A cold chain logistics distribution optimization model: Beijing-Tianjin-Hebei region low-carbon site selection

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Purpose

This study reduces carbon emission in logistics distribution to realize the low-carbon site optimization for a cold chain logistics distribution center problem.

Design/methodology/approach

This study involves cooling, commodity damage and carbon emissions, and establishes the site selection model of low-carbon cold chain logistics distribution center aiming at minimizing total cost, and grey wolf optimization algorithm is used to improve the artificial fish swarm algorithm to solve a cold chain logistics distribution center problem.

Findings

The optimization results and stability of the improved algorithm are significantly improved and compared with other intelligent algorithms. The result is confirmed to use the Beijing-Tianjin-Hebei region site selection. This study reduces composite cost of cold chain logistics and reduces damage to environment to provide a new idea for developing cold chain logistics.

Originality/value

This study contributes to propose an optimization model of low-carbon cold chain logistics site by considering various factors affecting cold chain products and converting carbon emissions into costs.Prior studies are lacking to take carbon emissions into account in the logistics process. The main trend of current economic development is low-carbon and the logistics distribution is an energy consumption and high carbon emissions.

Keywords: low-carbon cold chain logistics; distribution center site selection model; grey wolf optimization algorithm; artificial fish swarm algorithm

Nomenclature

Full Name	Abbreviations
Artificial fish swarm algorithm	AFSA
Grey wolf optimization	GWO
Grey wolf optimization- Artificial fish swarm algorithm	GWO-AFSA
Deoxyribonucleic acid- Artificial fish swarm algorithm	DNA-AFSA
Genetic Algorithm	GA
Simulated annealing	SA

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1 Introduction

Cold chain products are easy to deteriorate and have higher requirements for temperature. The consumption of electric energy and fuel is greater, carbon dioxide emission is more and to maintain low temperature in complete stage of cold chain logistics. Especially, the low-carbon cold chain logistics distribution industry is characterized by high energy consumption and carbon emissions. Low carbon economy means that use of technology and industrial innovation to achieve sustainable development by reducing energy consumption and carbon emissions (Tseng et al., 2021; Mariosa et al., 2022). Many studies have analyzed the environmental problems existing in rag trade (Nikouei et al., 2022; Ocran et al., 2022; Peters et al., 2021), takeaway packaging (Alejandro et al., 2019), business model (Bocken et al., 2021), campus ecology (Adenle et al., 2022) and other aspects, providing effective advice to develop of low-carbon economy (Jabbour et al., 2021). Still, distribution has multi-sites, and different distribution schemes produce different energy consumption and carbon emissions. There is a need to optimize the route of distribution sites.

In the literature, Naderi et al. (2021) confirmed that energy consumption and sustainable development have significant effect in management of supply chain, and use exergy analysis to help supply chain managers achieve low-carbon development. The characteristics of logistics restrict the sustainable development of economy (Yao et al., 2018; Zhang et al., 2022; Alqadhi et al., 2022). Deng et al. (2020) believed development of logistics industry acts a momentous role in economy, and carbon emissions must be included in the measurement index to make the logistics industry develop with high quality and high efficiency. Leng et al. (2020) believed that carbon emissions and energy consumption mainly come from logistics industry, so it is important for cold chain logistics to consider sustainable development about environment and economy. However, the relevant information and studies on cold chain logistics are relatively few in involving cooling, commodity damage and carbon emissions together for a cold chain logistics distribution center site selection problem.

The cold chain arises at the right moment as vegetables and fruits, dairy products, meat and other foods are prone to deterioration and have higher requirements for distribution. Cold chain is supply chain system for the food could be kept at low temperature in production, storage, transportation and other links from supplier to consumer to ensure product quality (Yang, 2018). Different from ordinary logistics, cold chain logistics is to use of certain transportation technology and equipment to strictly control the conditions of transportation, and transport perishable food at low temperature, thereby reducing the occurrence of loss and deterioration (Zheng et al., 2021). As food transported by cold chain has higher requirements on temperature and other conditions, cold chain logistics usually has strong timeliness, high cost, high energy consumption and carbon emissions. Yao et al. (2020) included energy consumption and carbon emissions into indicators to measure logistics industry. Developing low-carbon cold chain logistics is an inevitable choice to improve the logistics system and promotes Low carbon distribution.

A growing demand for cold chain products and continuous progress of technology resulting in higher quality requirements for products (Lu, 2021). The rapid development of economy has brought a negative impact on nature, and notion of protecting environment has been enhanced. All industries should develop their economy in a green and low-carbon way. The energy consumption of cold chain logistics is larger to reduce loss of cold chain product quality, which is contrary to low-carbon development, and few studies exists on low-carbon logistics at the present stage.

Pei et al. (2021) studied how to transport in logistics system to reduce transportation cost. Liu (2020) established a distribution center site selection model containing fixed cost and management cost. Li et al. (2020) set up a logistics distribution model with a goal of cutting cost including distribution, transportation fuel consumption and carbon emission, and solved it by using analytic hierarchy process and data envelopment analysis. Liu et al. (2020) established an open logistics site-path problem including fuel consumption and carbon emissions based on general logistics. Wang et al. (2020) believed that carbon dioxide emissions would increase with the increase of driving distance and loading capacity, and based on this, a dual-objective model was established. In lieu of this, the cost in the current study only contains a few costs. The main study is the logistics problem without carbon emissions or the general logistics model including carbon emissions, but there is few studies about cold chain logistics site selection model including carbon emissions and multiple costs. This study integrates the carbon emission factors, considers the various factors that affect the logistics cost of cold chain products, establishes the low-carbon cold chain logistics site optimization model, and uses improved intelligent optimization algorithm to solve it.

Hybrid algorithm has better search performance and is widely used in various problems. Deng et al. (2023) used hybrid algorithm to solve multi-strategy hybrid optimization problem. AFSA is a swarm intelligence optimization algorithm based on animal autonomous body model, including foraging, clustering, following and other behaviors (Li et al., 2002). The algorithm carries out global optimization through the behavior of artificial fish, and has the advantages of simple and easy implementation, strong parallel processing ability and low requirements for parameters. However, the algorithm has the shortcomings of low precision and slow searching speed in the late stage.

It is widely used in complex application problems. Cheng et al. (2021) optimized the AFSA by improving view field, step size and setting self-new neighborhood structure, and combined with BP neural network, effectively improved the accuracy of fault diagnosis. Zhang et al. (2021) introduced the movement strategy and mutation operation into to help algorithm escape from local extreme value, and applied modified algorithm to deal with combinatorial optimization problem of large-scale units. Wu et al. (2021) used the method of good point set to optimize the initial distribution of artificial fish, and used bacterial foraging optimization algorithm and Levi flight to improve foraging behavior and random behavior. Experimental simulation showed that the improved algorithm could identify key nodes in the network and improve stability. Jiao et al. (2021) use A* algorithm to initialize the fish swarm, and use Pareto dominating relation and adaptive vision to improve the optimization ability, to provide the robot with an optimal path free of obstacles. In our paper, When the solution effect of AFSA is not good, the hierarchical system and predation strategy of gray wolf optimization algorithm are introduced, and GWO-AFSA is employed to deal with the site problem of distribution center in logistics.

The study uses grey wolf optimization algorithm (GWO -AFSA) for sake of optimizing site selection of low-carbon cold chain logistics distribution center. The innovation is to improve the cold chain low-carbon logistics site selection model and solution method. The study contributes to propose an optimization model by considering various factors affecting cold chain products and converting carbon emissions into carbon emission cost, which includes fixed cost, transportation cost, cooling cost, commodity damage cost, penalty cost and carbon emission cost. The GWO is introduced into later stage of fish swarm algorithm to avoid problems existing in later stage of fish swarm algorithm. Improved algorithm’s effectiveness is proved by function test, and it is used to deal with site selection model, and site selection scheme with lower cost is obtained.

2. Literature Review

Society urgently needs to develop sustainable technology systems (Reddy et al., 2022). Aiming at low carbon, Conlon et al. (2022) built models to balance costs and carbon emissions. Based on system dynamics, Zhang et al. (2021) set up a complex sustainable development path model with less carbon and provided corresponding policy suggestions.

Distribution center's site affects distribution distance and cost, so it is a great significance and is a complicated problem to be solved by traditional methods (Nikouei et al., 2022; Xu et al., 2020; Zhang et al., 2022). Compared to uaual logistics, cold chain logistics consumes more energy to guarantee the quality of products. Reasonable site of distribution center helps to reduce quality loss of cold chain products, reduce carbon emissions and logistics costs to maximize benefits. In addition, it can improve customer satisfaction and delivery efficiency. Therefore, site optimization is significant. There are many studies in analysis the site sites using different methods. For instance, Wang et al., (2019) improved the leapfrog algorithm by using the mutation operation in the differential evolution algorithm to provide a scientific site scheme for the joint replenishment problem. Bilisik et al. (2019) used grey correlation analysis to solve the site selection problem of fruit tree market in Istanbul. Yu et al. (2019) established a site selection model for competitive facilities considering customer will and facility capacity, and obtained a site selection scheme that could consider both cost and service quality through simulated annealing (SA) algorithm. Yang et al. (2022) built a path model about multiple demand centers. Lim et al. (2022) built an optimization model for site selection that considered elements containing cost, time-varying traffic conditions, commodity damage and consumer service level.

About logistics's analysis, Singh et al. (2018) introduced factors such as consumer site, demand uncertainty and warranty period into service distance constraints, and built a mixed integer linear programming model to obtain reasonable cold chain distribution address. Shang et al. (2019) adopted the method of comprehensive variation and random weight to improve the whale optimization algorithm and get a more reasonable site of distribution center. Jiang et al. (2019) used probability function and traffic factor to represent the uncertainty of path. Based on this, a dynamic low-carbon open site-path model was established and solved by an intelligent optimization algorithm. Szymczyk et al. (2019) thought about the issues about carbon emissions, smart city and sustainable development and analyzed the new delivery solutions on basic of intelligent freight.

Song et al. (2019) studied how to select emergency supplies distribution center's site regarding changes in demand and road conditions. Li et al. (2020) proposed that time window constraints should be taken into full consideration when making site decisions for distribution centers in view of the perishable feature of cold chain food. Xu(2023) proposed a mathematical model to minimize the sum of vehicle fixed costs, fuel costs, carbon emissions costs, cooling costs, time penalty costs, and segmentation compensation costs. A two-stage hybrid heuristic path solution algorithm combining taboo table, genetic algorithm, optimal path generation algorithm, load capacity constraint algorithm, and time window constraint algorithm was designed to address the complexity of the model and the uniqueness of the solution. The distribution cost is increasing from different cold chain products have different deterioration speed, and with the increase of distance. Assumptions are set in the model to simplify the analysis.

In sum, the current literature contains less costs, including only a few costs, and most of them do not consider carbon emissions. There are few logistics models that consider many factors such as carbon emissions. The proposed model is established regarding the comprehensive analysis about various factors including carbon emissions. As the literature shows, the changes of demand, road conditions, distance and other factors complicate the model, which is not conducive to the solution of the problem. Some assumptions are set in the model to simplify the analysis. To better decide distribution center site selection, (1) this study sets up some basic assumptions and establishes a double-level low-carbon cold chain logistics distribution center site selection model containing supplier, distribution center and consumer with the target of minimizing total cost, including fixed cost, transportation cost, cooling cost, commodity damage cost, penalty cost and carbon emissions cost; (2) social hierarchy and predation strategy of GWO are introduced into the fish swarm algorithm to help late stage of the basic AFSA escape from slow optimization speed and low solving accuracy; and (3) the improved GWO-AFSA is implemented to solve the site selection model.

3. Method

3.1 Description of problem

According to the number of nodes, the site problem has three categories: single-level, double-level and multi-level. Single-level means that the distribution network only contains two types of nodes: distribution center and consumer. The double-level distribution network consists of three nodes: supplier, distribution center and consumer, multi-level refers to a network containing at least three types of different nodes (Lin et al., 2020). Multiple distribution centers site problem refers to that several distribution centers are chose from known multiple distribution centers to be selected so as to reduce total cost of the distribution network formed under constraints of satisfying needs of consumers. At present, most studies are about single-layer level, while there are few studies about two-layer level, and the existing models contain fewer costs

This study takes the Beijing-Tianjin-Hebei metropolitan area as the research objects, which is a large urban agglomeration consisting of Beijing, Tianjin, Hebei province and some surrounding cities. It is one of the most dynamic and promising regions in northern China and an important center for politics, culture, science and technology, and economy. Taking Binhai New Area as the supply point, 5 out of 13 municipal administrative units within the metropolitan area (Beijing, Tianjin, Shijiazhuang, Chengde, Zhangjiakou, Qinhuangdao, Langfang, Tangshan, Baoding, Cangzhou, Hengshui, Xingtai, Handan) are selected as distribution centers to provide distribution services to 26 demand points.

3.2 Hypotheses of problem

- The demand, site and time window requirements about consumers are known, and delivery service of products in demand is completed at one time.
- The fixed costs of each selected distribution center are known.
- The distances from supplier to the selected distribution centers and from selected distribution centers to consumer are known.
- There is only one cold chain product.
- The unit transportation cost of the product is known, and the transportation cost between the supplier and distribution centers, and between distribution centers and demand point increases with the increase of the distance between them.
- There is no limit to the number of vehicles, and they are a single vehicle type.
- Vehicles speed remains the same, whatever road conditions are.

3.3 Analysis of distribution costs

Total cost in site of cold chain low-carbon logistics distribution center contains fixed cost, transportation cost, commodity damage cost, cooling cost, penalty cost and carbon emission cost, and cost composition could be seen in Figure 1

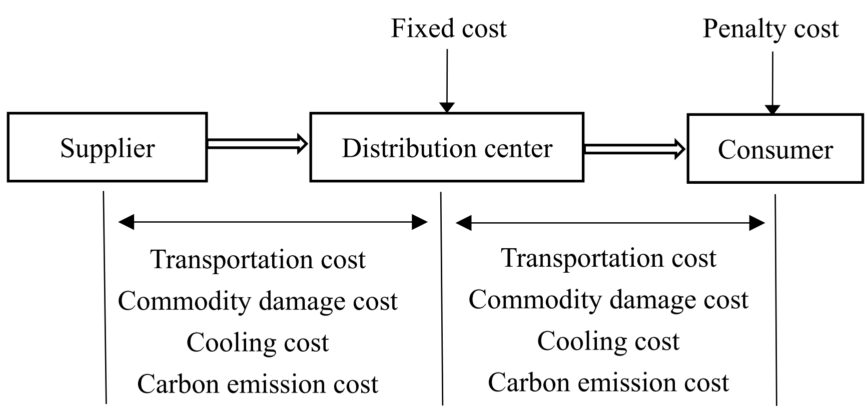

Figure 1. Cost composition of distribution network

(1) Fixed cost

Fixed cost is cost that has nothing to do with transportation, including operating costs like the distribution centers's capital cost, vehicles's depreciation cost and wages of employees. If there are I suppliers, J distribution centers and M consumers in the logistics network, c_j ($j=1,2,\cdots,J$) represents fixed cost of the j_{th} distribution center, and then total fixed cost C_1 is:

$$C_1=\sum_{j=1}^{J}c_j\alpha_j \quad (1)$$

Where: $\alpha_j=\begin{cases}1, & \text{the } j_{th} \text{ distribution center is selected}\\ 0, & \text{the } j_{th} \text{ distribution center is not selected}\end{cases}$

(2) Transportation cost

Transportation cost refers to the cost related to freight volume and haul distance. Suppose p_2 is the cost of transporting unit product in unit distance, q_{ij} is the freight volume from i to j, q_{jm} is freight volume from j to m, d_{ij} is the distance between i and j, and d_{jm} is the distance between j and m, and then the transportation cost C_2 is:

$$C_2 = \sum_{i=1}^{I}\sum_{j=1}^{J} p_2 q_{ij} d_{ij} \alpha_j + \sum_{j=1}^{J}\sum_{m=1}^{M} p_2 q_{jm} d_{jm} \alpha_{jm} \quad (2)$$

Where: $\alpha_{jm} = \begin{cases} 1, & distribution\ center\ j\ provides\ distribution\ service\ to\ consumer\ m \\ 0, & distribution\ center\ j\ does\ not\ provide\ distribution\ service\ to\ consumer\ m \end{cases}$

(3) Commodity damage cost

Commodity damage is loss cost of cold chain products owing to the passage of time and temperature change during transportation and unloading. Suppose p_3 is unit price of cold chain product, β_1 and β_2 are product's deterioration rate in transportation and unloading process, t_{ij} is the vehicle's delivery time from i to j, t_{jm} is vehicle's delivery time between j and m, and T_m is the time required for the vehicle to be unloaded at consumer m. The cost of commodity damage is:

$$C_3 = \sum_{i=1}^{I}\sum_{j=1}^{J} p_3 q_{ij} \alpha_j \left(1 - e^{-\beta_1 t_{ij}}\right) + \sum_{j=1}^{J}\sum_{m=1}^{M} p_3 q_{jm} \alpha_{jm} \left(1 - e^{-\beta_1 t_{jm}}\right) + \sum_{j=1}^{J}\sum_{m=1}^{M} p_3 q_{jm} \alpha_{jm} \left(1 - e^{-\beta_2 T_m}\right) \quad (3)$$

(4) Cooling cost

Cooling cost refers to cost of cooling caused by refrigerated vehicles during transportation and unloading. Suppose that in the transportation process, the cooling cost of products transported by refrigerated vehicles per unit time is p_{41}; in unloading process, cooling cost unloading products per unit time is p_{42}. Then the cooling cost is:

$$C_4 = \sum_{i=1}^{I}\sum_{j=1}^{J} p_{41} t_{ij} \alpha_j + \sum_{j=1}^{J}\sum_{m=1}^{M} p_{41} t_{jm} \alpha_{jm} + \sum_{m=1}^{M} p_{42} T_m \alpha_{jm} \quad (4)$$

(5) Penalty cost

Penalty cost refers to the cost incurred when vehicle can't deliver product to consumer within a specified period of time. There is the waiting cost if vehicle arrives before the earliest time requested by the consumer, and the lateness cost if vehicle arrives after the latest time requested by the consumer. Suppose t_m is the time when the vehicle reaches consumer m, p_w and p_l are waiting and lateness cost per hour, (ET_m, LT_m) is time window expected by consumer m, and (EET_m, LLT_m) is the time window acceptable to the consumer m. Then the penalty cost at consumer m is:

$$C_5(m) = \begin{cases} \inf, & t_m < EET_m \\ p_w(ET_m - t_m), & EET_m < t_m < ET_m \\ 0, & ET_m < t_m < LT_m \\ p_l(t_m - LT_m), & LT_m < t_m < LLT_m \\ \inf, & t_m > LLT_m \end{cases} \quad (5)$$

Where $\inf$ is an infinite positive number

The total penalty cost is:

$$C_5 = \sum_{m=1}^{M} C_5(m) \quad (6)$$

(6) Carbon emission cost

Carbon emission cost is cost of carbon dioxide emissions caused by energy consumption and refrigerant caused by cooling equipment during transportation. The vehicle's fuel consumption is in relation to elements like driving distance, load weight and speed, and more fuel consumption, the more carbon dioxide emissions. Set p_c as unit carbon tax price, e as carbon dioxide emission coefficient, q_M as maximum load of refrigerated vehicles, ε_0 and ε_m are fuel consumption per kilometer when vehicle is not loaded and fully loaded, and E_2 as cooling equipment's energy consumption per hour. Relationship between fuel consumption and deadweight per unit distance of refrigerated vehicles between supplier and distribution center and between distribution center and consumer (Zhang et al., 2019) is as follows:

$$E_1(x_{ij}) = \frac{\varepsilon_m - \varepsilon_0}{q_M} x_{ij} + \varepsilon_0 \quad (7)$$

$$E_1(x_{jm}) = \frac{\varepsilon_m - \varepsilon_0}{q_M} x_{jm} + \varepsilon_0 \quad (8)$$

Therefore, the total carbon emission cost of vehicles and cooling equipment is:

$$C_6 = p_c \sum_{i=1}^{I} \sum_{j=1}^{J} eE_1(x_{ij}) d_{ij} \alpha_j + p_c \sum_{j=1}^{J} \sum_{m=1}^{M} eE_1(x_{jm}) d_{jm} \alpha_j + p_c \sum_{i=1}^{I} \sum_{j=1}^{J} eE_2 t_{ij} + p_c \sum_{j=1}^{J} \sum_{m=1}^{M} eE_2 t_{jm} \quad (9)$$

3.4 Model construction

In summary, site selection model of low-carbon cold chain logistics distribution center is:

$$\min C = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 \quad (10)$$

Constraints:

$$\sum_{j=1}^{J} \alpha_{jm} = 1, m \in M \quad (11)$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} q_{ij} = \sum_{j=1}^{J} \sum_{m=1}^{M} q_{jm} \quad (12)$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} q_{ijm} = 0 \quad (13)$$

$$\sum_{j=1}^{J} q_{jm} \geq \sum_{m=1}^{M} q_m \quad (14)$$

$$\sum_{j=1}^{J} \alpha_j \leq N \quad (15)$$

$$\sum_{n=1}^{N} V_n \geq \sum_{m=1}^{M} q_m \quad (16)$$

Equation (10) is goal function, aiming to reduce total cost as much as possible including fixed cost, transportation cost, commodity damage cost, cooling cost, penalty cost and carbon emission cost. Equation (11) indicates that each customer can only be provided with distribution service by one distribution center. Equation (12) means total freight volume between supplier and distribution center is equal to that between distribution center and customer. Equation (13) indicates that there are no vehicles running between distribution centers. Equation (14) means total amount of products transported from distribution centers to customers is greater than or equal to total amount of customer demand, q_m is the quantity demanded by customer m. Equation (15) is the limit on distribution center's total number, that is, at most N distribution centers are constructed, $n = 1,2,\cdots,N$. Equation (16) indicates that total capacity of selected distribution centers must be able to meet customers' needs, and V_n represents capacity about the n_{th} distribution center.

3.5 The basic principle of GWO-AFSA

Due to the advantages of wide adaptability and strong generality, AFSA is implemented to do with complex real problems like fault diagnosis (Wang et al., 2020), parameter control (Zhang et al., 2019), path planning (Yuan et al., 2018), image processing (Wang et al., 2020), fault site of power system (Hu et al., 2020). However, in late phase, convergence speed of AFSA is slow, it is not hard to fall into local extreme value, and the solving accuracy is not high. Therefore, studies have mainly improved the fish swarm algorithm from three aspects: fish school initialization (Zhang et al., 2019), algorithm parameters (Zhang et al.,2019), and fusion with other algorithms (He et al., 2020). The GWO involves few parameters, is easy to implement, and has good solution performance, so it has been used to improve the performance of AFSA.

GWO is a new algorithm proposed by simulating the population of grey wolves (Mirjalili et al., 2014). The GWO mainly realizes the optimization process through social hierarchy and predation strategy (Feng et al., 2019).

Social hierarchy and predation strategy of GWO are introduced into fish swarm algorithm to enhance solving accuracy and speed. Specific operations are as follows: when bulletin board has no change or little change, social hierarchy is used to preserve the currently obtained optimal, suboptimal and third-optimal solutions, and the predation strategy is carried out for other candidate solutions. The social hierarchy can enable the algorithm to maintain the obtained optimal solution, the predation strategy can increase the variation of the population, and the adaptive parameters in the predation strategy can ensure both local and global optimization.

(1) Social hierarchy

In the GWO, each grey wolf represents one candidate solution, and the grey wolf population has a strict social hierarchy, with low-ranking wolves following the command of high-ranking wolves, as shown in Figure 2. Where, α is located at pyramid's top and is highest leader in group, representing the optimal solution. β is the deputy leader, representing the suboptimal solution; δ obeys the arrangement of α and β, and can dominate the individuals of γ, representing the third optimal solution; γ is the ordinary individual and represents other solutions (Zhang et al., 2019).

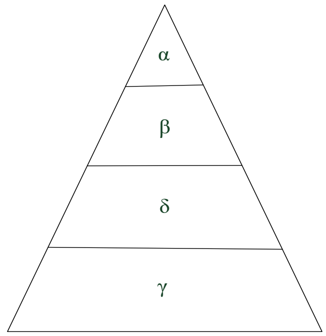

Figure 2. The social hierarchy of grey wolves

(2) Predation strategy

The predation strategy includes three stages: encircling, hunting and attacking prey (Duan et al., 2018).

The first stage: the wolves' approach and surround the prey, and its behavior is described as shown in Equation (19).

$$X(t+1) = X_p(t) - A\left|LX_p(t) - X(t)\right| \quad (19)$$

In this formula, $X(t)$ is grey wolf's current position, $X(t)$ is prey's direction vector, A and L are coefficient variables, which satisfy that $A = 2a \cdot r_1 - a$, $L = 2 \cdot r_2$, r_1 and r_2 are random variables in the interval $[0,1]$, and a decreases linearly from 2 to 0 with iteration times, that is,

$$a = 2\left(1 - current \text{ number of iterations} / \max imum\ number\ of\ iterations\right)$$
(20)

The second stage: in the hunting stage, γ can update the position through positions of α, β and δ, as shown in Equation (21). Equation (22) is the direction and step size of α, β and δ relative to γ.

$$X(t+1) = (X_1 + X_2 + X_3)/3 \quad (21)$$

$$\begin{cases} X_1 = X_\alpha(t) - A_1\left|L_1 X_\alpha(t) - X(t)\right| \\ X_2 = X_\beta(t) - A_2\left|L_2 X_\beta(t) - X(t)\right| \\ X_3 = X_\delta(t) - A_3\left|L_3 X_\delta(t) - X(t)\right| \end{cases} \quad (22)$$

The third stage: the grey wolf attacks its prey through the change of coefficients A and L for obtaining optimal solution. Where, value range of A is $[-a, a]$, and it changes positively with a. When $|A| > 1$, grey wolf separates from the prey, thus expanding search range to realize the global search. When $|A| \le 1$, the grey wolf attacks the prey, reduces exploitation range, and improves the local search ability. L is a random variable in interval $\left[0,2\right]$, indicating prey's random weight, can randomly enhance ($L>1$) or attenuated ($L>1$) the distance between the prey and the grey wolf.

3.6 Solving steps of the model

The steps of GWO-AFSA to solve site of low-carbon cold chain logistics distribution center are as follows:

- Step 1: Input the original data in site selection model of cold chain logistics distribution center, for example, site of the suppliers; the coordinate, capacity and fixed cost of the possible distribution centers; the coordinate, demand and time window of the consumers, etc.
- Step 2: Set the parameters in the algorithms, including iteration number and maximum number of iteration thresholds with no change or extremely small changes on the bulletin board, artificial fish's number, the step size, the field of vision, iteration number, trials's maximum number, crowding factor and so on.
- Step 3: Initialize artificial fish school to generate the initial fish school.
- Step 4: Initialize the bulletin board, that is, calculate current artificial fish's total cost and record it on bulletin board.
- Step 5: According to the constraint condition that selected distribution center's capacity should be more than total demand, all feasible solutions for at most n distribution centers are obtained.
- Step 6: Clustering, following and foraging behaviors are conducted by fish school, and the behavior with less cost is chose to execute. Foraging behavior is the default behavior.
- Step 7: Compare the cost in the bulletin board with the cost calculated after each operation of artificial fish, and record the smaller one on the bulletin board. If the number of iterations with no change or minimal change in the status of bulletin board has reached the threshold of the maximum number of iterations, then social hierarchy and predation strategy in GWO are introduced, and step 8 is performed; otherwise, step 9 is performed.
- Step 8: Record the optimal cost of feasible solutions of all distribution centers, and find the minimum cost.
- Step 9: Determine whether iterations's maximum number is reached. If so, terminate algorithm and output minimum total cost. Otherwise, step 6 is performed.
- The flow chart of GWO-AFSA implemented to site selection model of low-carbon cold chain logistics distribution center is shown in Figure 5.

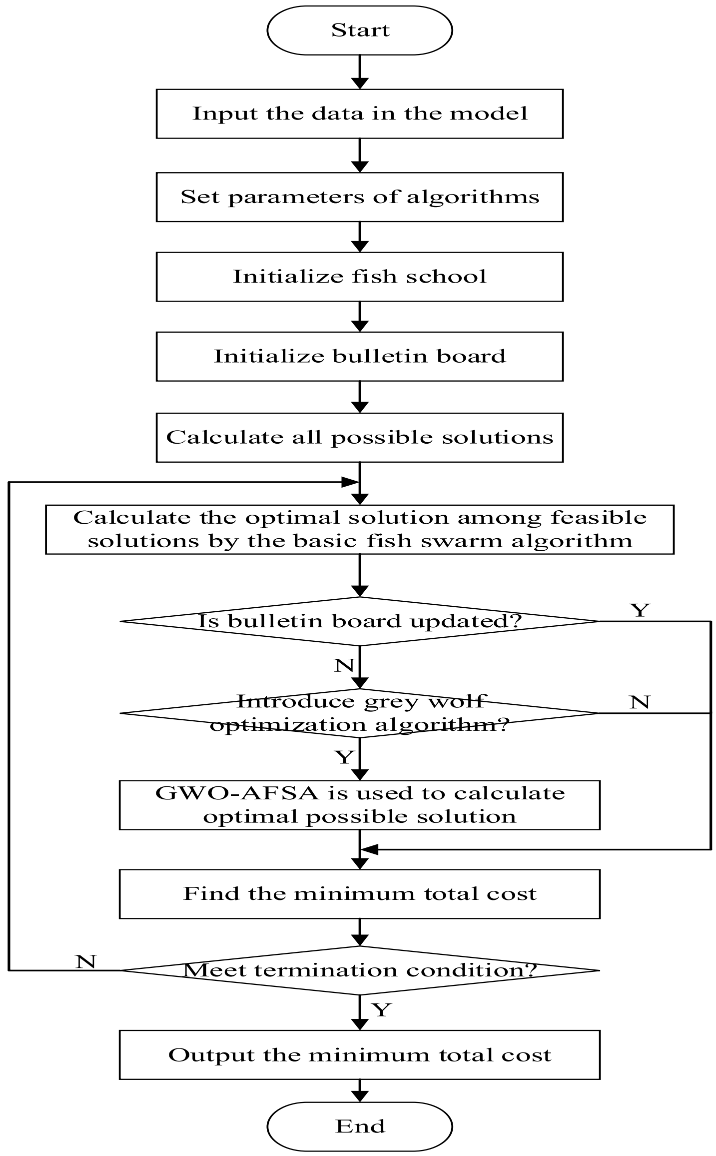

Figure 3. Flowchart of solving model

4. Simulation Results

This section includes functional simulation test and Simulation example

4.1 Functional simulation test

Four test functions implemented to identify algorithm's performance are displayed in Table 1.

Table 1 Testing function

Function name	Function expression	Dimension	Data range	Optimal value

Rastrigin	$f(x)=20+x_1^2+x_2^2-10(\cos 2\pi x_1+\cos 2\pi x_2)$	2	[-10,10]	0
Eggcrate	$f(x)=x_1^2+x_2^2+25(\sin^2 x_1+\sin^2 x_2)$	2	[-10,10]	0
Step	$f(x)=\sum_{i=1}^{n}\left(\lvert x_i+0.5\rvert\right)^2$	10	[-10,10]	0
Griewank	$f(x)=\sum_{i=1}^{n}\frac{x_i^2}{4000}-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	10	[-10,10]	0

The parameters are set as follows: Probability of crossover and mutation in GA are 0.8 and 0.01. Markov chain's length is 200, the attenuation parameter is 0.999, and temperature at the beginning is 500. Artificial fishes's number is 20, perceived distance is 1.8, step size is 0.4, crowding factor is 0.618, maximum number of trials is 20, maximum iterative threshold is 5, probability of DNA crossover and mutation are 0.9 and 0.01. GA, SA, AFSA, DNA-AFSA (Fei et al., 2016) and GWO-AFSA are used to solve the four test functions for 30 times. Table 2 and Table 3 show the solution results of five algorithms when the number of iterations and accuracy are fixed. Figure 4-figure 7 show the convergence process diagram of five algorithms for solving four functions.

Table 2. Results obtained by five algorithms under fixed iteration times

Function		Rastrigin	Eggcrate	Step	Griewank
Iterations		200	200	5000	5000
GA	Mean value	8.483759363	3.970444151	13.433546355	0.029990696
	Best value	0.489185809	0.002627296	1.396542762	0.012936138
	Worst value	21.58256126	16.40715243	26.864981764	0.044714337
	Standard deviation	5.328522966	4.574352035	6.275242968	0.008686731
SA	Mean value	4.018570271	2.685235058	1.256477579	0.013246481
	Best value	0.009199148	4.62664E-05	0.446850420	0.002506366
	Worst value	18.14293683	12.55202825	1.822969676	0.038170921
	Standard deviation	4.575206148	3.621144071	0.400257846	0.007971387
AFSA	Mean value	0.991539478	0.11810237	1.297169819	0.001261565
	Best value	0.001563154	3.58683E-07	0.285973064	0.000550053
	Worst value	2.843251796	3.131612422	1.960062388	0.001795013
	Standard deviation	0.620142644	0.564077485	0.414493448	0.000315763
DNA-AFSA	Mean value	0.017591882	0.008714641	0.124701906	0.000867434
	Best value	0.000226978	7.59E-08	0.000115183	3.76186E-06

	Worst value	0.340883271	0.251098714	1.335808366	0.001312492
	Standard deviation	0.063717966	0.045026132	0.350844184	0.000295907
GWO-AFSA	Mean value	0.005008462	2.56534E-06	0.00035643	3.0202E-07
	Best value	7.43693E-05	3.16076E-08	8.50981E-05	1.614E-08
	Worst value	0.012022214	1.22994E-05	0.000953898	9.52018E-07
	Standard deviation	0.003056486	2.70534E-06	0.000189126	2.19994E-07

Table 3. Results obtained by five algorithms under fixed precision

Function		Rastrigin	Eggcrate	Step	Griewank
Accuracy		0.1	0.001	1	0.001
GA	Mean convergence algebra	—	—	—	—
	Success rate	0.00%	0.00%	0.00%	0.00%
SA	Mean convergence algebra	109	87.75	4731.90	—
	Success rate	3.33%	26.67%	33.33%	0.00%
AFSA	Mean convergence algebra	67	61.48	3585.33	2436
	Success rate	3.33%	76.67%	20%	16.67%
DNA-AFSA	Mean convergence algebra	39.29	46.31	2639.56	2123.56
	Success rate	93.33%	86.67%	90%	60%
GWO-AFSA	Mean convergence algebra	21.91	26.03	2087.77	1913.27
	Success rate	100%	100%	100%	100%

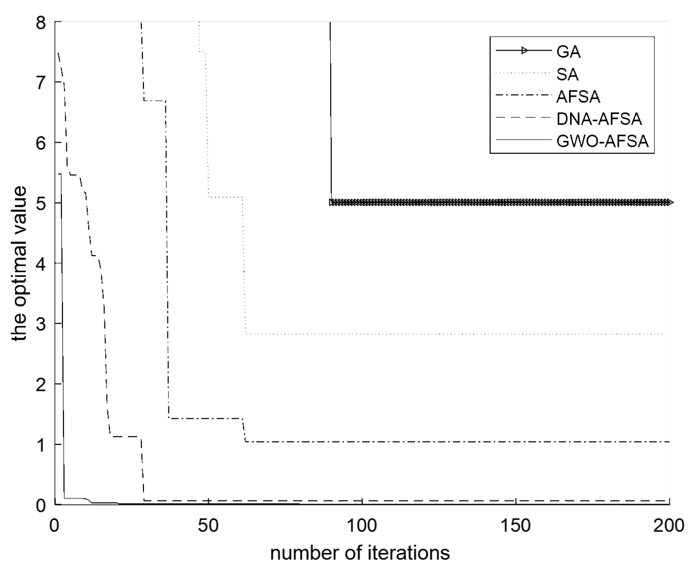

Figure 4. Convergence process diagram (Rastrigin)

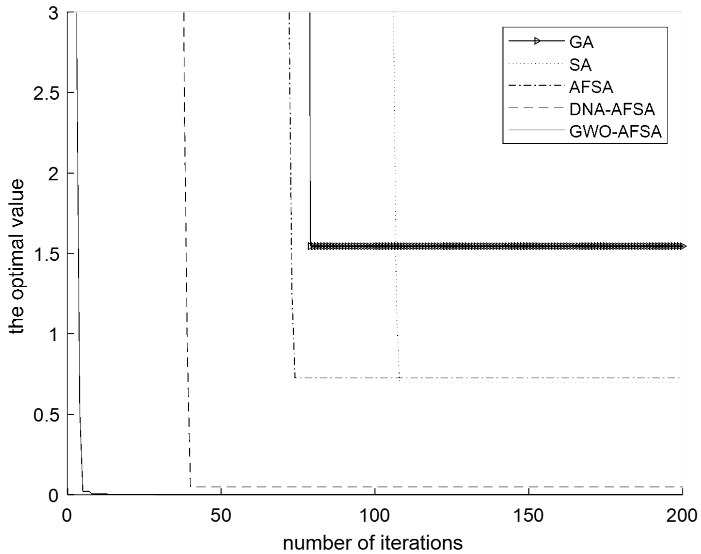

Figure 5 Convergence process diagram (Eggcrate)

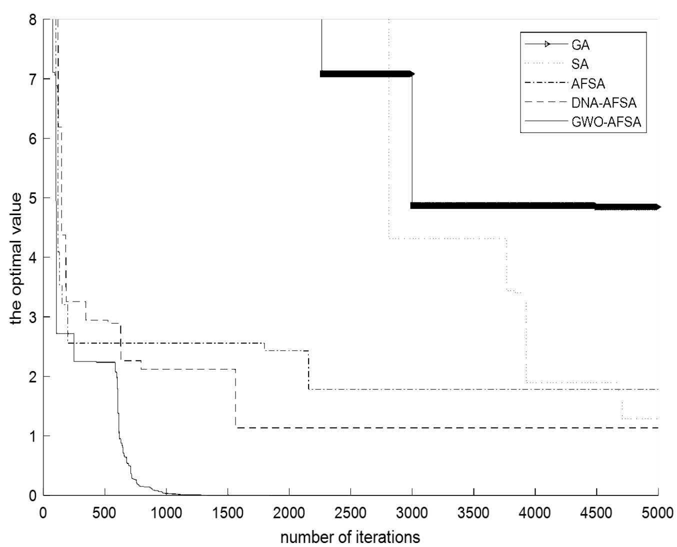

Figure 6 Convergence process diagram (Step)

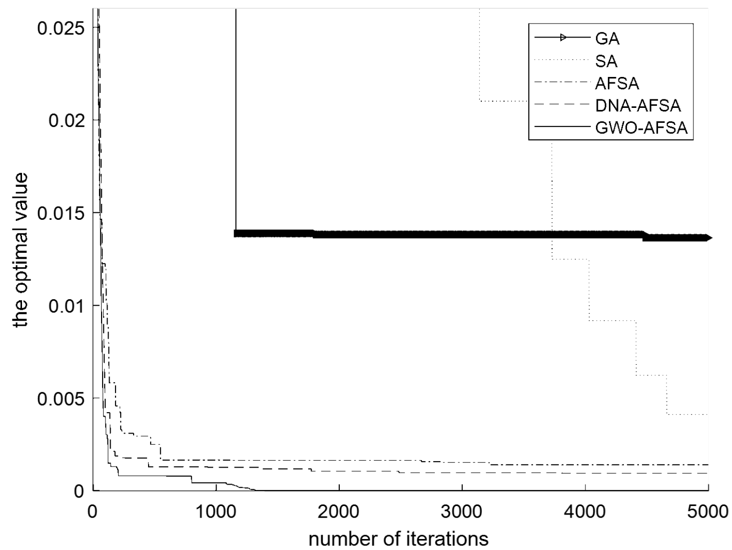

Figure 7 Convergence process diagram (Griewank)

Iterations' average number reflects convergence rate. Since theoretical optimal value of the four typical test functions is 0, the robustness is measured by the standard deviation indicator. The result displays mean, best and worst value of grey wolf-AFSA are all smaller than those of GA, SA, ASFA and DNA- AFSA. Therefore, GWO-AFSA can get higher precision solutions. And because GWO-AFSA has the minimum standard deviation, its stability is proved. When the fixed precision is set, GWO-AFSA's success rate is higher than that of other four algorithms, indicating that it has higher reliability. Moreover, according to the minimum average convergence algebra of GWO-AFSA accuracy in Table 3 and the convergence process diagrams in Figures 4-e 7, the optimization speed of GWO-AFSA is the fastest.

4.2 Simulation example

Suppose the Binhai New Area is taken as supplier with a site of (117.68, 39.03), and 5 of the 13 municipal administrative units are selected to provide distribution service to 26 customers. Assuming that vehicles depart from distribution center at 5:30 at speed of 60km/h; price of a unit product transported within a unit distance is 0.5 yuan; unit price of product is 5000 yuan; each unit of unloading volume requires 5/60 hours; deterioration rate during transportation and unloading is 0.03 and 0.06; the cooling cost generated by transporting and unloading products is 15 yuan /h and 20 yuan /h; waiting and lateness cost generated by vehicle are 5 yuan/h and 10 yuan/h; carbon tax price is 20 yuan/kg, the fuel consumption per unit distance are 0.165L/km and 0.255L/km, when vehicle is unloaded and fully loaded, cooling equipment's energy consumption is 0.0025L/t.km, and carbon dioxide emission coefficient is 2.61kg/L (Zhang et al., 2019). The coordinates, capacity and fixed cost of the alternative distribution centers are displayed in Table 4, and consumers' relevant data are displayed in Table 5.

Table 4 The coordinates, capacity and fixed cost of the alternative distribution centers

Distribution center	Longitude and latitude	Fixed cost	Capacity
Beijing City	(116.42, 39.92)	5000	8
Tianjin City	(117.20, 39.13)	4500	8
Shijiazhuang City	(114.30, 38.02)	4500	9
Chengde City	(117.57, 40.59)	3000	7.5
Zhangjiakou City	(114.53, 40.48)	4000	8
Qinhuangdao City	(119.35, 39.55)	3500	8.5
Langfang City	(116.70, 39.52)	4000	9
Tangshan City	(118.11, 39.36)	3000	7
Baoding City	(115.30, 38.51)	3500	9
Cangzhou City	(116.52, 38.18)	4000	9
Hengshui City	(115.42, 37.44)	3500	9.5
Xingtai City	(114.30, 37.04)	3000	7.5
Handan City	(114.28, 36.36)	4500	8

Table 5 The relevant data of consumers

No.	Customer	Longitude and latitude	Acceptable time window	Expected time window	Quantity Demand
1	Huairou District, Beijing	(116.63, 40.32)	5: 45-9: 30	6: 00-9:00	1
2	Fangshan District, Beijing	(116.13, 39.75)	5: 30-10: 10	5: 45-9: 40	2
3	Jinghai District, Tianjin	(116.92, 38.93)	5: 40-10: 10	5: 50-9: 45	1.5
4	Ninghe County, Tianjin	(117.82, 39.33)	5: 30-10: 20	5: 50-10: 00	2
5	Pingshan County, Shijiazhuang	(114.20, 38.25)	5: 50-9: 10	6: 00-8: 45	0.5
6	Xinji City, Shijiazhuang	(115.22, 37.92)	6: 00-8: 40	6: 15-8: 15	1
7	Fengning County, Chengde	(116.65, 41.20)	6: 30-10: 20	7: 00-9: 40	1
8	Longhua County, Chengde	(117.72, 41.32)	5: 30-10: 30	5: 45-10: 00	1.5
9	Chongli County, Zhangjiakou	(115.27, 40.97)	5: 40-10: 20	6: 10-9: 50	0.5
10	Huai'an County, Zhangjiakou	(114.42, 40.67)	5: 30-10: 30	6: 00-10: 00	2
11	Changli County, Qinhuangdao	(119.17, 39.70)	5: 30-10: 10	5: 50-9: 40	1.5
12	Qinglong County, Qinhuangdao	(118.95, 40.40)	5: 45-9: 30	6: 10-8: 50	2
13	Gu' an County, Langfang	(116.30, 39.43)	5: 30-10: 20	5: 40-9: 50	1
14	Xianghe County, Langfang	(117.00, 39.77)	5: 30-9: 40	5: 50-9: 00	2.5
15	Zunhua City, Tangshan	(117.95, 40.18)	5: 40-10: 10	6: 00-9: 40	1.5

16	Tanghai County, Tangshan	(118.45, 39.27)	5: 30-10: 30	5: 45-10: 00	1
17	Laisyuan County, Baoding	(114.68, 39.35)	5: 30-10: 40	5: 40-10: 15	2
18	Shunping County, Baoding	(115.13, 38.83)	5: 30-9: 50	5: 35-9: 10	0.5
19	Renqiu City, Cangzhou	(116.10, 38.72)	5: 30-10: 10	5: 50-9: 40	1
20	Haixing County, Cangzhou	(117.48, 38.13)	6: 00-10: 30	6: 20-10: 00	1.5
21	Fucheng County, Hengshui	(116.15, 37.87)	5: 45-9: 20	6: 10-8: 45	1.5
22	Gucheng County, Hengshui	(115.97, 37.35)	5: 50-10: 10	6: 00-9: 50	1
23	Lincheng County, Xingtai	(114.50, 37.43)	5: 30-10: 30	6: 00-8: 00	0.5
24	Guangzong County, Xingtai	(115.15, 37.07)	5: 45-10: 10	6: 20-9: 30	2
25	Shexian County, Handan	(113.67, 36.57)	5: 40-10: 30	6: 00-9: 50	2
26	Wei County, Handan	(114.93, 36.37)	5: 30-10: 20	6: 00-10: 00	1.5

AFSA, DNA-AFSA and GWO-AFSA are used to solve site selection model of low-carbon cold chain logistics distribution center for 30 times. Thirty artificial fish are set, maximum iterations are 200, try it up to 5 times, crowding factor is 0.618, range of visual field is 65, step length is 20, threshold of iterations' maximum number without change is 5, DNA crossover probability is 0.9, and DNA mutation probability is 0.01. Running results are displayed in Table 6.

Table 6. Three algorithms' running results

	Mean value	Optimal value	Maximum value	Standard deviation	Mean convergence algebra
AFSA	119030.74	102768.10	137014.78	8415.79	72.97
DNA-AFSA	113189.32	99236.14	130599.46	7411.86	54.93
GWO-AFSA	108638.73	94172.60	125647.90	6972.77	30.23

Table 6 indicated that, in the light of cost, optimal, maximum and mean value of AFSA solving the total cost of the model are 119030.74, 102768.10 and 137014.78; the optimal value, maximum value and mean value of DNA-AFSA solving the total cost of the model are 113189.32, 99236.14 and 130599.46; and the optimal value, maximum value and mean value of GWO-AFSA solving the total cost of the model are 108638.73, 94172.60 and 125647.90, respectively. The solution results of GWO-AFSA are 10392.01、8595.5 and 11366.88 smaller than those obtained by AFSA, and 4550.59、5063.54 and 4951.56 smaller than those obtained by DNA-AFSA. Therefore, GWO-AFSA is used in site selection model of low-carbon cold chain logistics distribution center to get lower total cost. From the standpoint of average convergence algebra, in contrast to other two algorithms, GWO-AFSA has smallest average convergence algebra, indicating the best convergence efficiency. In the light of standard deviation, standard deviation of GWO-AFSA is smaller than that of AFSA and DNA-AFSA, which indicates that GWO-AFSA is more stable in solving the model.

Optimal site selection schemes solved using AFSA, DNA-AFSA and GWO-AFSA are shown in Tables 7-9, and the corresponding site selection schematic diagrams are shown in Figures 8- 10. The comparison diagram of three algorithms’ optimization curves is shown in Figure 11.

Table 7. Site selection scheme of basic AFSA

The selected distribution center	Consumers
Tianjin City	3，4，7，9，15，21
Qinhuangdao City	2，5，6，10，18，26
Baoding City	20，22，24，25
Cangzhou City	11，14，16，17，19，23
Langfang City	1，8，12，13

Table 8. Site selection scheme of DNA-AFSA

The selected distribution center	Consumers
Tianjin City	3，9，14，16，19，22，23
Tangshan City	2，4，8，18，20
Baoding City	1，10，11，25
Cangzhou City	5，6，15，17，24，26
Langfang City	7，12，13，21

Table 9. Site selection scheme of GWO-AFSA

The selected distribution center	Consumers
Tianjin City	1，5，14，17，20
Tangshan City	7，12，16，21，25
Baoding City	6，9，11，13，18，19，26
Cangzhou City	3，8，10，22，23，24
Langfang City	2，4，15

Figure8. AFSA site selection diagram

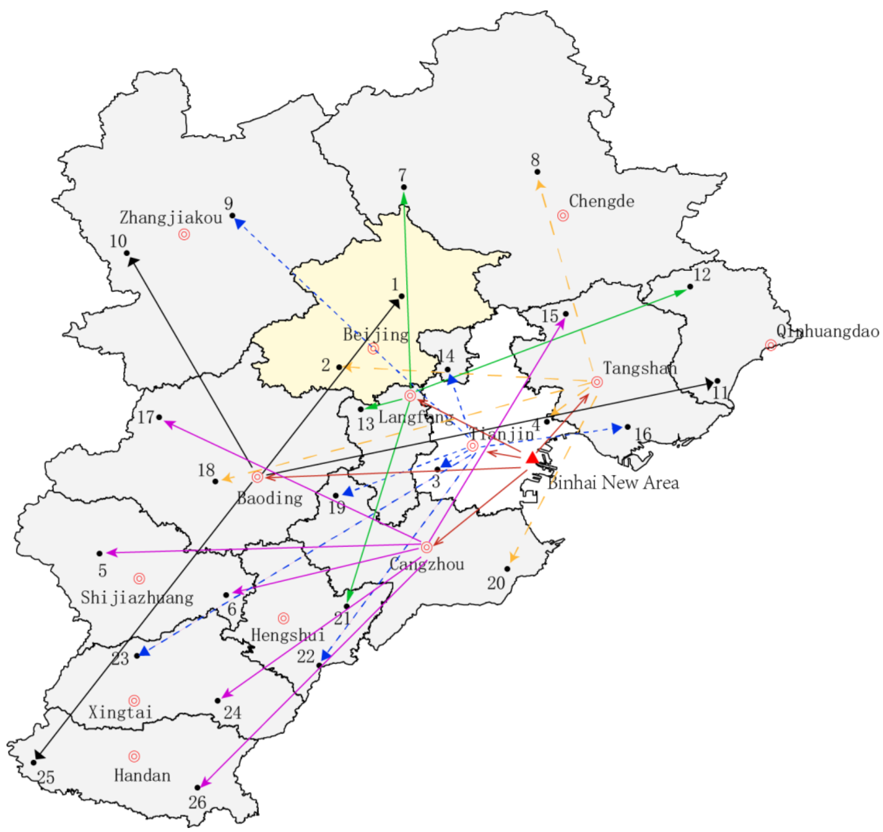

Figure 9. DNA-AFSA site selection diagram

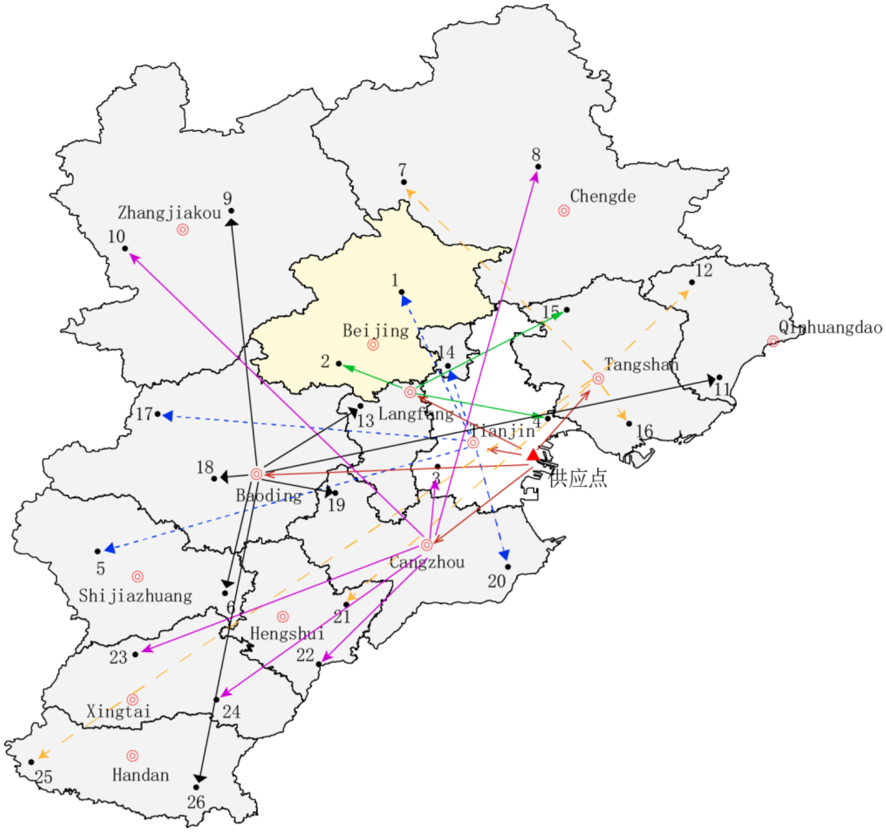

Figure 10. GWO-AFSA site selection diagram

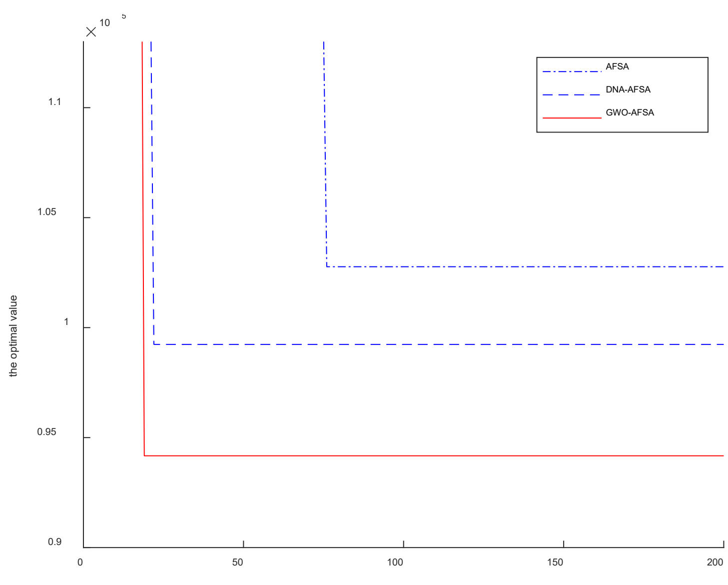

Figure 11. Optimization curves's comparison diagram of three algorithms

Table 7 and Figure 8 indicate that the site scheme solved by basic AFSA is as follows: the cold chain products are first departed from Binhai New Area to Tianjin, Qinhuangdao, Baoding, Cangzhou and Langfang, and then from Tianjin to customers 3, 4, 7, 9, 15 and 21, and

Qinhuangdao to customers 2, 5, 6, 10, 18 and 26, Baoding to customers 20, 22, 24 and 25, Cangzhou to customers 11, 14, 16, 17, 19 and 23, and Langfang to customers 1, 8, 12 and 13.

Table 8 and Figure 9 presented the site scheme solved by DNA-AFSA is as follows: the cold chain products are first departed from the supplier to Tianjin, Tangshan, Baoding, Cangzhou and Langfang, and then from Tianjin to customers 3, 9, 14, 16, 19, 22 and 23, Tangshan to customers 2, 4, 8, 18 and 20, Baoding to customers 1, 10, 11 and 25, Cangzhou to customers 5, 6, 15, 17, 24, 26, and Langfang to customers 7, 12, 13 and 21.

Table 9 and Figure 10 indicated thatthe site scheme solved by GWO-AFSA is as follows: the cold chain products are first departed from supplier to Tianjin, Tangshan, Baoding, Cangzhou and Langfang, and then from Tianjin to customers 1, 5, 14, 17 and 20, Tangshan to customers 7, 12, 16, 21 and 25, Baoding to customers 6, 9, 11, 13, 18, 19 and 26, Cangzhou to 3, 8, 10, 22, 23, 24, and Langfang to customers 2, 4 and 15. Lastly, Figure 11 indicated that convergence speed and solving accuracy of GWO-AFSA are better than those of basic AFSA and DNA-AFSA.

5. Discussion

Cold chain logistics has stricter demands on temperature compares with usual logistics. Energy consumptions are generated correspondingly to create the required low-temperature environment, resulting in increased carbon emissions. Purpose of developing low-carbon logistics is to cut down carbon emissions, which is obviously different from cold chain logistics' development law. The analysis of the low-carbon cold chain logistics distribution centers site selection is vital for both reduction of carbon emissions and cold chain logistics' healthy development. Optimizing site of cold chain logistics can make transportation more efficient, guarantee product quality, reduce commodity damage rate, and make logistics more timely. The energy consumption of the logistics link lower and act well in improving efficiency and benefits of logistics activities, as well as reducing energy consumption. Enterprises pay more attention to economic benefits and cost control. More emphasis on logistics efficiency is consistent with the resource-saving society development.

Low-carbon economy is the mainstream trend in current social development, but due to the stringent requirements of cold chain products on transportation conditions such as temperature, cold chain logistics have significant energy consumption and carbon emissions. Therefore, studying how to reduce carbon emissions in cold chain logistics is of great practical significance. Cold chain distribution centers serve as an important hub connecting suppliers and customers, and their location can significantly affect distribution efficiency and logistics costs. Therefore, this study first proposes an improved artificial fish swarm algorithm based on the artificial fish swarm algorithm, and then applies the improved artificial fish swarm algorithm to solve the location of distribution centers. Empirical evidence shows that the improved algorithm can optimize the location of distribution centers and reduce the cost of the logistics system. Furthermore, this study takes the Beijing-Tianjin-Hebei region as the research object, which has certain reference value for promoting the integration of Beijing-Tianjin-Hebei.

This study considers various factors of low-carbon cold chain logistics site, and considers fixed, penalty, transportation, commodity damage, cooling and carbon emission in the composite cost. A cold chain low-carbon cold chain logistics site optimization model aiming at minimizing composite costs is constructed. Mathematical model of cold chain logistics site optimization has been enriched and improved to make it closer to reality, which provides an approach and theoretical foundation for cold chain enterprise distribution center site selection. The search accuracy of the fish swarm algorithm is improved by introducing social hierarchy and predation strategy of the gray wolf algorithm combined the gray wolf algorithm with the AFSA. The improved algorithm enhances competence to escape from local optimum. This study improves optimization performance of fish swarm algorithm in solving discrete problems, and expands the improvement of AFSA.

6 Conclusion

This study constructs a low-carbon cold chain logistics distribution center site selection model that includes costs of cooling, commodity damage, and carbon emissions according to the characteristics of cold chain products that are prone to deterioration. The requirements for the environment and cold chain are also getting higher and higher with the continuous progress of economy. It is the general trend to reduce carbon emissions and protect the environment. Many studies don't take low carbon into account. Aiming at the shortcomings of basic fish swarm algorithm, GWO is introduced to increase the population's diversity and algorithm's convergence performance, and then the proposed GWO-AFSA is implemented to cold chain logistics distribution center site selection model. Simulation results show that GWO-AFSA can provide a solution with lower total cost in the site problem.

The GWO-AFSA is superior to SA, GA, basic AFSA and DNA-AFSA regarding accuracy, convergence, speed, stability and reliability according to the function simulation test results. GWO-AFSA can solve the solution with the least total cost, and speed is the fastest in the example simulation of the site selection model. GWO-AFSA has better optimization effect and can provide a more reasonable site selection scheme compared with the other two algorithms. This study provides a strong theoretical support for green development of cold chain logistics activities.

The study has some limitations. The impact of traffic conditions on the logistics system is not considered and the real traffic conditions are changeable to simplify the analysis. Using the positioning technology to reflect traffic conditions in real time in the model is the future work. In addition, the instance model contains only one supplier, and there may be multiple suppliers in real life, so it is necessary to study the case of the model when there are multiple suppliers in the future.

Declaration of Competing Interest: The authors wish to state that this study has no competing interests.

Data availability: Not Applicable

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