EAI Endorsed Transactions
on Energy Web

Research Article EAI.EU

Cold Chain Low-carbon Logistics Path Optimisation Method Based on Improved Hummingbird Optimisation Algorithm

Xuan Long[1,*]

[1] School of international trade Hainan College of Economics and Business, Hai'kou 571127, Hainan , China

Abstract

INTRODUCTION:The research of scientific and reasonable logistics and distribution programme time the pursuit of each logistics enterprise, not only can improve customer satisfaction and corporate image, but also help to reduce distribution costs.
OBJECTIVES: For the current cold chain low-carbon logistics distribution path optimisation methods there are problems such as easy to fall into the local optimum, optimisation time-consuming.
METHODS: This paper proposes a cold chain low-carbon logistics distribution path optimisation method based on the improved Hummingbird optimisation algorithm. Firstly, by analyzing the characteristics of the cold chain low-carbon logistics distribution path optimization problem, designing the cold chain low-carbon logistics path optimization objective function and constraints, and constructing a cold chain low-carbon logistics distribution path optimization model based on a soft time window; then, the hummingbird optimization algorithm is improved by using the initialization strategy of the set of good points and the cardinality leap strategy, to overcome the defects of the hummingbird optimization algorithm; secondly, a method based on intelligent optimization algorithm is proposed by designing the double-layer array coding and the adaptive function, combined with the improved hummingbird optimization algorithm. A cold chain low-carbon logistics path optimization method based on intelligent optimization algorithm is proposed; finally, the superiority and robustness of the proposed method are verified by simulation experimental analysis.
RESULTS: The results show that the proposed method not only improves the optimisation time, but also increases the optimisation fitness value.
CONCLUSION: This paper solves the problem that the optimisation of the green low-carbon logistics path optimisation problem is time-consuming and prone to falling into local optimum.

Keywords: cold chain low-carbon logistics path optimisation; Hummingbird optimisation algorithm; Jiaden set improvement strategy; two-layer coding approach

Received on 21 September 2023, accepted on 25 January 2024, published on 31 January 2024

Copyright © 2024 Long, licensed to EAI. This is an open access article distributed under the terms of the CC BY-NC-SA 4.0, which permits copying, redistributing, remixing, transformation, and building upon the material in any medium so long as the original work is properly cited.

doi: 10.4108/10.4108/ew.4991

*Corresponding author. Email: cnhnjmxy1_228@163.com

1. Introduction

As the consumption capacity of China's residents continues to climb, more and more large-scale e-commerce platforms layout fresh food retail [1]. Fresh products are easy to deteriorate in the transport process, it is necessary to take refrigeration and thermal insulation measures to transport, but also to meet the customer's time needs [2]. The research of scientific and reasonable logistics and distribution programme time the pursuit of each logistics enterprise, not only can improve customer satisfaction and corporate image, but also conducive to reducing distribution costs [3]. Therefore, it is very necessary to study the optimisation of cold chain low-carbon logistics path [4].

Cold chain low-carbon logistics and distribution path optimisation is essentially a Vehicle Routing Problem (VRP) [5]. The cold chain low-carbon logistics distribution path optimisation technique considers all the costs in the cold chain low-carbon logistics distribution process on the basis of meeting the maximum vehicle load, and solves the cold chain low-carbon logistics distribution path optimisation model with the minimum total cost based on the constraints of customer demand, vehicle load and time window [6]. Commonly used logistics path optimisation methods include exact optimisation algorithms and heuristic algorithms [7]. Logistics distribution methods based on exact optimisation algorithms can fall into dimensional explosion, making it difficult for the algorithm to be met with a satisfactory solution in a short period of time [8]. Logistics path optimisation methods based on heuristic algorithms converge quickly and are easy to implement, but they are also prone to the local optimum problem [9]. Literature [10] combines cuckoo algorithm and intelligent water droplet algorithm to improve the ability to solve the logistics vehicle path planning problem; Literature [11] proposes an improved ant colony algorithm for the multi-warehouse green vehicle planning problem by comprehensively considering the cost of economy and environmental pollution; Literature [12] introduces a pheromone oscillation process to transform the firefly algorithm and applies it to the logistics vehicle planning problem; Literature [13] proposes a logistics vehicle planning problem with time windows based on improved particle swarm algorithm considering distribution and recovery costs; literature [14] designed a joint adaptive large-scale optimization algorithm and solved the time-dependent logistics vehicle problem under fuzzy demand; literature [15] proposed a stochastic logistics and distribution vehicle method for multi-centre demand based on neighbourhood searcher strategy to improve the cultural gene algorithm; literature [16] combined the scanning algorithm and improved particle swarm algorithm to propose a time-uncertain logistics distribution vehicle path optimisation method. Review and collation of related literature, although logistics distribution research has achieved relatively fruitful results, but there are still shortcomings: 1) traditional intelligent optimisation algorithms are simple in structure, and can easily fall into the local optimum; 2) the current logistics distribution model can not comprehensively consider the constraints and costs [17].

Aiming at the shortcomings of the current logistics path optimisation method, this paper proposes a logistics path optimisation method based on the improved Hummingbird optimisation algorithm considering cold chain features and low-carbon features. Firstly, we analyse the constraints and costs of low-carbon logistics path optimization for cold chain, and construct a logistics path optimization model considering cold chain and low-carbon factors; then we improve the performance of the hummingbird optimization algorithm through two effective strategies, and put forward a low-carbon logistics path optimization problem for cold chain based on the improved hummingbird optimization algorithm. Compared with other optimisation algorithms, the proposed improved Hummingbird optimisation algorithm shows better convergence speed and accuracy in the cold chain low-carbon logistics path optimisation problem.

2. Optimisation model for cold chain low-carbon logistics and distribution routes

According to the characteristics of the cold chain low-carbon logistics distribution path optimisation model, the soft time window-based cold chain low-carbon logistics distribution path optimisation model was constructed by comprehensively considering the fixed cost of the distribution vehicle, the transportation cost, the cost of cargo damage arising from the delivery of products to consumers, the refrigeration cost of ensuring that the items in the vehicle are in a low-temperature environment, the carbon emission cost arising from the distribution, and the penalty cost [18].

Fixed costs

Fixed costs include salaries of distribution vehicle drivers, vehicle depreciation costs, and maintenance and upkeep costs [19]. The specific calculations are as follows:

$$C_1 = \sum_{k=1}^{m} f_k \tag{1}$$

where f_k denotes the fixed cost of the kth vehicle and m is the number of vehicles required for distribution.

Transport costs

Transportation cost is the cost incurred by the amount of fuel consumed by the distribution vehicle to complete the distribution, which is proportional to the distance travelled for transportation, and is calculated by the following formula:

$$C_2 = \sum_{k=1}^{m} \sum_{i,j=0}^{n} c_k d_{ij} x_{ij}^{k} \tag{2}$$

Where n denotes the number of consumers, $x_{ij}^{k}=1$ denotes the kth delivery vehicle from i to j, $x_{ij}^{k}=0$ denotes the kth delivery vehicle that did not travel from i to j, d_{ij} denotes the distance between i and j, and c_k denotes the cost per kilometre of the vehicle.

Cargo damage costs

Cargo damage costs mainly include the logistics and distribution process with the increase in time decay and deterioration of the cost of cargo damage and loading and unloading cost of cargo damage, its cost and time showing exponential changes in the relationship [20], the specific calculations are as follows:

$$C_3=\sum_{k=1}^{m}\sum_{i,j=0}^{n}p_1Q_jy_j^k\left(1-e^{-a_1t_{ij}^k}\right)+\sum_{k=1}^{m}\sum_{j=0}^{n}p_1Q_jy_j^k\left(1-e^{-a_2T_j}\right) \tag{3}$$

Where p_1 denotes the price per unit of distributed goods, a_1 denotes the deterioration rate of goods, a_2 denotes the deterioration rate of loading and unloading of goods, t_{ij}^{k} is the travelling time of vehicle k from consumer i to consumer j, T_j is the unloading time of the distribution vehicle at consumer j, and Q_j denotes the load of the jth vehicle.

Refrigeration costs

Refrigeration costs include those incurred during distribution and those incurred during loading and unloading [21].

$$C_4=C_{41}+C_{42} \tag{4}$$

$$C_{41}=\sum_{k=1}^{m}\sum_{i,j=0}^{n}p_{21}x_{ij}^{k}t_{ij}^{k} \tag{5}$$

$$C_{42}=\sum_{k=1}^{m}\sum_{j=0}^{n}p_{22}T_j \tag{6}$$

Where C_{41} and C_{42} denote the cost of refrigeration in the distribution process and the cost of refrigeration in the loading and unloading process respectively, p_{21} denotes the cost of refrigeration per unit of time in the distribution process, t_{ij}^{k} denotes the travelling time of the kth vehicle from consumer i to consumer j, and p_{22} denotes the cost of refrigeration per unit of time in the loading and unloading process.

Penalty costs

Penalty costs are additional costs incurred during the delivery process, which are incurred if the delivery vehicle does not deliver within the specified time period, including waiting costs earlier than the time window and late costs later than the time window. Consumer j penalty cost is calculated as follows:

$$C_5(j)=\begin{cases} M & t_j^k<EET_j \\ p_e\left(ET_j-t_j^k\right) & EET_j\le t_j^k<ET_j \\ 0 & ET_j\le t_j^k\le LT_j \\ p_l\left(t_j^k-LT_j\right) & LT_j\le t_j^k\le LLT_j \\ M & t_j^k>LLT_j \end{cases} \tag{6}$$

where t_j^k denotes the time for delivery vehicle k to reach demand point j, p_e denotes the cost of waiting per unit of time, p_l denotes the cost of tardiness per unit of time, and the acceptable time window for demand node j is $\left[EET_j, LLT_j\right]$.

$$C_5=\sum_{k=1}^{m}\sum_{i=0}^{n}\left(p_e\max\left(ET_i-t_i^k\right)+p\max\left(t_i^k-LT_i,0\right)\right) \tag{7}$$

Cost of carbon emissions

Carbon emission cost refers to the cold chain low-carbon logistics and distribution process, vehicle driving fuel consumption and consumption of refrigerant will produce carbon dioxide, and the fuel consumption is related to the vehicle weight and travelling distance [22]. The formula for calculating the carbon emission cost of vehicle travelling fuel consumption is as follows:

$$C_{61}=p_c\sum_{k=1}^{m}\sum_{i,j=0}^{n}eE_1\left(q_{ij}\right)d_{ij}x_{ij}^{k} \tag{8}$$

where p_c denotes the price of the carbon tax, E_1 denotes the carbon emissions per kilometre, e denotes the CO_2 gas emission factor, and q_{ij} denotes the amount of freight transported from vehicle i to j.

The cost of carbon emissions from refrigeration equipment is:

$$C_{62}=p_c\sum_{k=1}^{m}\sum_{i,j=0}^{n}eE_2t_{ij}^{k}x_{ij}^{k} \tag{9}$$

where E_2 denotes unit consumption.

The total carbon cost is:

$$C_6=C_{61}+C_{62} \tag{10}$$

Modelling

In summary, the total cost model for cold chain distribution path optimisation includes objective function and conditional constraints. The cold chain distribution path optimisation objective function is designed as follows:

$$\min Z=C_1+C_2+C_3+C_4+C_5+C_6 \tag{11}$$

Cold chain logistics and distribution vehicle constraints:

$$\sum_{j=1}^{n} x_{ij}^{k} = \sum_{j=1}^{n} x_{ji}^{k} \le 1, i = 0, k = 1, 2, \cdots, m \quad (12)$$

Vehicle constraints required for distribution:

$$\sum_{k=1}^{m} y_{j}^{k} = \begin{cases} m & j = 0 \\ 1 & j = 1, 2, \cdots, n \end{cases} \quad (13)$$

Where m indicates the number of vehicles required for distribution.

Consumer constraints on distribution needs:

$$\sum_{j=1}^{n} \sum_{k=1}^{m} y_{j}^{k} = n \quad (14)$$

where n denotes the number of consumers.

Maximum load capacity constraints for cold chain logistics and distribution vehicles:

$$\sum_{j=0}^{n} y_{j}^{k} Q_{j} \le Q_{M} \quad (15)$$

Where, Q_M denotes the maximum load capacity of the delivery vehicle, and Q_j denotes the delivery weight of the jth consumer.

Cold chain logistics and distribution vehicle constraints:

$$EET_{j} \le t_{j}^{k} \le LLT_{j} \quad (16)$$

3. Improved Hummingbird Optimisation Algorithm

3.1. Hummingbird Optimisation Algorithm

Hummingbird optimisation algorithm (HOA) algorithm is a stochastic optimisation algorithm that simulates the process of honey harvesting by hummingbirds [23]. Initially, the algorithm creates multiple hummingbird individuals randomly in the search space. The position of each individual corresponds to a feasible solution of the optimisation problem. The quality of the food source is the objective function value, and the best food source is the global optimal solution.The whole optimisation process of HOA can be divided into two phases: self search and guided search. The specific form of the algorithm is as follows:

(1) Self-search phase

Assume that the size of the hummingbird population is NP and the dimension in the search space is D . $X_{i}^{t} = \left\{ x_{i,1}^{t}, x_{i,2}^{t}, x_{i,3}^{t}, \cdots, x_{i,D}^{t} \right\}$ It is the i th hummingbird individual in the t th moment. In the self-searching stage, hummingbirds can find food sources based on their previous experience. When the hummingbird can continuously find better food sources ($X_{i}^{t} \ne X_{i}^{t-1}$), it indicates the correctness of previous experience. Therefore, the position of each hummingbird is updated based on the previous gradient information:

$$X_{i}^{t+1} = X_{i}^{t} + rand \cdot (X_{i}^{t} - X_{i}^{t-1}) \quad (17)$$

Where X_i^t and X_i^{t-1} denote the position of the i hummingbird at t and $t-1$ respectively, and $rand$ denotes a random number in the range $[0,1]$.

When a hummingbird keeps searching but cannot find better results ($X_{i}^{t} \ne X_{i}^{t-1}$), it means that the hummingbird's previous experience is no longer applicable. In this case, the hummingbird randomly changes the direction of its search. This process is simulated using Levy flights, which are important non-Gaussian random walks whose random steps obey a large-tailed probability distribution. Due to the infinite and rapid growth of the variance, the most important feature of this flight pattern is the ability to maximise the exploration of space in uncertain environments.Levy flight is able to search more efficiently than conventional random walks such as Brownian motion. Figure 1 shows the two-dimensional motion trajectories of Levy flight and Brownian motion over 1000 time steps.

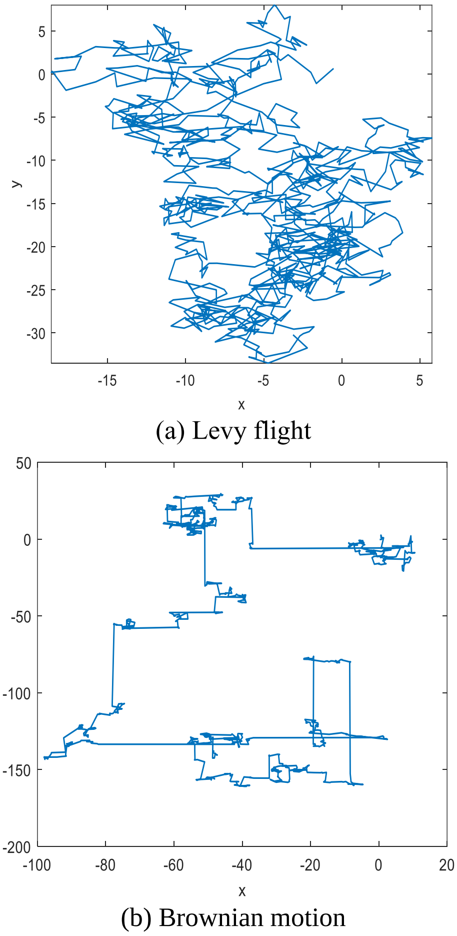


Figure 1. Comparison of two random motions

As shown in Figure 1, the Levy flight is able to produce larger jumps than the Brownian motion, thus exploring space more extensively. Therefore, it is more suitable for large-scale search. The search process based on Levy flight is represented as follows:

$$X_i^{t+1} = X_i^t + \alpha_0 (X_i^t - X_{best}^t) \oplus Levy(\beta) \quad (18)$$

Where X_{best}^t denotes the global optimal solution at the time of t , $\alpha_0 = 0.01$ denotes the scale factor, $\oplus$ denotes the number multiplication, and $Levy(\beta)$ is calculated as follows:

$$Levy(\beta) = \frac{\mu}{|\upsilon|^{1/\beta}} \quad (19)$$

where μ and υ denote two random numbers that obey Gaussian distributions $N(0,\sigma_\mu^2)$ and $N(0,\sigma_\upsilon^2)$ respectively, where

$$\sigma_\mu = \left(\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}} \right)^{1/\beta}, \sigma_\upsilon = 1 \quad (20)$$

where $\Gamma(z)$ denotes the gamma function and the size of β is set to 1.5 .

2) Guided search phase

At this stage, the best current individual hummingbird is called the territorial bird and the others are called followers. This territorial bird patrols up and around its territory to prevent other companions from approaching. This behaviour can be expressed as:

$$X^{T,t+1} = X^{T,t} + r_d \cdot \lambda \quad (21)$$

Where $X^{T,t}$ denotes the position of the territorial bird at the time of t , $X^{T,t}$ is a random number with a value in the range of $[-1,1]$, and λ is a step factor, defined as follows:

$$\lambda = 0.1 \cdot (ub - lb) \quad (22)$$

where ub and lb denote the upper and lower bounds of the search space, respectively.

There are two scenarios for following hummingbird movement patterns. Scenario 1: When the territorial bird does not detect a threat, the following bird will quickly approach its territory:

$$X_j^{F,t+1} = X_j^{F,t} + rand \cdot (X^{T,t} - MF \cdot X_j^{F,t}) \quad (23)$$

where $X_j^{F,t}$ is the position of the first j-th following bird at the moment T, and MF randomly takes the value 1 or 2.

Scenario 2: When the territorial bird spots the following bird, the following bird is driven away and flies away in a peripheral direction. During this process, the follower bird j will randomly pick a companion (k $k \neq j$) to follow. If the position of k is better, j will move towards it, otherwise, it will move away. The above can be expressed by the following equation:

$$X_j^{F,t+1} = X_j^{F,t} + rand \cdot (X_k^{F,t} - X_j^{F,t}) \quad if \ \ fitX_k^{F,t} \le fitX_j^{F,t} \quad (24)$$

$$X_j^{F,t+1} = X_j^{F,t} - rand \cdot (X_k^{F,t} - X_j^{F,t}) \quad if \ \ fitX_k^{F,t} \ge fitX_j^{F,t} \quad (25)$$

Where, , , $j,k \in \{1,2,3,\cdots,N-1\}$ $j \neq k$ $fitX_k^{F,t}$ and $fitX_j^{F,t}$ are the adaptation values of $X_k^{F,t}$ and $X_j^{F,t}$ respectively.

In summary, the complete search process for following birds is described as follows:

$$if \ \ PF^t \ge rand$$

PF^t denotes the probability of a following bird being detected by a territorial bird, which can be calculated by Eq:

$$PF^t = \frac{rank(fit\,X_j^{F,t})}{N-1} \quad (26)$$

where $rank(fit\,X_j^{F,t})$ indicates that the following bird J is ranked from smallest to largest among all peers according to the fitness value.

In addition, a boundary control strategy for preventing invalid searches can be described as follows:

$$X_{i,d}^t = ub - rand \cdot (ub - lb) \ \ if \ X_{i,d}^t < lb \ or \ X_{i,d}^t > ub \quad (27)$$

Finally, the HOA uses a greedy strategy for population updating, i.e., retains X_i^{t+1} only if the fitness value of X_i^{t+1} is better than that of X_i^t , otherwise the individual is not updated. This scheme is described as follows:

$$X^{t+1} \begin{cases} X^{t+1} & if \quad f(X^{t+1}) < f(X^t) \\ X^t & otherwise \end{cases} \quad (28)$$

The pseudo-code of the HOA algorithm is shown in Figure 2:

Algorithm 1: Pseudo code of the HOA
Assign values to the parameters of HOA;
Initialize the population;
Compute the fitness value of each bird;
while termination condition is not satisfied do
Carry out self-search stage;
Perform search stage;
Evaluate the fitness value of each tree;
end
Output the best solution found.

Figure 2. Pseudo-code of HOA algorithm

3.2. Improvement strategies

In order to enhance the algorithm's full-domain exploration capability and avoid the algorithm from falling into local optimum, this paper adopts the good point set initialisation strategy [24] and the cardinal leap strategy [25] to improve the Hummingbird optimisation algorithm.

Good point set initialisation strategy

The quality of the initialised population of HOA algorithm affects the solution optimisation speed of the algorithm, and an excellent population initialisation strategy can make the individuals of the population traverse the whole search space more evenly, increase the population diversity and improve the convergence speed of the algorithm. In order to improve the diversity of the population search and make the population evenly distributed in the search space, this paper proposes a good point set initialisation strategy to improve the initialisation of the HOA algorithm. Suppose G_s is a unit cube in s-dimensional Euclidean space, if $r \in G_s$, for:

$$P_n(k) = \left[\left(r_1^{(n)} \cdot k\right), \left(r_2^{(n)} \cdot k\right), \cdots, \left(r_s^{(n)} \cdot k\right)\right], 1 \le k \le n \tag{29}$$

Its deviation is satisfied:

$$\phi(n) = C(r, \varepsilon) n^{\varepsilon - 1} \tag{30}$$

Then $P_n(k)$ is called the set of good points and r is the good point. $\left(r_1^{(n)} \cdot k\right)$ represents the fractional part, ε is any positive number, $C(r, \varepsilon)$ is a constant related only to r, ε, n denotes the number of points, and r is:

$$r = \{2\cos(2\pi k/p), 1 \le k \le s\} \tag{31}$$

where p is the smallest prime number satisfying $(p-3)/2 \ge s$. The initialised population distribution graph using the set of good points is shown in Figure 3.

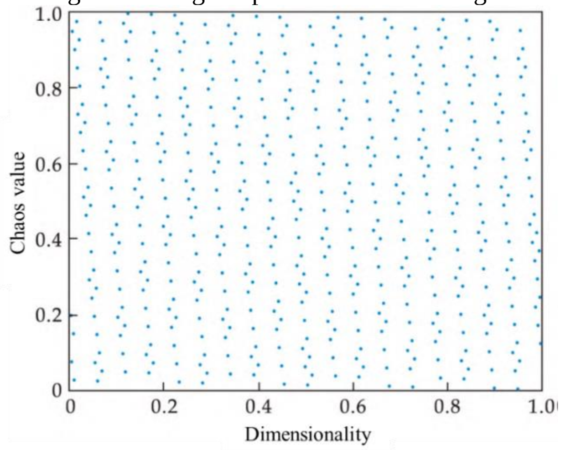


Figure 3. Distribution of initialised populations in the good point set

Cardinality leapfrog strategy

In the HOA algorithm, hummingbird individuals can increase the diversity of the algorithm by using the Levy flight strategy during the population iteration process, but with the increase of iteration number, the population variability decreases, and the distribution of algorithm diversity is limited. To address the above problems, this paper proposes the cardinal leap strategy, which makes the hummingbird jump out of the local optimum in the self-search phase and improves the algorithm's ability to find the optimum. The mathematical model of the cardinal leap strategy is as follows:

$$X_{id}^{t+1} = X_{id}^{t} + \gamma \oplus L(\lambda) \tag{32}$$

where X_{id}^{t+1} denotes the value of the i[th] hummingbird in the d[th] dimension in the first $t+1$ iteration, γ is the step control coefficient(Figure 4), and $L(\lambda)$ is the Lévy flight random search path.

In order to manipulate the step size control of the leaps, the cardinality adaptive step size is proposed based on the cardinality distribution function, γ solving Eq:

$$\gamma = f_n\left(n\left(\frac{t}{t_{\max}} + n^2\right)\right) \tag{33}$$

Where, n denotes the degree of freedom, t is the current number of iterations, $t_{\max}$ is the maximum number of iterations, and $f_n(\cdot)$ is the probability density function of the chi-square distribution, Eq:

$$f_n(x) = \begin{cases} \dfrac{1}{2\Gamma(n/2)}\left(\dfrac{x}{2}\right)^{\frac{n}{2}-1} e^{-\frac{x}{2}} & x > 0 \\ 0 & x \le 0 \end{cases} \tag{34}$$

where $\Gamma(n/2)$ is the gamma function, i.e:

$$\Gamma(\alpha) = \int_0^{+\infty} x^{\alpha-1} e^{-x} dx \tag{35}$$

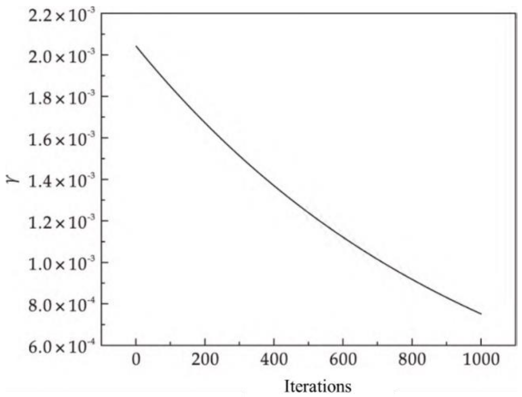


Figure 4. γ change curve

3.3. Improvement of algorithm flow

According to the HOA algorithm with improved optimisation strategy, the flowchart of HOA algorithm (HOA based on good point set initialisation strategy and chi-square transition, GChiHOA) is shown in Figure 5 with the following steps:

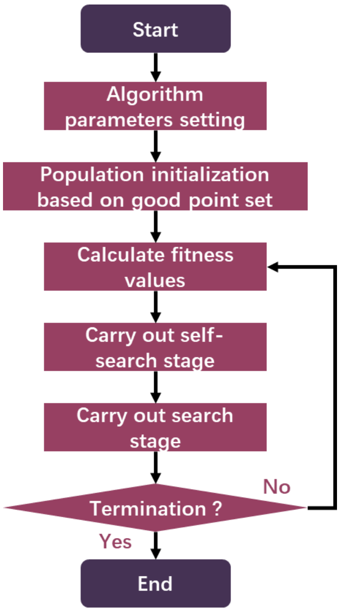


Figure 5. Flowchart of GChiHOA algorithm

Step 1: Initialise the population position using the good point set strategy, set the maximum number of iterations and other parameters;

Step 2: Calculate the fitness value and record the current optimal individual;

Step 3: Improve the Levy flight operator using the cardinality leapfrog strategy to perform the self-search phase;

Step 4: Execute the search phase for territorial and following birds;

Step 5: Calculate the fitness value and update the optimal individual;

Step 6: Determine whether the number of iterations reaches the maximum number of iterations. If the maximum number of iterations is reached, carry out the output of the optimal solution and optimal value; otherwise, go to step 3.

4. A cold chain low carbon logistics path optimisation method based on CChiHOA algorithm

4.1. Optimising solutions

In the cold chain low carbon logistics path optimization method based on GChiHOA algorithm, the population individuals represent the feasible solution of the cold chain low carbon logistics path optimization problem, i.e., the feasible path traversing the target distribution nodes; the optimal individuals represent the optimal solution obtained from the cold chain low carbon logistics path optimization problem, i.e., the optimal logistics and distribution paths; the change of the position of the population individuals represents the path passing through the changes of the distribution nodes or the optimization planning process, and the fitness value corresponds to the value of the objective function. The change of individual position of the population represents the change of the path through the distribution node or the planning optimisation process, and the fitness value corresponds to the value of the objective function, and the specific relationship is shown in Figure 6.

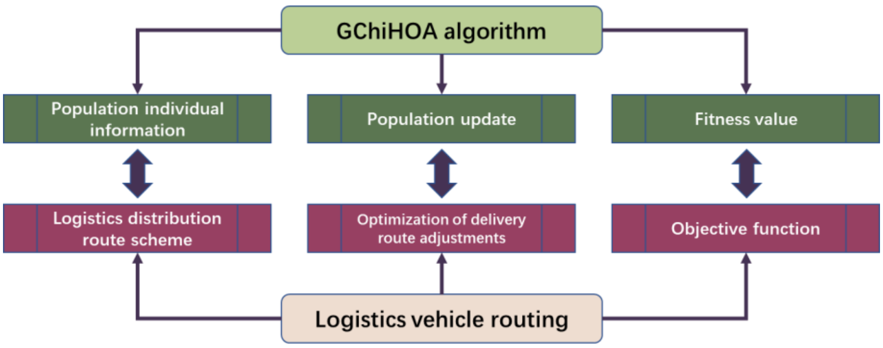


Figure 6. Schematic diagram of the optimised solution

4.2. Individual information design

According to the correspondence between the GChiHOA algorithm and the problem in Fig. 6, it can be seen that in this paper, the population individual position indicates the feasible path traversing the target distribution node, and the array coding method is used to explain the structure of the population individual position, i.e., $2\times\dim$, in which the dim dimension denotes the number of the distribution node, and the structure of the solution is shown in Figure 7. From Figure 7, it can be seen that the distribution centre and customer points are discrete points, and a two-layer array coding approach is introduced to encode the GChiHOA algorithm to solve the cold chain low-carbon logistics path optimization problem. The position-order coding expression formula is as follows:

$$X_i^t = \begin{bmatrix} x_{i1}, x_{i2}, \cdots, x_{in} \\ r_{i1}, r_{i2}, \cdots, r_{in} \end{bmatrix} \tag{36}$$

Where, X_i^t denotes the location of the ith individual in generation t of the GChiHOA algorithm, and r_{i1} denotes $r_{i1}, r_{i2}, \cdots, r_{in}$ sorted in ascending order, i.e., the distribution vehicle path code.

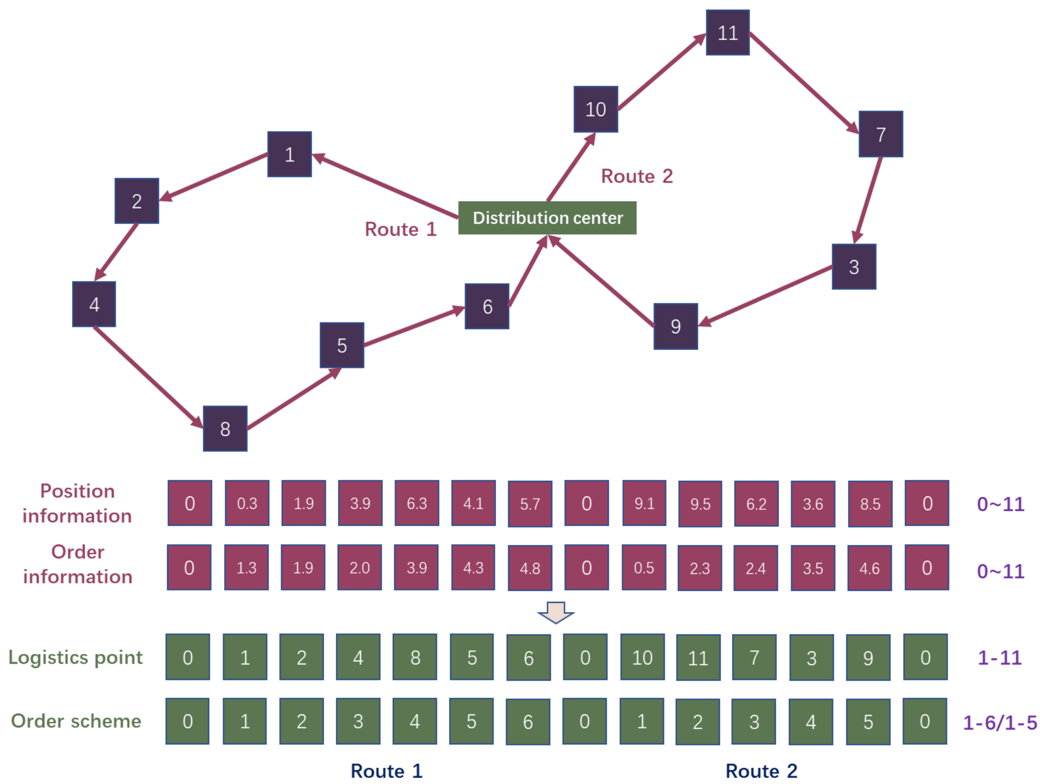


Figure 7. The solution structure

From Figure 7, it can be seen that the distribution centre number dimension 0 and the customer point is $1,2,\cdots,N$, and the vehicle returns to the distribution centre after serving a certain number of customers. According to the constraints such as the loading capacity of each vehicle, the structure of two groups of solutions is given in Figure 7, the first group of solution location information is 0.3, 1.9, 3.9, 6.3, 4.1, 5.7, and the distribution order information is 1.3, 1.9, 2.0, 3.9, 4.3, 4.8, and the distribution node information after the solution is discretised is 1, 2, 4, 8, 5, 6, and the distribution order serial no, 4, 5, 6, which means that the first car starts from the distribution centre and returns to the distribution centre after serving the customer nodes 1, 2, 4, 8, 5, 6, and the distribution services are carried out by different cars without repetition.

4.3. Adaptation function design

The individual fitness function is used to analyse the constraints of the cold chain low-carbon logistics path optimisation problem, and to generate fitness values for evaluating the individual strengths and weaknesses of the distribution scheme by combining the fixed costs, transportation costs, the cost of damage to the product delivered to the consumer, the cost of refrigeration to ensure that the items in the vehicle are in a low-temperature environment, the cost of carbon emissions generated by the distribution, and the cost of penalties. The individual fitness function in this paper is specified as:

$$\min Z = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 \qquad (37)$$

4.4. Methodological steps

The essence of the cold chain low-carbon logistics path optimisation problem is to solve the optimal solution problem with multiple constraints and multiple objectives, i.e., the cold chain low-carbon logistics and distribution path optimisation problem based on the soft time window. The application process of the improved Hummingbird optimisation algorithm in cold chain low-carbon logistics path optimisation is shown in Figure 8, and the specific steps are as follows:

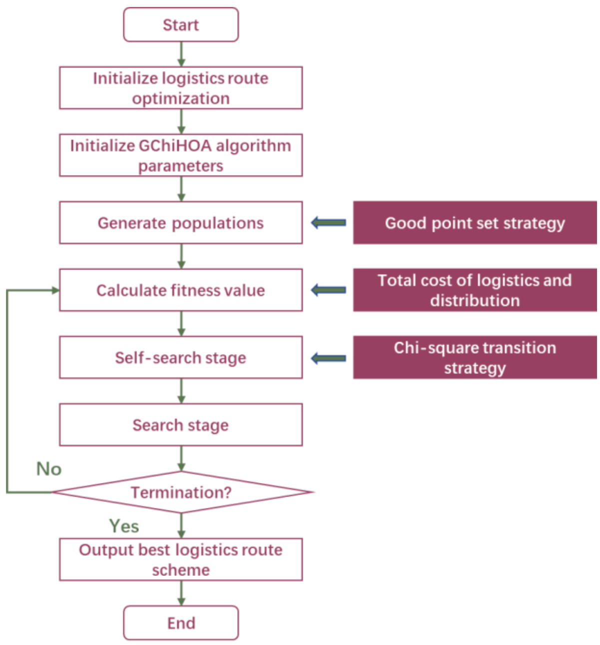


Figure 8. Optimisation of low-carbon logistics paths in the cold chain

Step 1: Initialise the cold chain low carbon logistics path optimisation parameters, including the parameters of the mathematical model of the problem and the parameters of the improved Hummingbird optimisation algorithm. The parameters of the cold chain low carbon logistics path optimisation model include as well as the relevant constraints, and the parameters of the GChiHOA algorithm include the population size, the maximum number of iterations, and so on.

Step 2: Select the search population randomly and uniformly using the given boundary constraints.

Step 3: The mapping between population individuals to the problem solution is done using the position-order array coding approach.

Step 4: Calculate the fitness value of the individual.

Step 5: Optimally updating the logistics delivery solution individual based on the improved Hummingbird optimisation algorithm self search strategy and search strategy.

Step 6: Determine whether the algorithm termination conditions are satisfied. If the number of search iterations is greater than the maximum number of iterations, the search is terminated and the optimal cold chain low-carbon logistics path distribution scheme is output; otherwise, continue with **steps 4** to **6**.

5. Results and analysis

In order to verify the effectiveness of the cold chain low carbon path optimisation method based on the improved Hummingbird optimisation algorithm, using the distribution logistics data of an enterprise, this paper selected five analysis algorithms for comparison. MATLAB 2021a was used to write the programme, and the test environment was a Windows 10 system, the processor was AMD Ryzen 9 5900HX with Radeon Graphics, and the memory was 16.0 GB.The parameters of each algorithm are shown in Table 1. Distribution logistics data for 16 consumers to deliver goods, the distribution centre is (0,0), the delivery service departs from the distribution centre at 5:30, and the consumers are shown in Table 2.

Table 1 Parameter settings of green low-carbon logistics path optimisation algorithm

arithmetic	parameterisation
LSHADE	Memory size H=5 and archive rate H=1.4
LSA	The channel time is set to 10
NRO	PFi = 0.75, Pβ = 0.1, freq = 0.05
HOA	Parameter-free optimisation
GChiHOA	Parameter-free optimisation

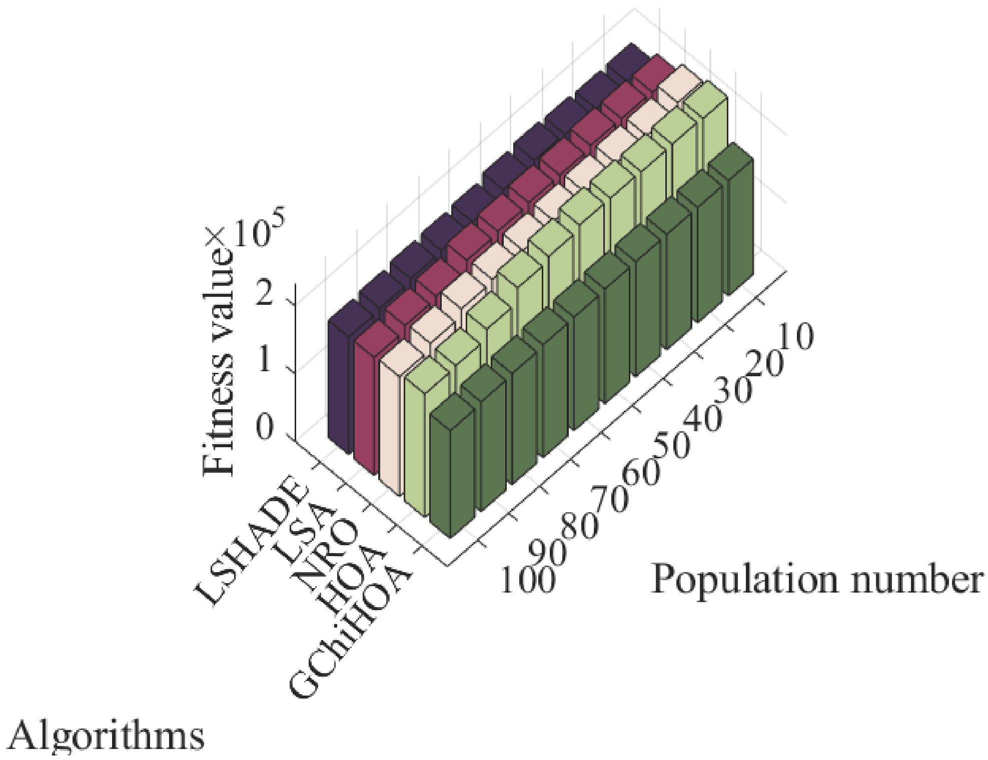
Table 2 Descriptive table of experimental data

No.	Position	Demand	Time window accepted	Time window desired	Degree of door opening coefficient
1	（6， 4）	15	6: 20-9: 10	6: 35-9: 00	0.5
2	（-30， 8）	18	5: 45-9: 20	6: 20-9: 05	1.5
3	（8， 33）	20	6: 55-9: 40	7: 25-9: 10	0.25
4	（188， 20）	8	6: 50-9: 50	7: 00-9: 20	1.5
5	（34， 28）	15	5: 50-10: 00	6: 10-9:30	1.5
6	（-25， 15）	10	6: 35-10: 20	7: 20-10: 10	1.5
7	（35， -5）	25	6: 30-9: 20	6: 55-9: 10	1.5
8	（42， 10）	30	6: 35-9: 40	6: 45-9: 25	0.5
9	（-10， 20）	17	6: 35-10: 10	6: 55-9: 45	0.5
10	（-8， 10）	6	7: 10-9: 40	7:20-9: 25	0.5
11	（-12， -32）	2	6: 20-10: 10	6: 25-10: 00	1.5
12	（-32， -40）	24	6: 10-10: 20	6: 25-9:30	0.5
13	（28， 15）	19	7: 05-10: 50	7: 40-10: 00	2
14	（-18， 0）	20	5: 30-10: 00	5: 55-9: 40	0.25
15	（-9， 25）	7	6: 30-9: 45	6: 50-9: 25	1
16	（-18， 8）	10	6: 35-9: 40	6: 40-9: 10	1.5

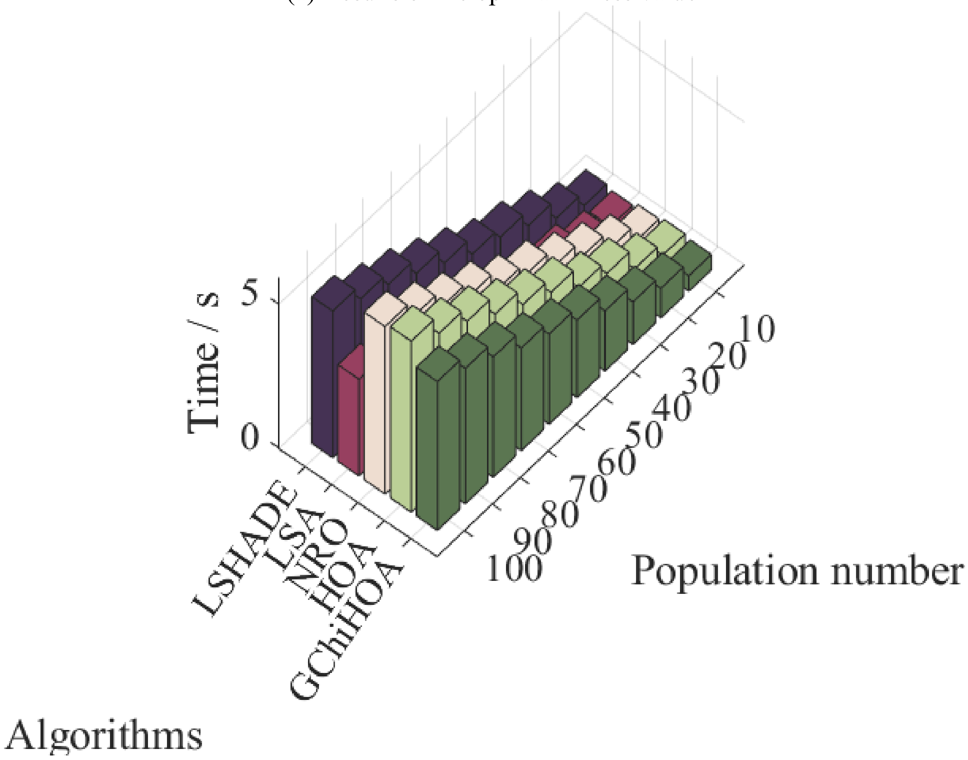
5.1. Algorithm parameter analysis

In order to investigate the impact of GChiHOA algorithm parameters on the performance of cold chain low carbon road logistics path optimisation, this paper analyses the population size and the number of iterations of the GChiHOA algorithm.

The effect of different population sizes on the performance of the cold chain low carbon road logistics path optimisation based on the intelligent optimisation algorithm is given in Figure 9. From Figure 9(a), it can be seen that the fitness value of the algorithm decreases as the population size increases. From Figure 9(b), it can be seen that as the population size increases, the elapsed time of the algorithm increases. On a comprehensive analysis, the population size should take a value of 60.



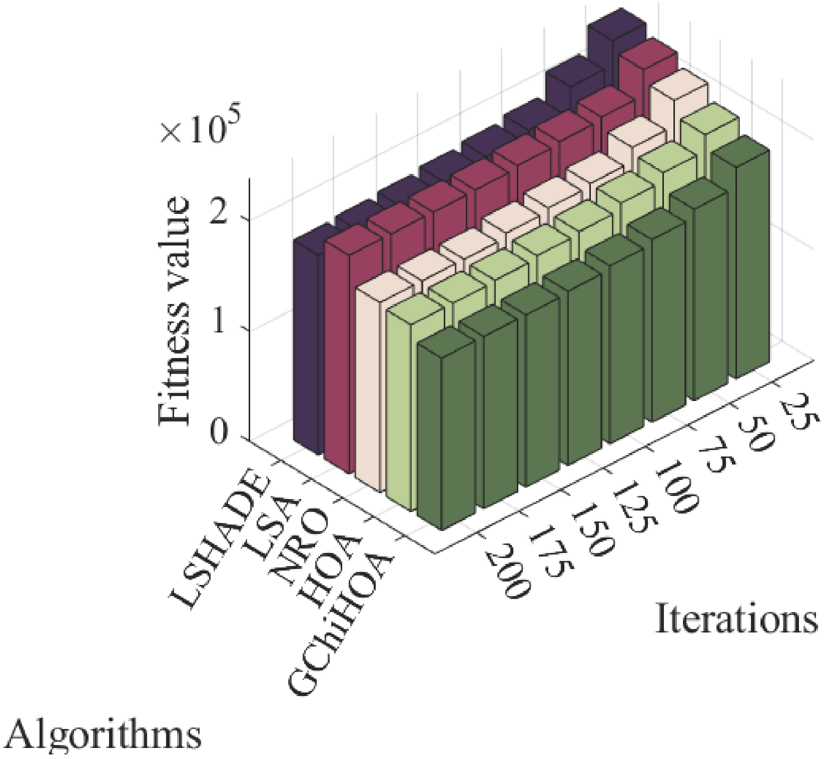
(a) Results of the optimal fitness value



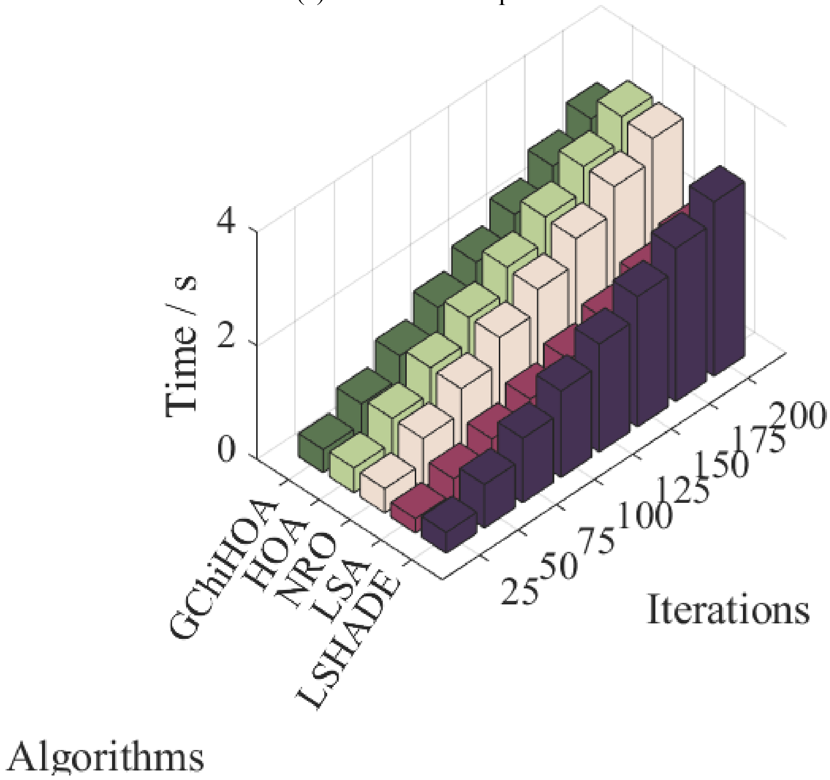
(b) Time-consuming results

Figure 9. Effect of population size on the performance of logistics path optimisation methods

The effect of different number of iterations on the performance of cold chain low carbon road logistics path optimisation based on intelligent optimisation algorithms is given in Figure 10. From Figure 10(a), it can be seen that as the number of iterations increases, the fitness value of each algorithm decreases. From Figure 10(b), it can be seen that the elapsed time of each algorithm increases as the number of iterations increases.



(a) Results of the optimal fitness value



(b) Time-consuming results

Figure 10. Impact of the number of iterations on the performance of logistics path optimisation methods

5.2. Analysis of path optimisation results

Based on the above parameter analysis, this subsection presents a comparative analysis of the performance of the five compared optimisation algorithms, each of which is run 20 times, and the specific results are shown in Figures. 11, 12 and 13.

The optimisation convergence curves for each algorithm are given in Figure 11. From Figure 11, it can be seen that the GChiHOA algorithm has the highest convergence accuracy and faster convergence speed; in terms of convergence accuracy, the GChiHOA algorithm is the best, followed by HOA, NRO, LSHADE, and LSA algorithms in that order.

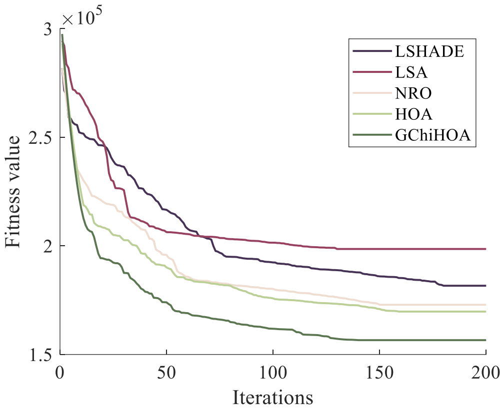


Figure 11. Iterative convergence curve of cold chain low carbon logistics path optimisation based on each algorithm

From Figure 12, it can be seen that the GChiHOA algorithm is better than other algorithms in terms of the mean value of optimal fitness value for distribution path optimisation, and the standard deviation of the fitness value is also the smallest, and the robustness is better than other algorithms; the optimisation time consumed by the GChiHOA algorithm is less than that of other algorithms, and the standard deviation of the time consumed is also the smallest; the optimised convergence iteration number of the GChiHOA algorithm is greater than that of the LSAHDE, the NRO, and the HOA However, it is less than LSA algorithm, and the variance of optimisation convergence iterations is less than other algorithms.

Algorithms	Mean-fitness	SD-fitness	Mean-time	SD-time	Mean-iteration	SD-iteration
LSHADE	181656	2.12	3.0707	0.11	178	1.45
LSA	198569	4.82	2.0525	0.04	132	2.33
NRO	172897	2.41	3.4754	0.15	155	2.54
HOA	169754	1.29	3.5066	0.12	157	3.66
GChiHOA	156600	0.74	3.1148	0.06	138	0.32

Figure 12. Comparison of the performance of green low-carbon logistics path optimisation methods based on each algorithm

According to the GChiHOA algorithm running 20 times the optimal results, this section gives the results of the optimal distribution scheme with a schematic diagram, the specific results are shown in Figures 13 and 14.Figure 13 gives the results of the optimal distribution scheme for logistics based on the GChiHOA algorithm and the HOA algorithm. As can be seen from Figure 13, in the GChiHOA algorithm, the four-vehicle distribution path through the nodes is relatively uniform, taking into full account the total cost of distribution; in the HOA algorithm, the four-vehicle distribution path through the nodes is not uniform, and does not take into full account the distribution cost calculation.

Vehicle	Route scheme based on CGhiHOA
#1	0->10->16->9->15->0
#2	0->11->12->14->2->6->0
#3	0->1->4->3->0
#4	0->7->8->13->5->0

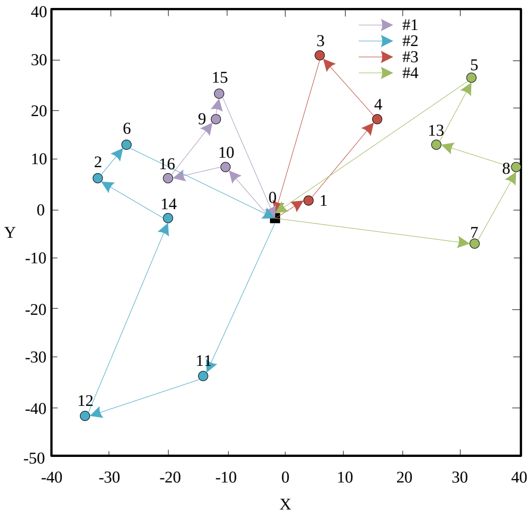
(a) Optimisation results of the GChiHOA algorithm

Vehicle	Route scheme based on HOA
#1	0->1->4->13->5->0
#2	0->7->8->0
#3	0->10->16->14->11->12->0
#4	0->3->15->9->6->2->0

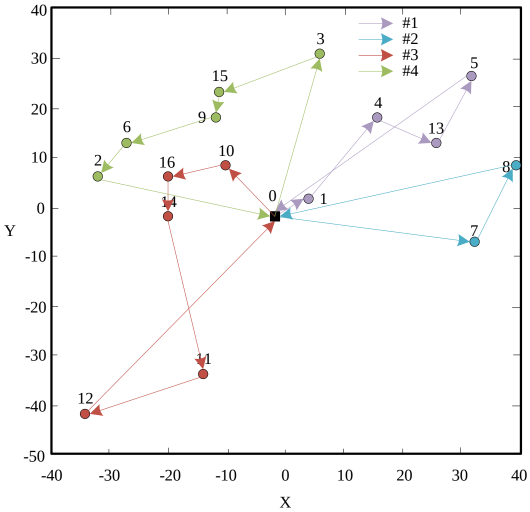
(b) Optimisation results of the HOA algorithm

Figure 13. Cold chain low carbon logistics and distribution vehicle routes based on GChiHOA algorithm and HOA algorithm

A schematic diagram of the optimal distribution scheme is given in Figure 14. From Figure 14, it can be seen that in the GChiHOA algorithm, each vehicle travelling path starts from the distribution centre, passes through the customer nodes, and finally returns to the starting point; Vehicle No. 3 departs and returns to the starting point after passing through five points, and then there is a departure, and finally returns to the starting point again. In the HOA algorithm, vehicle number one and vehicle number three distribution paths cross each other and are not optimised enough.



(a) Optimisation results of the GChiHOA algorithm



(b) Optimisation results of the HOA algorithm

Figure 14. Schematic diagram of cold chain low carbon logistics distribution path based on GChiHOA algorithm and HOA algorithm

6. Conclusion

Aiming at the current cold chain low-carbon logistics and distribution path optimisation method, which is prone to fall into local optimum and takes a long time to optimise, this paper proposes a cold chain low-carbon logistics and distribution path optimisation method based on the improved Hummingbird optimisation algorithm. By analysing the characteristics, costs and constraints of the cold chain low-carbon logistics distribution path optimisation problem, a soft time window-based cold chain low-carbon logistics distribution path optimisation model is constructed; combining the double-layer array coding method and the fitness function, the hummingbird optimisation algorithm is improved by using the good point set initialisation strategy and the cardinality leap strategy to solve the cold chain low-carbon logistics distribution path optimisation problem. The results show that the cold chain low-carbon logistics path optimisation method proposed in this paper can find the optimal scheme of logistics and distribution paths in a shorter time, with uniform and reasonable node distribution and stable performance.

References

[1] Liu S , Zhang C .Multiobjective optimization of railway cold-chain transportation route based on dynamic train information[J]. transport planning & management, 2023.

[2] Bai Q , Yin X , Lim M K ,Dong C.Low-carbon VRP for cold chain logistics considering real-time traffic conditions in the road network[J].Industrial management & data systems, 2022.

[3] Jin J , Wen Q , Cheng S , Qiu Y, Zhang X, Guo X. Optimization of carbon emission reduction paths in the low-carbon power dispatching process[J].Renewable Energy, 2022, 188.

[4] Andoh E A , Yu H .A two-stage decision-support approach for improving sustainable last-mile cold chain logistics operations of COVID-19 vaccines[J]. .Annals of Operations Research, 2022:1-31.

[5] Yang Y , Ma C , Zhou J , Dong J, Ling G, Li J. A multi-dimensional robust optimization approach for cold-chain emergency medical materials dispatch under COVID-19: A case study of Hubei Province[J]. Journal of Transport Engineering: English Edition, 2022, 9(1):1-20.

[6] Wangsa I D , Vanany I , Siswanto N .An optimisation model for fresh-food electronic commerce supply chain with carbon emissions and food waste[J]. Journal of Industrial and Production Engineering, 2023.

[7] Lim M K , Li Y , Wang C , Tseng M L. Prediction of cold chain logistics temperature using a novel hybrid model based on the mayfly algorithm and extreme learning machine[J].Industrial management & data systems, 2022(3):122.

[8] Shi Y , Lin Y , Lim M K , Tseng M L, Tan C, Li Y. An intelligent green scheduling system for sustainable cold chain logistics[J].Expert Systems with Application, 2022.

[9] Wu D , Zhu Z , Hu D , Mansour R F. Optimizing Fresh Logistics Distribution Route Based on Improved Ant Colony Algorithm[J]. Computers, Materials and Continuum (English), 2022(10):17.

[10] Teymourian E , Kayvanfar V , Komaki G M , Zandieh M. Enhanced intelligent water drops and cuckoo search algorithms for solving the capacitated vehicle routing problem[J].Information Sciences, 2016, 334:354-378.

[11] Jabir E , Panicker V V , Sridharan R .Design and development of a hybrid ant colony-variable neighbourhood search algorithm for a multi-depot green vehicle routing problem[J].Transportation Research Part D: Transport and Environment, 2017, 57(12):422-457.

[12] Okulewicz M ,Mańdziuk, Jacek.The impact of particular components of the PSO-based algorithm solving the Dynamic Vehicle Routing Problem[J]. Applied Soft Computing, 2017, 58: 586-604.

[13] Lagos C, Guerrero G, Cabrera E. An improved particle swarm optimisation algorithm for the VRP with simultaneous pickup and delivery and time windows [J]. IEEE Latin America Transactions, 2018, 16(6): 1732-1740.

[14] Zhang Xiaonan,Fan Houming. Fuzzy demand vehicle path optimisation and real-time adjustment[J]. Journal of Shanghai Jiao Tong University, 2016, 50(1):9.

[15] FAN Houming, LIU Pengcheng, LIU Hao, HOU Dengkai. VRPSDP problem with stochastic collection demand under multi-centre joint distribution model[J]. Journal of Automation, 2021, 47(7):15.
[16] Ke-Wei J, San-Yang L, Xiao-Jun S. A hybrid algorithm for time-dependent vehicle routing problem with soft time windows and stochastic factors[J]. Engineering Applications of Artificial Intelligence, 2022, 109: 104606.
[17] Zhang J , Ding B .Multi-Objective Cold Chain Path Optimization Based on Customer Satisfaction[J]. Applied Mathematics and Applied Physics(English), 2023, 11(6):1806-1815.
[18] Zheng C , Sun K , Gu Y , Shen J, Du M, Guo Y. Multimodal Transport Path Selection of Cold Chain Logistics Based on Improved Particle Swarm Optimization Algorithm[J].Journal of advanced transportation, 2022.
[19] Abdallah A , Dauwed M , Aly A A , Felemban B F, Khan I, Choi B J. An Optimal Method for Supply Chain Logistics Management Based on Neural Network[J]. Computers, Materials and Continuum (English), 2022.
[20] Kate T .ASHP's second cold chain forum tackles excursion management challenges and optimisation[J]. 2022(2):2.
[21] Yang Y , Ma C , Zhou J , Dong S, Ling G, Li J. A multi-dimensional robust optimization approach for cold-chain emergency medical materials dispatch under COVID-19:A case study of Hubei Province[J].Journal of Traffic and Transportation Engineering (English Edition), 2022, 9(1):1-20.
[22] Liu S .Multimodal Transportation Route Optimization of Cold Chain Container in Time-Varying Network Considering Carbon Emissions[J]. Sustainability, 2023.
[23] Zhang Z , Huang C , Huang H ,et al. An optimisation method: hummingbirds optimization algorithm[J]. 2018, 29(2):386-404.
[24] J. Chen,Q. He. Sparrow optimisation algorithm with mixed-strategy improvement[J]. Small Microcomputer Systems, 2023, 44(7):1470-1478.
[25] Xiaoxin Du, Zhenfei Wang, Bo Wang, Hao Wang, Tianru Hao, Lianhe Cui. Black spider optimisation algorithm based on cardinality leaping strategy with applications[J]. Journal of Shaanxi University of Science and Technology, 2023, 41(6):162-175.