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# APPLICATION OF IMPROVING ABC IN COLD CHAIN LOW CARBON LOGISTICS PATH PLANNING

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**Abstract.** The market has set higher efficiency and environmental requirements for cold chain logistics, and path planning plays an important role. This study proposes a low-carbon cold chain logistics path planning model based on an improved artificial bee colony algorithm (this paragraph refers to "fusion algorithm"). The study first establishes the fusion algorithm. Then, in response to the shortcomings of this algorithm, the artificial fish swarm algorithm and genetic algorithm are used to improve it. The final results express that the shortest distance for solving Eil51 using this algorithm is 421.38, the longest distance is 448.58, and the average distance is 439.34; The shortest distance for solving Ulysses22 is 72.46, the longest distance is 73.63, and the average distance is 72.84. The average convergence times for Eil51 and Ulysses22 are 133.57 and 7.86, and the optimal performance ratios for relative error are 0.0076 and 0.0051. The robust performance ratios are 0.0362 and 0.0117. The optimal total cost solution and the average value for solving the relevant distribution problem are 47,894.6 yuan and 48,562.7 yuan, respectively. In summary, the model proposed in the study has good application effects in cold chain low-carbon logistics path planning, and has a certain promoting effect on the development of cold chain logistics.

**Key words:** ABC algorithm; Cold chain low-carbon logistics; Artificial fish school algorithm; Path optimization; Genetic algorithm

**1. Introduction.** As the market grows and consumer demands continue to evolve, the cold chain logistics (CCL) industry faces more opportunities and challenges. Distribution centers need to minimize food consumption, reduce costs and carbon emissions while meeting consumer needs, and path planning plays a critical role in this process. Cold Chain Low-Carbon Logistics Path Planning (CCLCLPP) is a variant of the Vehicle Routing Problem (VRP), which refers to planning suitable paths for a set of loading and unloading points. Under certain constraints, the achievement of certain objectives and the use of efficient routes provide transportation companies with a direct competitive advantage. The Artificial Bee Colony Algorithm (ABC) is inspired by the process of bees picking honey. Due to its fast computing speed and high accuracy, it has occupied a vital position in solving VRP in recent years. However, ABC also has the drawbacks of slow convergence speed and a tendency to fall into local optima. Some scholars have used SURF, RANSAC, and particle swarm optimization algorithms to improve the ABC algorithm [3, 12]. To improve the transportation efficiency and economic benefits of cold chain logistics, reducing transportation time plays a crucial role. Proper planning of the transportation route of cold chain logistics can greatly reduce the transportation time. In this context, the Artificial Fish School (AFS) and Genetic Algorithm (GA) were utilized to improve the ABC algorithm and construct a CCLCLPP model based on AFS-GA-ABC. There are two main innovative points in this study. The first point is to introduce the clustering behavior of the AFS algorithm, while adopting a perception range based on under damping motion adaptation to compensate for the lacks of ABC, which is prone to falling into local optima and slow convergence speed. The second point is to introduce the partial mapping crossover operator in the GA to lift the slow convergence speed of the ABC. The main structure of the study is segmented into four parts: Part 1 analyzes the current relevant research status; the second part is to perfect the shortcomings of ABC by combining AFS and GA, and construct a CCLCLPP model based on improved ABC; the third part is to analyze the application effectiveness of the proposed CCLCLPP model based on AFS-GA-ABC; the final part is a summary of the entire study.

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**2. Related works.** ABC is an optimization method proposed to mimic the foraging behavior of bee populations, with fast convergence speed. It is widely used to solve various optimization problems and multi-dimensional problems. The probability method used by ABC and most of its modifications selects good food sources during the foraging phase of the bee population, but its possibility selection does not take effect with increasing iterations. ˆOzbay E proposed an active deep learning approach using a new multi-layer structure to automatically detect the stages of retinopathy, and used the ABC algorithm for image segmentation. The results show that the proposed method has high performance in detecting retinopathy and determining its severity from different fundus images [5]. Guo H et al. proposed a mathematical model based on the ABC algorithm to maximize the expected recovery profit in the case of task failure in real life, where scrapped products may experience different degrees of wear and tear during the disassembly process. The results show that the solution performance of this method is superior to the other three existing methods [5]. Toktas A et al. proposed for the first time a parameter chaos mapping optimization method based on three-objective optimization, and then used Pareto based three-objective ABC algorithm for optimization. The results show that the algorithm exhibits applicability in image encryption, as well as optimal traversal and complexity [13]. Sefati S et al. focused on load balancing and routing issues in wireless sensor networks, using Markov models and ABC algorithms to find the best candidate nodes for each cluster. The results show that this method outperforms the comparison method in terms of energy efficiency and the number of active nodes [9]. Yolcu V et al. optimized the wavelength and power values of pump lasers used in distributed fiber Raman amplifiers by using an adaptive ABC algorithm based on binary search equations to find the optimal pump wavelength and power level [17]. Satoh T et al. utilized the ABC algorithm to solve the design problem of a discrete-time stable unknown input estimator based on parameter optimization, and compared the proposed design method with previous design methods [8]. Wang H et al. proposed an improved multi-objective ABC algorithm based on decomposition and dimension learning to help ABC solve multi-objective optimization problems. The results indicate that the proposed method has achieved good performance [14].

CCLCLPP is a VRP developed on the foundation of CCL and environmental protection, which is quit vital for developing the CCL. Tian G et al. systematically reviewed several papers and constructed the overall structure of multi-criteria decision-making technology, in response to the lack of comprehensive review of multi-criteria decision-making in the fields of low-carbon transportation and green logistics. They also proposed the future development direction of multi-criteria decision-making technology for green logistics and low-carbon transportation systems [11]. Wang Z et al. established a multi-objective hazardous material transportation route planning model considering road traffic elasticity and low-carbon to address the increasing proportion of hazardous materials in domestic road transportation, filling the gap in research on hazardous material transportation in the low-carbon field [15]. Tao N et al. established a mathematical model for optimizing the path of cold chain logistics delivery vehicles with the lowest comprehensive cost. The proposed improved hybrid ant colony optimization algorithm solves the problems of increasing difficulty in path optimization and carbon emissions in the cold chain logistics distribution process. [10] . Raman P et al. studied low-carbon performance based on low-carbon supply chain practices in the manufacturing industry. The research results indicate that low-carbon production is insignificant in reducing overall carbon emissions and can be used to develop and extend a low-carbon supply chain framework [7]. Arora M et al believe that due to the various challenges faced by the entire frozen food industry, it is necessary to study in India. So they reviewed the existing literature in an attempt to explain the issues that affect frozen food in India and strategies to address these issues. They also proposed a conceptual model and described the relationship [1]. Xu L et al. systematically reviewed the current academic literature on the role of technology in low-carbon supply chain management and provided a novel and comprehensive roadmap for future research on technology-enabled low-carbon supply chains. [16] . Cheng C et al. proposed a selection standard from the perspective of low-carbon level to address the issue of how enterprises can select a logistics supplier that can provide low-carbon and high-quality services [4].

In summary, although many previous scholars and scientists have recognized the importance of CCLCLPP in reducing logistics costs, improving customer satisfaction, and protecting the environment. ABC has played a significant role in solving various optimization problems and has been proven, but the effectiveness of the ABC-based CCLCLPP is still not ideal. To make up for this deficiency, studying the AFS and GA algorithms to improve the ABC algorithm has important practical application value and prospects for CCL.

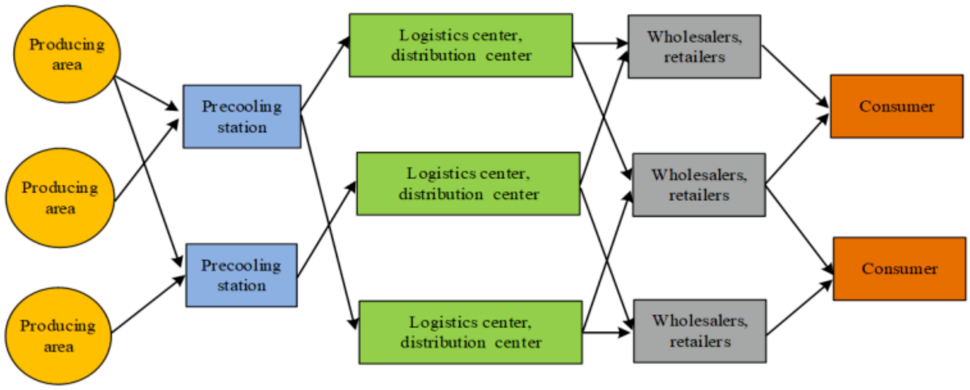



Fig. 3.1: Cold chain logistics network structure

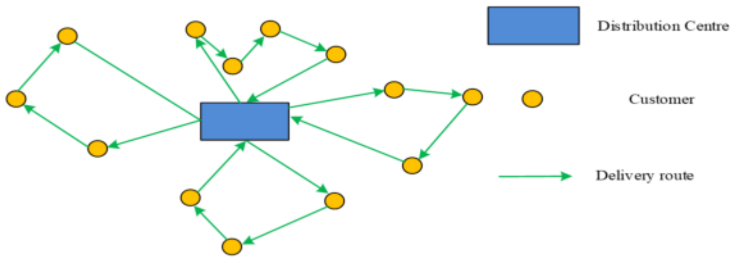



Fig. 3.2: Schematic diagram of vehicle routing issues

**3. Construction of CCLCLPP model based on improved ABC.** The ABC can be taken to deal with various optimization matters and has certain effectiveness in the application of traditional CCL path planning. But with the improvement of users' demands, the market has put forward higher efficiency, economy, and low-carbon requirements for cold chain transportation. The path planning method for CCL should also be updated with the times. Therefore, a ABC-based CCLCLPP algorithm was studied and constructed, and the traditional ABC algorithm was improved using AFS and GA to build a new CCLCLPP model grounded on improved ABC.

**3.1. Construction of CCLCLPP model based on ABC.** According to the definition of the European Union, CCL means a systematic engineering process in which refrigerated foods are always kept in a specified low-temperature space from production to consumption, to reduce food loss and ensure food quality. It involves multiple technological fields such as information technology, modern refrigeration technology, logistics technology, and has the characteristics of high cost, high timeliness, high carbon emissions, easy product wear and tear, and complex technology [2]. The structure of CCL is listed in Figure 3.1.

The CCLCLPP problem is an evolution of the VRP problem. To reduce the delivery cost of refrigerated and frozen food, improve the delivery efficiency, reduce the carbon emission, and meet the basic needs of consumers, it is necessary to scientifically plan the route of delivery vehicles. The Figure 3.2 shows the diagram of VRP.

The VRP problem includes five basic characteristic elements: delivery vehicles, delivery centers, consumers, delivery routes, and optimization objectives. Its classical mathematical model is Equation 3.1.

$$MinZ = \sum_{i=0}^{n} \sum_{i=1}^{n} \sum_{k=1}^{K} cd_{ij} x_{ij}^{k} \tag{3.1}$$

In Equation 3.1, $K$ is the amount of vehicles, $n$ is the consumer numbers, $c$ represents the transportation cost per kilometer, and $d_{ij}$ means the distance between $i$ and $j$. When $x_{ij}^{k}$ is equal to 1, it means that vehicle $k$ arrives at consumer $j$ from consumer $i$ , and in other cases, $x_{ij}^{k}$ is equal to 0. ABC algorithm was originally used to solve function optimization problems, and now it has been applied to data processing, image processing, cold chain logistics, and other fields. However, it is easy to fall into local optimization and has a slow convergence rate. Therefore, ABC algorithm is selected as the basic algorithm for this study and further optimized. The ABC is superior in fewer parameters, convenient calculation, easy implementation, and strong robustness. It is widely used to solve multidimensional problems and model optimization problems, as well as to solve path planning problems. ABC divides the foraging bees into 3 types: leading, following and scouting bees, and sets the maximum cycle times and the limit value of the times that the leading bees do not update the food source to convert to the scouting bees. The initialization bee colony is a honey source of randomly generated -dimensional vectors, and the generation of each honey source is Equation 3.2.

$$\begin{cases} x_{ij} = x_{\min j} + rand(x_{\max j} - x_{\min j}) \\ \quad i = 1, 2, ..., m, \ j = 1, 2, ..., n \end{cases} \tag{3.2}$$

In Equation 3.2, $x_i$ is the $i$-th honey source in the bee colony, *rand* represents a random number uniformly distributed between (0,1). $x_{\min j}$ and $x_{\max j}$ represent the lower and upper bounds of vector $j$. After initialization, calculate the fitness value of the honey source, see Equation 3.3.

$$fit(x_i) = \begin{cases} 1 + f(x_i), f(x_i) \geq 0 \\ \frac{1}{1+|f(x_i)|}, f(x_i) \leq 0 \end{cases} \tag{3.3}$$

In Equation 3.3, $f(x_i)$ expresses the concentration of the $i$-th honey source. In the leading bee stage, each leading bee conducts a domain search around the current honey source to find a new one, see Equation 3.4.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}), \quad k = 1, 2, ..., SN \tag{3.4}$$

In Equation 3.4, $v$ represents the new honey source, $k$ and $j$ represent the randomly selected index, and $\phi_{ij}$ represents the random number between [-1,1]. When a new honey source is found, the leading bee evaluates it based on the principle of greedy selection and compares it with the old honey source. If the new honey source has a higher fitness, the old one is replaced by the new one, otherwise it remains unchanged. Later, the following bee evaluates all the information received from the leading bee and chooses a honey source, if possible, depending on the fitness value of the honey source in the population. The selection mechanism based on fitness can adopt the roulette wheel algorithm, and the calculation method is Equation 3.5.

$$p_i = \frac{f_i}{\sum_{j=i}^{m} f_j} \tag{3.5}$$

In Equation 3.5, $f_i$ represents the fitness value of the $i$ honey source, and the greater the $f_i$, the greater the probability of honey source being selected. A CCLCLPP model was designed using the ABC algorithm, and the solution process of this model is Figure 3.3.

However, ABC has drawbacks in solving complex problems, such as too many iterations, tendency to fall into local extreme traps, low optimization accuracy, and slow speed. To ensure the actual operational effect of the CCLCLPP model, further optimization of the ABC algorithm is needed.

**3.2. Construction of CCLCLPP Model Based on AFS-GA-ABC.** With the growing needs of the cold chain transportation industry and the implementation of green concepts, improving the CCLCLPP method is becoming increasingly important. To compensate for the shortcomings of the ABC algorithm, which is prone to local optima and slow convergence speed, the clustering behavior of the AFS algorithm is introduced, and a perceptual domain based on underdamping motion adaptation is adopted. AFS algorithm is a bionic algorithm that realizes optimal target search by simulating fish feeding, tail chasing, clustering and other methods, and realizes global optimization by local optimization. It is flexible with fast conversion and insensitive to the original parameter settings [6]. The specific process is shown in Figure 3.4.

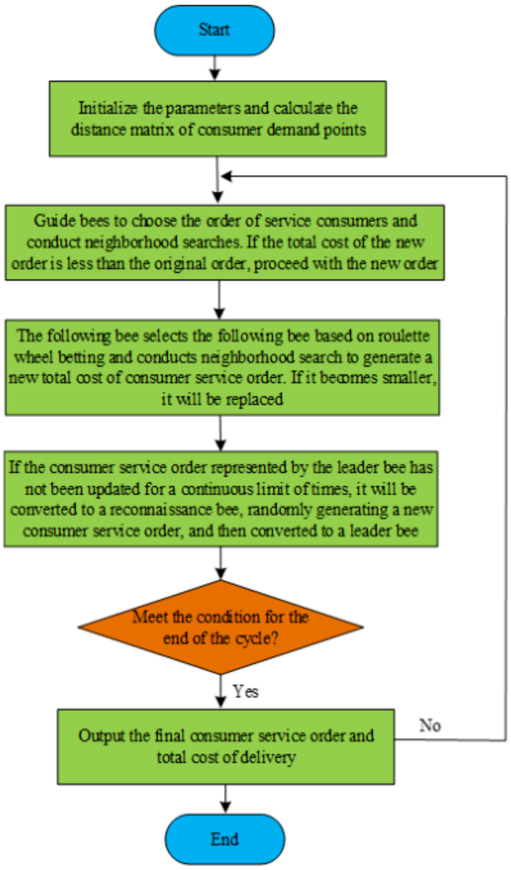



Fig. 3.3: Solution Process for the Optimization Model of ABC-based CCLCLPP

When implementing the AFS algorithm, it is necessary to assign a perception area to each bee and to determine the perception distance between bees using the following Equation 3.6.

$$\begin{cases} d_i = d_i + 1 \\ Xik \neq X_{jk} \end{cases}, \quad k = 1, 2, ..., N, \quad i \neq j \tag{3.6}$$

In Equation 3.6, $X_{ik}$ and $X_k$ are the path order of the i-th and $j$ bee. $k$ represents the vector dimension. $N$ is the amount of leading peaks. The calculation of the bee amounts with a perception distance less than the perception range is Equation 3.7.

$$\begin{cases} p_i = p_i + 1 \\ di \leq Visual \end{cases} \tag{3.7}$$

In Equation 3.7, $Visual$ represents the perceptual range of bees. Then determine whether the bees with a perception distance less than the perception range are crowded around them, as shown in Equation 3.8.

$$\frac{p_i}{N} \leq \det al \tag{3.8}$$

In Equation 3.8, the quantity of leading, following, and reconnaissance bees is the same, and is the crowding factor. In the leading bee stage, when the center position is not crowded, a clustering behavior with the characteristic of accelerating convergence speed is introduced for neighborhood search. At the same time, the

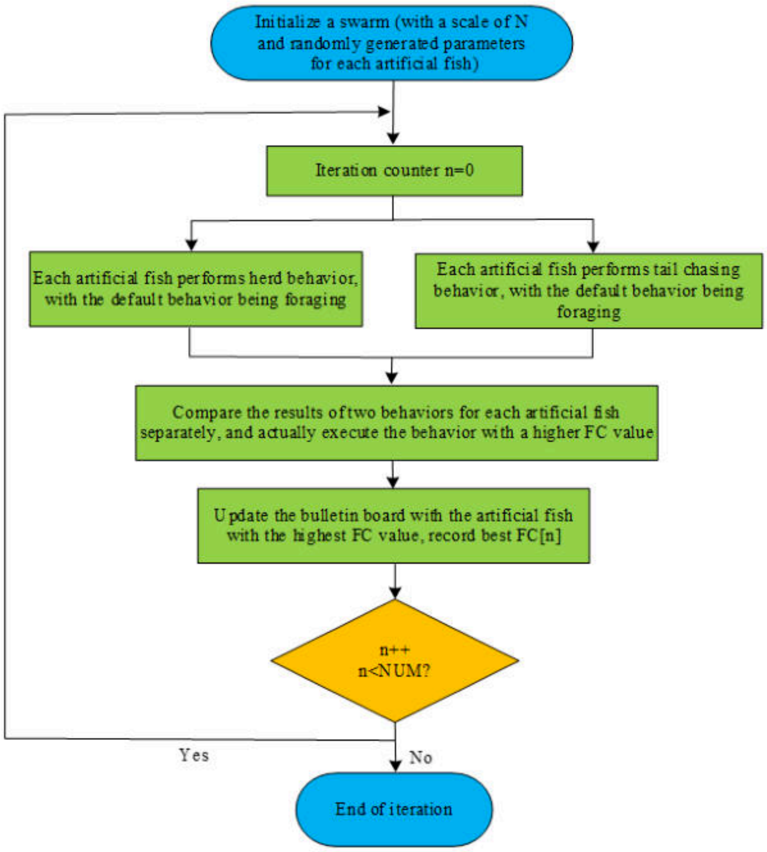



Fig. 3.4: Diagram of AFS

calculation method of the bee's perception distance is introduced into the underdamped motion in physics by using an adaptive update strategy. In the early stages of iteration, it is better to have a larger perception distance; in the later stages of iteration, it is better to have a smaller perception distance. The motion law of the spring oscillator in underdamped motion under the condition of no constraining force is Equation 3.9.

$$\begin{cases} X = A^0 \cdot e^{\delta t} \cos(\omega t + \phi) \\ 2\delta = \sqrt{\frac{g}{m}} \end{cases} \tag{3.9}$$

In Equation 3.9, $\omega$ represents the damping factor, $t$ is time, $\phi$ represents vibration frequency, and $m$ is the mass of the oscillator. The adaptive update strategy for designing the perception range based on the damping motion law is Equation 3.10.

$$Visual = 2 + \frac{10 \log(iter)}{\log(Maxiteration)} \times \cos\left(0.5\pi - 0.5\pi \frac{Maxiteration - iter}{Maxiteration}\right) \tag{3.10}$$

In Equation 3.10, $Maxiteration$ is the max iterations, and $iter$ is the current iterations. The GA algorithm is an optimization algorithm that simulates phenomena such as crossover, replication, and mutation during the evolution of species, and is often used to solve optimization problems. To improve the slow convergence speed of ABC, some mapping crossover operators are introduced into the GA algorithm for optimization. In the leading bee stage, if the center position is crowded, a new solution is obtained by the crossover operation based on the partial mapping crossover operator to reduce the probability. Later, if the neighborhood search results in a new

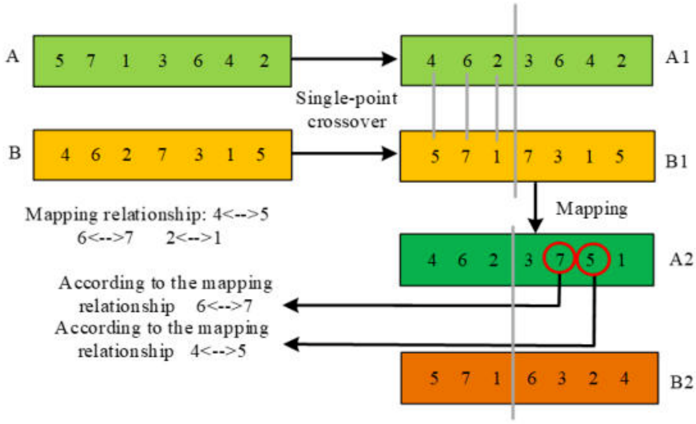


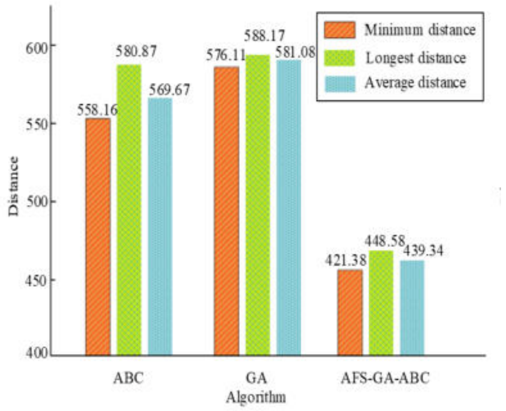

Fig. 3.5: Partial mapping crossover operator flowchart

solution that is not excellent than that of the original leading bee, this new solution is obtained by performing a crossover operation based on the partial mapping crossover operator. The partial mapping crossover operator is mainly divided into two steps: partial crossover operation and generation of new individuals based on the corresponding mapping relationship. The specific process is shown in Figure 3.5.

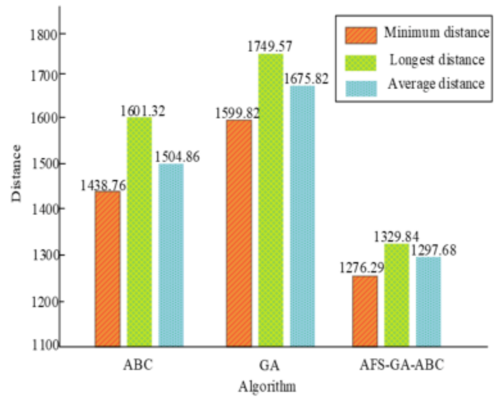
The solution of the CCLCLPP model based on AFS-GA-ABC is divided into 5 steps. First, the parameters of the improved ABC are initialized and the distance matrix of consumer demand points is calculated. Second, in the leading bee stage, the leading bee first flies out of the hive to select the order of serving consumers, and conducts neighborhood search to compare the total cost of the new order with the original order. If the cost decreases, a new order is performed, otherwise clustering behavior is performed. If the clustering behavior is successful and the total cost decreases, it is replaced, otherwise it remains unchanged. If the clustering behavior fails, a new service order is obtained by performing a crossover operation based on the partial mapping crossover operator, which is the same as above. Third, in the follower bee stage, the follower bee selects the lead bee to follow based on the roulette wheel bet, and performs neighborhood search to generate a new total cost of consumer service order. If it becomes smaller, replace it; otherwise, perform the crossover operation based on the partial mapping crossover operator to obtain a new order; If the total cost decreases, replace it, otherwise it remains unchanged. Fourth, if the consumer service order represented by a leader bee has not been continuously updated for a limit number of times, the leader bee is transformed into a scout bee. Upon entering the scout bee stage, the scout bee randomly generates new consumer service orders, and then the scout bee turns into a leader bee. Fifthly, determine whether the conditions for the end of the cycle have been met. If not, repeat steps two through four of the cycle until the end-of-cycle conditions are met, and output the end user service order and total delivery cost.

**4. Effect Analysis of AFS-GA-ABC Cold Chain Low Carbon Logistics Path Planning Model.** The AFS-GA-ABCCCLCLPP model is used to plan reasonable distribution routes, which is beneficial for improving distribution efficiency and reducing distribution costs. This has a certain positive significance for the promotion of CCL, but the actual application effect of this model still needs further verification. The research mainly analyzes from two aspects. The first part is to conduct simulation experiments and analysis on the AFS-GA-ABC algorithm, and the second part is to analyze the practicability effect of it in the CCLCLPP.

**4.1. Simulation Experiment Analysis of AFS-GA-ABC.** To verify the effectiveness of the AFS-GA-ABC, Eil51 and Ulyssses22 were selected for simulation experiments. The experiment verifies the performance of the algorithm using four indicators: path, convergence times, optimal performance ratios, and robust performance ratios. The shorter the path, the better the optimization effect of path planning. The shorter the convergence time, the higher the efficiency. The lower the optimal performance ratios and the lower the robust performance ratios, the better the stability of the algorithm. And compares it with the ABC and GA. The




(a) The Results of Solving Eil51




(b) The Results of Solving Rat99

Fig. 4.1: The results of solving Eil51 and Rat99 using three algorithms

Table 4.1: Eil51 Solves the Optimal Performance Ratio

| **Algorithm** | **Avg. Convergence Times** | **Relative Error Optimal Perf. Ratio** | **Robust Perf. Ratio** |
|---|---|---|---|
| ABC | 428.37 | 0.3186 | 0.3396 |
| GA | 365.87 | 0.3576 | 0.3654 |
| AFS-GA-ABC | 133.57 | 0.0076 | 0.0362 |

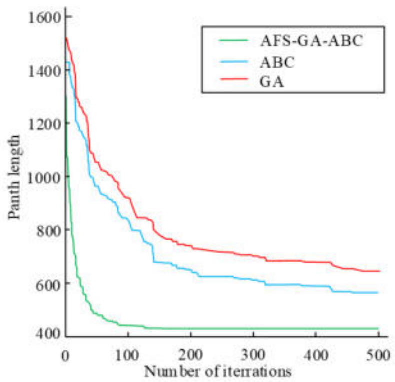
amount of leading bees and following bees are set to 50; is 70; is 500; The max attempt number in group behavior is 250; The probability of partial mapping crossover is 0.8; The crowding coefficient is 0.625. The shortest known distance for Eil51 is 419, and the experiment was run 25 times separately. To use three algorithms to solve Eil51 and compare them with Rat99, which solves for the shortest distance of 1205 4.1. The shortest distance for AFS-GA-ABC to solve Eil51 is 421.38, the longest distance is 448.58, and the average distance is 439.34, both lower than the results obtained by ABC and GA. The best algorithm to solve Eil51 and Rat99 is AFS-GA-ABC.

The performance of the three algorithms for solving Eil51 is shown in Table 4.1. The average convergence number obtained by AFS-GA-ABC for Eil51 is 133.57, with the best relative error and robustness performance ratios of 0.0076 and 0.0362, both of which are better than the results obtained by ABC and GA solutions.

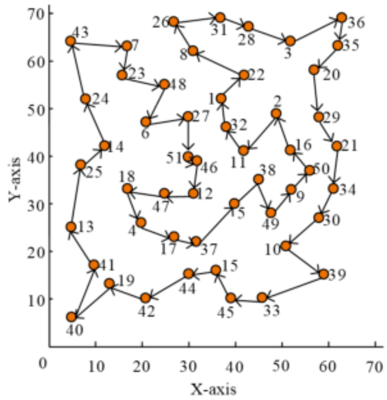
The performance of the three algorithms in solving Eil51 is shown in Table 4.1 . The average convergence number obtained by AFS-GA-ABC for Eil51 is 133.57, with the best relative error and robustness performance ratios of 0.0076 and 0.0362, both of which are better than the results obtained by ABC and GA solutions.

The shortest known distance is 72, and the experiment is run 25 times separately. Three algorithms were used to solve Ulyssses22 and compared to KroB100 with the shortest distance of 22136 as shown in Figure 4.3. The shortest distance obtained by solving Ulyssses22 using AFS-GA-ABC is 72.46, the longest distance is 73.63, and the average distance is 72.84, both lower than the results of ABC and GA; Moreover, the most effective algorithms for solving Ulysses22 and KroB100 are AFS-GA-ABC.

Table 4.2 shows the comparative results of three algorithms for solving Ulyssses22. The average convergence number obtained by using AFS-GA-ABC to solve Ulyssses22 is 7.86, the optimal relative error performance

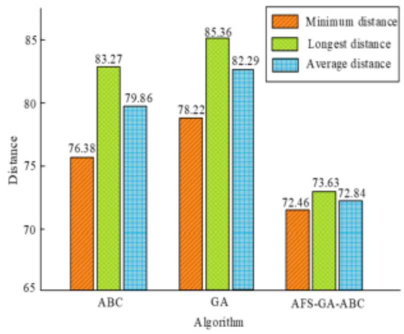



(a) Eil51 Optimal Curve

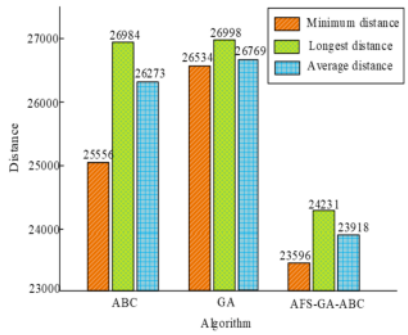



(b) Eil51 shortest path graph

Fig. 4.2: Two Algorithms for Solving Eil51's Optimization Curve and Shortest Path




(a) The results of solving Ulysses22




(b) The results of solving KroB100

Fig. 4.3: The results of solving Ulysses22 and KroB100 using three algorithms

ratio is 0.0051, and the robust performance rate is 0.0117, both of which are better than the results of ABC and GA.

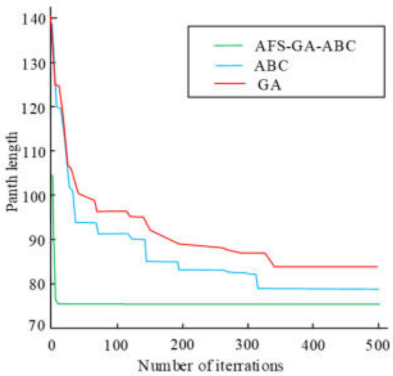
Figure 4.4 shows the optimization curves and shortest paths of three algorithms for Ulysses22. The path length obtained by AFS-GA-ABC for Ulysses22 and the iterations required to obtain it are much smaller than those using ABC and GA, therefore AFS-GA-ABC has higher accuracy and efficiency.

In summary, AFS-GA-ABC solves a shorter shortest path compared to ABC and GA, resulting in better search accuracy, higher efficiency, faster convergence speed, and better stability and robustness.

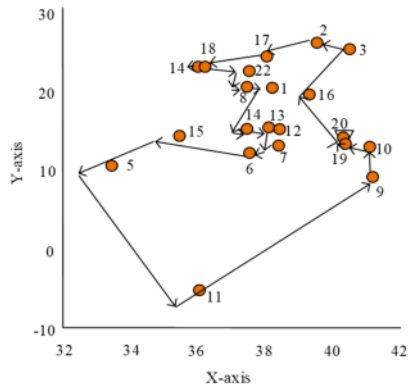
**4.2. Analysis of the Application Effect of AFS-ABC Cold Chain Low Carbon Logistics Path Planning Model.** Initializing the improved ABC parameters, setting the quantity of leading bees and following bees to 20; is 20; is 200; The max number of attempts in group behavior is 100; The probability of partial mapping crossover is 0.9; The crowding factor is 0.618. Taking one of the distribution centers of a CCL distribution company as an example, 15 consumers were provided with distribution services, and the CCLCLPP model was simulated 25 times using Simulated Annealing(SA), ABC and AFS-GA-ABC, respectively. The final total cost solution is Table 4.3. The optimum solution and mean value of the total cost gained by ABC are

Table 4.2: Ulysses22 Solves the Optimal Performance Ratio

| **Algorithm** | **Avg. Convergence Times** | **Relative Error Optimal Perf. Ratio** | **Robust Perf. Ratio** |
|---|---|---|---|
| ABC | 308.43 | 0.0597 | 0.1008 |
| GA | 358.26 | 0.0858 | 0.1128 |
| AFS-GA-ABC | 7.86 | 0.0051 | 0.0117 |




(a) Ulysses22 Optimal Curve




(b) Ulysses22 Shortest Path Graph

Fig. 4.4: Two Algorithms for Solving Ulysses22's Optimization Curve and Shortest Path

58,152.4 yuan and 61,028.3 yuan, respectively; The optimum solution and mean value of the total cost gained by SA are 51213.6 yuan and 53524.3 yuan, respectively; The solutions of AFS-GA-ABC are 47,894.6 yuan and 48,562.7 yuan, both lower than SA and ABC, and the average iterations is also lower than SA and ABC. The data shows that the total cost, stability, and convergence speed obtained by using AFS-GA-ABC solution are better than SA and ABC.

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The distribution path obtained by solving the CCLCLDPP issue using ABC and AFS-GA-ABC is Figure 4.3. Due to the fact that AFS-GA-ABC reduces unnecessary intersections of delivery paths when solving related planning problems, the total distance of delivery paths is shorter, resulting in lower total cost.

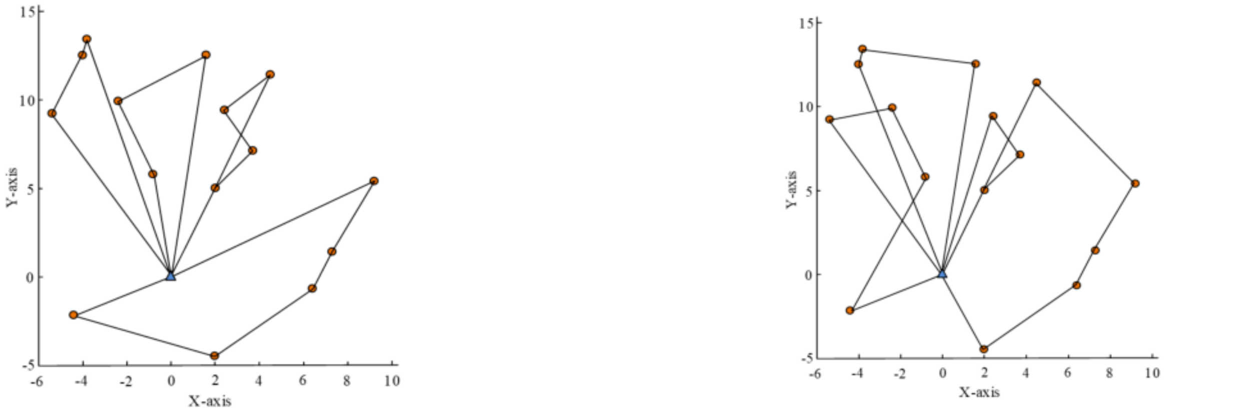
The convergence process of the two algorithms is shown in Figure 3.1. Comparison of the convergence process diagram of ABC and AFS-GA-ABC: Compared with ABC, AFS-GA-ABC has faster convergence speed and better solution effect in solving the CCLCLDPP problem.

In summary, using AFS-GA-ABC to solve path planning problems results in lower total cost, higher efficiency, and better stability compared to using ABC.

**5. Conclusion.** With the development of the market and the increasing demand of consumers, the CCL industry is facing new challenges. High efficiency, low carbon, low cost and low loss have become the mainstream development trend of CCL distribution. A CCLCLDPP model based on AFS-GA-ABC is proposed for the issue of CCLCLDPP. The conclusion is that the shortest distance for AFS-GA-ABC to solve Eil51 is 421.38, the longest distance is 448.58, and the average distance is 439.34. The shortest distance for solving Ulysses22 is 72.46, the longest distance is 73.63, and the average distance is 72.84, both of which are lower than the results of ABC. The average convergence times obtained by solving Eil51 and Ulyssses22 are 133.57 and 7.86, respectively.

Table 4.3: SA, ABC, and AFS-ABC Solution Results

| Algorithm | Total Cost Optimal Solution (yuan) | Optimal Number of Iterations | Avg. Total Cost (yuan) | Avg. Convergence Algebra |
|---|---|---|---|---|
| ABC | 58152.4 | 113 | 61028.3 | 169 |
| SA | 51213.6 | 87 | 53524.3 | 92 |
| AFS-GA-ABC | 47894.6 | 12 | 48562.7 | 43 |




(a) ABC's Delivery Path Diagram

(b) AFS-GA-ABC's Delivery Path Diagram

Fig. 4.5: Delivery Path Map

The optimal performance ratios for relative error are 0.0076 and 0.0051, and the robust performance ratios are 0.0362 and 0.0117, both of which are better than ABC. The optimal total cost solution and the average value obtained by solving the CCLCLDPP problem are 47894.6 yuan and 48562.7 yuan, respectively, which are lower than ABC and reduce unnecessary crossing of distribution paths. The total distance of the distribution paths is shorter, and the total cost is lower. In summary, AFS-GA-ABC solves a shorter shortest path compared to ABC, resulting in better search accuracy and faster convergence speed. AFS-GA-ABC has better stability and robustness, with lower total cost and higher efficiency. However, this study only considered the problem of distribution path planning without analyzing other factors that affect distribution efficiency, cost, and carbon emissions. Therefore, it is necessary to consider more influencing factors, such as the weight and quantity of transported goods, vehicle model, etc., and adopt the control variables to conduct simulation experiments to better support the development of cold chain logistics.

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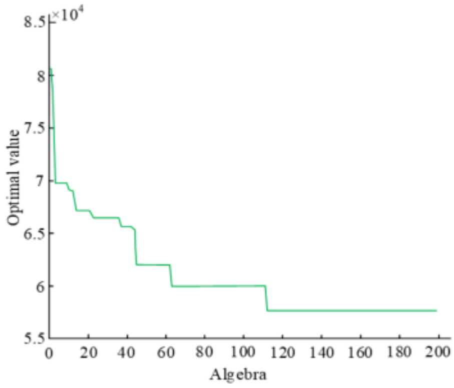
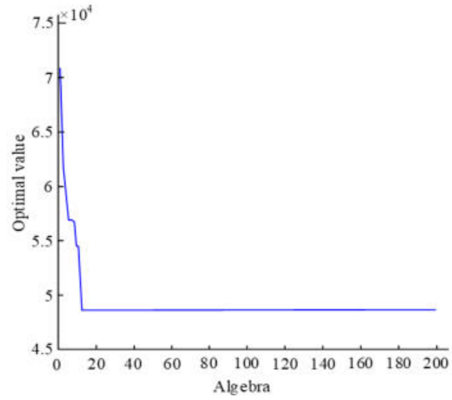



(a) ABC Convergence Process Diagram




(b) AFS-GA-ABC's Convergence Process Diagram

Fig. 4.6: Convergence process diagram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