of the actual logistics distribution problem is studied. Through the study of VRPTW modeling method and multi-objective optimization theory, a multi-objective function is established and unified into cost objectives. The modeling elements are determined, and the multi-objective vehicle routing optimization model with time window is established by combining the objective function. 3) The algorithm parameters are set according to the actual distribution data of an enterprise, and then the effectiveness and optimization of the algorithm are tested to check the mutual constraints between the constraints of the model, as well as the optimization of the target value of the algorithm to solve the problem. The obtained path optimization scheme has more advantages than the original scheme.

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