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OPTIMIZATION MODEL OF COLD CHAIN LOGISTICS DELIVERY PATH BASED ON GENETIC ALGORITHM

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This study is for optimizing the distribution path problem of cold chain logistics. This study proposes an improved genetic algorithm that introduces natural number coding, elite preservation strategy and adaptive cross-mutation strategy. A cold chain logistics distribution path optimization model is constructed, taking into account various costs, including customer demand, time window requirements, maximum mileage of refrigerated trucks, payload, and other constraints. To address the cold chain logistics distribution path, an improved genetic algorithm is utilized. This study designs experiments to test the performance of improved genetic algorithms and applies the model to an example for experimental analysis. The results show that the improved genetic algorithm has better performance in convergence and convergence speed. From the perspective of distribution cost, the optimization model based on the improved algorithm significantly reduces the total distribution cost compared with that before optimization. The above results show that this study effectively optimizes the cold chain logistics distribution route by improving the genetic algorithm and significantly reducing the total distribution cost. This study not only proves the effectiveness of elite preservation strategy and adaptive cross-variation strategy but also shows the importance of considering various costs and constraints comprehensively. This provides a valuable optimization tool for the cold chain logistics industry, helps to improve efficiency and reduce costs, and has important practical significance.

Keywords: Genetic Algorithm; Cold Chain; Logistics Distribution; Path Optimization; Natural Number Encoding; Elite Preservation; Adaptive Cross-Mutation.

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1. INTRODUCTION

Recently, as the advancement of China's process and the guidance of e-commerce policies, both e-commerce and logistics industries have achieved rapid development. The growing need for fresh food and upgraded requirements has led to the broad development prospects of cold chain logistics (CCL), which is closely related to e-commerce. The path optimization problem is a research hotspot in the field of combinatorial optimization. It has important applications not only in logistics distribution but also in intelligent robots, intelligent transportation, intelligent shipping, air transportation and other fields (Gao *et al.*, 2020; Rath *et al.*, 2021). In the vehicle routing issue of low-carbon (LC) CCL, besides considering the transportation costs required for traditional path optimization, it is also essential for considering the characteristics of CCL. These include customer time window requirements, required refrigeration equipment, cargo damage rates, and carbon emission costs (Farooq *et al.*, 2021; Wang *et al.*, 2021). Studying the optimization issue of CCL paths can shorten delivery time while ensuring the safety and quality of cold chain products, meeting consumers' requirements for food safety and quality. Secondly, studying the path problem of a certain enterprise has reference value for other enterprises in the industry, leading to improved economic efficiency, reduced damage rates, and increased competitiveness. Finally, through the development of practical distribution routes and reduction of carbon dioxide emissions, it can alleviate the greenhouse effect, reduce energy waste, promote resource-saving management, and contribute to sustainable development (Chen *et al.*, 2020; Egota *et al.*, 2020). This study combines the actual background of the CCL field and proposes an improved genetic algorithm (GA) in view of the research outcomes of vehicle path optimization problems, further exploring the optimization model of path planning (PP) in CCL. Its research is in view of this criterion, establishing a reasonable model and solving it, providing a theoretical framework for path optimization problems in practical contexts. The research aims to provide theoretical support and practical reference for the sustainable development of CCL by solving the path optimization problem.

The study is separated into four. The first summarizes and summarizes relevant research both domestically and internationally. The second constructs a CCL distribution path optimization model and solves it in view of an improved GA.

The third conducts performance testing on the algorithm and conducts instance analysis. The fourth summarizes the research results.

There is a research gap in optimizing the distribution path of CCL. Current research primarily centers around path optimization for individual DC, with little attention given to optimizing the paths of multiple DC. Therefore, in-depth research can be conducted on the path optimization of multiple DC to meet the optimization needs of CCL distribution routes in different regions and customer needs. The study of vehicle routing concerns with LC requirements is quite restricted. Most of the existing research on path optimization focuses on room temperature logistics, with less research on CCL. Therefore, it is possible to combine factors such as energy consumption and carbon emissions with an LC economy as the goal to conduct research on path optimization based on CCL in order to reduce carbon emissions, energy consumption, and other environmentally friendly ways of logistics distribution. In terms of algorithm selection and improvement, the ant colony algorithm is more commonly used, while GA has fewer applications. In addition, current research mostly combines quantum ideas to improve the performance of GA. Therefore, there is potential to delve deeper into the utilization and advancement of GA in optimizing the route of CCL and discovering superior solutions.

Based on the above research gaps, the contributions of this study can be reflected in the following aspects. A model is built based on the characteristics of CCL. By introducing factors such as cargo damage cost, refrigeration cost, and penalty cost, a CCL distribution path optimization model based on the lowest objective function of distribution logistics transportation costs is established. Combined with a LC economy, introducing carbon emissions are introduced as an economic cost. It converts carbon emissions into economic costs and adds them to the objective function of distribution path optimization, constructing the objective function with the lowest sum of social and economic costs. Empirical analysis and application promotion. It verifies the effectiveness of the improved algorithm in optimizing the distribution path of CCL through empirical analysis and provides reference for enterprises and governments in the development of green distribution, promoting the application of this research result. In summary, this study fills the gap in the field of optimizing CCL distribution pathways and researching LC economies. By establishing a path optimization model suitable for CCL and improving GA, it provides research contributions in distribution efficiency, economic costs, and environmental protection.

2. LITERATURE REVIEW

The vehicle routing optimization problem, as one of the classic methods for solving vehicle delivery route planning, has been widely applied in many practical fields. Y. Pan et al. developed a method called Deep Learning GA (DL-GA), a fusion of deep learning and GA, to collect information on path and state data. The method uses deep neural network training to enable quick and efficient provision of optimal paths in familiar scenarios. The experiment showcases that DL-GA has faster solving speed and no loss of optimization effect compared to traditional GA and even performs better under certain conditions (Pan *et al.,* 2021). Liang and Wang presented a hybrid algorithm, which further improved the quality of PP [mention PP Reply: The introduction mentions PP, which has been explained in the introduction.] and reduced the cost (Liang *et al.,* 2020). Through experiments and practical software implementation, the results showcase that the hybrid algorithm is efficient as well as robust and could get the optimal path in single or multi-ship surveys, resulting in cost and time savings (Liang *et al.,* 2020). Chen and Gao proposed a PP method in view of S-adaptive GA (Chen *et al.,* 2020); this method allows the algorithm to adaptively adjust probability values in view of changes in genetic generations and individuals by changing the crossover and mutation probabilities in genetic operations. The experiment demonstrates that the S-adaptive algorithm-solved path achieves obstacle avoidance behavior quickly and outperforms the path obtained through traditional GA (Chen *et al.,* 2020). Cheng et al. proposed a system strategy to construct a hinged four-degree-of-freedom reconfigurable robot model in the workspace and conducted research on PP methods in view of GA (Cheng *et al.,* 2020). This algorithm considers PP as a multi-objective optimization (MOO) problem and estimates the function of the optimization results in view of the fitness objective function. This algorithm has been implemented and tested on practical reconfigurable robot platforms, and the framework can be applied to other multi-configuration robot platforms for multi-objective PP (Cheng *et al.,* 2020). Sarkar et al. proposed a new method for PP of mobile robots, which is a GA in view of domain knowledge (Sarkar *et al.,* 2022). This method aims to find the optimal collision-free route from the starting point to a single or multiple destination point. For addressing the PP problem of single or multiple independent objectives, four new domain knowledge operators are introduced. The approach is tested in various simulated environments of varying dimensions, and the relevant findings demonstrate that domain knowledge operators enhance the conventional GA's performance. For the PP problem of a single objective mobile robot, the proposed method is superior to the previous method in view of the Evolutionary algorithm (Sarkar *et al.,* 2022).

To achieve real-time solutions and complete drone trajectory planning in a limited time, Jamshidi et al. proposed a parallelization method to reduce the computational time (Jamshidi *et al.,* 2020). In industrial applications, this method can utilize communication platforms to achieve parallelization processes, such as Controller Area Network (CAN), which is a protocol utilized for reliable communication. Because of the advancement and characteristics of CAN protocol on unmanned aerial vehicles, it could be utilized for parallel optimization of PP problems. Subsequently, an asynchronous distributed multi-master parallel GA is achieved on the CAN bus to enhance the performance of UAV PP (Jamshidi *et al.*, 2020). Receveur et al. studied the trajectory optimization problem of autonomous ground vehicles in a specific range and proposed a potential field combinatorial optimization trajectory planning method through GA (Receveur *et al.*, 2020). This method utilizes GA for MOO to achieve optimal trajectory.

Meanwhile, it considers the properties and motion of obstacles, making the potential field highly reactive. The method also considers the direction of human drivers' attention, introduces constraints to avoid danger and considers vehicle dynamics. Simulation experiments have verified the performance of this method in the intersection and overtaking scenarios (Receveur *et al.*, 2020). Sarno et al. proposed a new autonomous reconfiguration method for distributed space systems, which optimizes the total propellant consumption while ensuring the safe guidance of spacecraft formation (Sarno *et al.*, 2020). They transform the orbit transfer problem into a convex optimization problem to ensure fast calculation of the control rate. Tasks are iteratively assigned to component platforms to find the best refactoring strategy. PP is performed by a reference satellite and coordinated with other satellites through a program in view of GA. Simulation results demonstrate that LEO cluster reconfiguration necessitates an average delta-v of 0.1m/s per satellite during an orbital period when the relative distance is hundreds of meters (Sarno *et al.*, 2020). Ortiz and Yu combined sliding mode control with classical simultaneous localization and mapping (SLAM) methods (Ortiz *et al.*, 2021). This combination can overcome some relevant issues in SLAM. With the help of GA, the new PP method studied has shown lots of merits compared to other popular methods (Ortiz *et al.*, 2021). Schfle et al. proposed a new offline optimization method for solving coverage PP problems (Schfle *et al.*, 2021). This method is in view of grid environment representation and adopts a hybrid genetic algorithm (HGA), which includes a turning starting point and a backtracking spiral algorithm for local search, by using three different fitness functions (FF) for validation, including cell visits, travel time, and a new energy FF in view of the basic motion energy values obtained from experiments. The results of the calculation indicate that HGA can enhance the path improvement rate by up to 38.4% compared to conventional approaches (Schfle *et al.*, 2021).

At present, researchers have conducted extensive research on vehicle path optimization problems and proposed various algorithms to meet different needs and problems in practical applications; however, there is still much room for progress in the dual coordination and optimization of the CCL path optimization and LC economy. Therefore, an improved GA will be proposed for the study of this optimization direction for addressing the LC CCL distribution path optimization model, and it will be applied to examples for simulation analysis to provide theoretical support and practical reference for sustainable development in this field.

3. CONSTRUCTION OF COLD CHAIN LOGISTICS DISTRIBUTION PATH OPTIMIZATION MODEL BASED ON IMPROVED GENETIC ALGORITHM

This study first constructs a distribution path optimization model for CCL, considering multiple distribution factors for constructing a distribution path optimization model. To enhance the GA's performance, methods such as adaptive cross-mutation (CM) and elite preservation strategy are introduced. The improved GA addresses the CCL distribution path optimization model more effectively.

3.1. Construction of Optimization Model for CCL Delivery Path

The research involves multiple CCL distribution centers (DC) that provide delivery services to various customer points through refrigerated trucks (RT) within a time window. Before planning the delivery path, it is necessary to comprehensively consider various costs, such as customer demand, time window requirements, maximum mileage of RT, load capacity, and other constraints, to construct a CCL path optimization model. This study focuses on the problem description and mainly considers the following constraints when constructing the model to ensure its feasibility. Each customer can only receive one RT delivery service, and the delivered goods cannot exceed the maximum load capacity of the truck (Wang *et al.*, 2020). The loading capacity (LCA) of a RT cannot exceed its maximum rated LCA; the RT needs to return to the same DC after performing delivery tasks. The number of RT performing delivery tasks within the same delivery cycle cannot exceed the total number of vehicles that the company can provide. The RT needs to satisfy the time window demands of each customer as much as possible.

Its DC are Pc, Pm, and Q, which are a collection of Q DC. k is the RT, $k \in L$; L is a collection of refrigerated vehicles, totaling K vehicles. The customer points are i and j, $i, j \in G$, $i \neq j$; G is the node set. The explanation of decision variables is showcased in Table 1.

Table 1. Decision variable description

Variable	Value	Illustration
x_{ijk}^{m}	1	The refrigerated truck k of distribution center m drives from node i to node j
	0	Otherwise
y_{ik}	1	Meet the cargo demand of node i by refrigerated truck k
	0	Otherwise

The decision variables x_{ijk}^{m} and y_{ik} are both 0-1 variables. For the value of variable x_{ijk}^{m}, when the RT k path (i, j) of DC m is set, then variable x_{ijk}^{m} is 1. Otherwise, it is 0; for the value of variable y_{ik}, when the demand for goods from customer i is met by RT k, then variable y_{ik} is 1, otherwise, it is 0. This model aims to achieve an optimal solution that maximizes customer satisfaction while minimizing cargo damage and balancing economic and environmental benefits. The objective function of the model covers five types of costs.

In this model, the comprehensive transportation costs of vehicles is defined as the sum of fixed cost (FC) and transportation costs, which is represented by Z_1. Among them, the FC Z_{11} is mainly composed of driver salary, vehicle depreciation, maintenance and other expenses. The unit FC of refrigerated vehicles is expressed in f_1, and the total FC of all vehicles can be expressed in Formula (1).

$$Z_{11} = f_1 \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} x_{ijk}^{m} \tag{1}$$

In Equation (1), M serves as the total quantity of logistics centers; K is the quantity of RT in the DC; N serves as the number of customers.

Transportation costs Z_{12} refers to the fuel and maintenance costs incurred by vehicles in carrying out transportation tasks during the delivery process. Distribute maintenance expenses uniformly along the traveled distance, while fuel costs increase directly with the distance traveled. The unit transportation costs of RT is represented by f_2, and the total transportation costs of all vehicles can be expressed as Equation (2).

$$Z_{12} = f_2 \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} d_{ij} x_{ijk}^{m} \tag{2}$$

In Equation (2), d_{ij} serves as the distance between node i and node j. The comprehensive cost of vehicle transportation Z_1 is shown in Equation (3).

$$Z_1 = f_1 \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} x_{ijk}^{m} + f_2 \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} d_{ij} x_{ijk}^{m} \tag{3}$$

During the transportation process of RT, the object being transported must remain fresh. This requires adjustment of the temperature inside the carriage to meet the fixed temperature required by the transported object. To simplify the model, the quality function $C(t) = C_0 e^{-\omega t}$ was introduced to show that the quality of fresh products declined exponential decay with time. Among them, C_0 represents the initial quality of the fresh product when it is first loaded, and ω represents the rate of quality decline. The rate of quality decline is usually influenced by factors such as oxygen content and temperature around the goods. Generally speaking, the smaller the value of ω Z, the more sensitive the product is to time. The cost of goods damage Z_2 in the model is represented by Equation (4).

$$Z_2 = P \sum_{k=1}^{K} \sum_{i,j=0}^{N} y_{ik} q_i (1 - e^{-\omega t_{ij}}) \tag{4}$$

In Equation (4), P serves as the unit price of the delivered product; q_i serves as the demand for goods at node i. The cooling cost (CCO) Z_3 mainly includes two aspects of consumption. The first is the CCO required to maintain the temperature inside the vehicle. The second is the CCO consumed due to external air entering when the doors are opened during loading and unloading. According to the previous assumptions, all refrigerated vehicles are of the same type, and the parameters of each vehicle are consistent. Therefore, these two CCO can be approximated as positively correlated with time. The former is proportional to the transportation time of RT k from customer node i to node j, while the latter is proportional to the loading and unloading time T_i of RT k at node i. Among them, a and b are the consumption coefficients of the refrigerant during transportation and during unloading. Consequently, the CCO Z_3 during vehicle transportation can be demonstrated as Equation (5)

$$Z_3 = \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} \left(at_{ij} x_{ijk}^{m} + bT_i y_{ik} \right) \tag{5}$$

According to relevant information, carbon emissions have an impact on the lifecycle of the entire industrial chain, including product manufacturing, logistics transportation, and recycling processes (Zan *et al.*, 2022). Enterprises need to pay the cost of controlling carbon emissions under the carbon tax mechanism. The main cost sources of carbon emissions are the fuel consumption cost Z_{41} of RT and the environmental cost Z_{42}; The latter is the cost of environmental pollution from CO2 emissions, which is positively correlated with the delivery path length and load capacity of RT. The load estimation method is used in the study to calculate fuel consumption, revealing the fuel consumption per unit distance as Equation (6).

$$\rho\left(Q_{ij}\right) = \rho_0 + \frac{\rho * - \rho_0}{Q} Q_{ij} \tag{6}$$

In Equation (6) ρ_0 serves as the unit distance fuel consumption (UDFC) rate of the RT when it is unloaded; $\rho *$ serves as the UDFC rate of the RT when fully loaded; Q serves as the maximum rated LCA of the RT, the value of Q is 10 t; Q_{ij} serves as the real-time loading volume of the RT. The fuel volume of the RT on the delivery path from node i to node j is $\rho\left(Q_{ij}\right) d_{ij}$. The carbon emission cost generated during the entire delivery process is shown in Equation (7).

$$Z_4 = (c + \alpha\beta) \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} x_{ijk}^{m} \rho\left(Q_{ij}\right) d_{ij} \tag{7}$$

In Equation (7), c represents the oil price; α and β represent the carbon tax and carbon emission coefficient. This function is not linear but rather complex, taking into account numerous variables and constraints. In practical situations, the cost of carbon emissions is often influenced by multiple factors, including energy use, production processes, logistics and transportation, etc. Therefore, the carbon emission cost formula involves complex properties such as nonlinear relationships, constraints, and interactions. In view of the timeliness of CCL, customer i has agreed to receive goods with DC m within a certain time period $[ET_i, LT_i]$. Due to the existence of many uncertain factors in the delivery process, the limitations of using a soft time window in the study are shown in Figure 1.

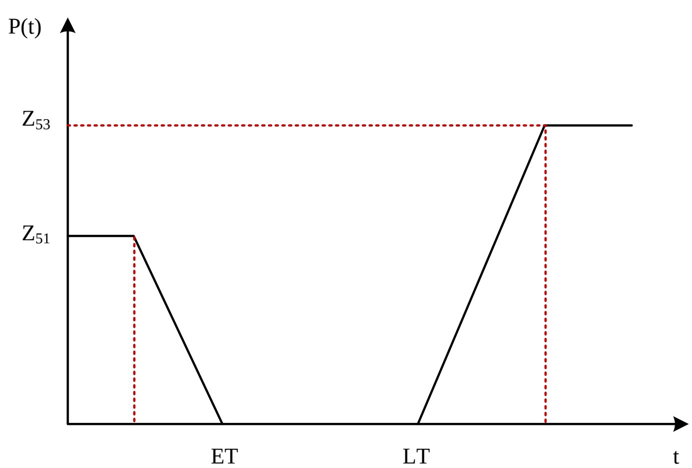


Figure 1. Soft time window

If the arrival time of the RT at the destination fails to meet the time window required by the customer, the company will be responsible for paying the corresponding fines, resulting in penalty costs as shown in Equation (8).

$$Z_5 = \begin{cases} Z_{51} = \lambda_1 \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} x_{ijk}^{m} (ET_i - t_i)\,, t_i < ET_i \\ Z_{52} = 0, ET_i \le t_i \le LT_i \\ Z_{53} = \lambda_2 \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i,j=0}^{N} x_{ijk}^{m} (t_i - LT_i)\,, L\,T_i < t_i \end{cases} \tag{8}$$

In Equation (8), λ_1 is the penalty coefficient (PCO) for early arrival of RT; λ_2 is the delay PCO. Based on the above assumptions and costs, a mathematical model has been developed to optimize the distribution path of CCL. The objective function is to minimize the comprehensive cost of vehicle transportation, including costs associated with cargo damage, refrigeration, carbon emissions, and time window penalties, as shown in Equation (9).

$$min\, Z = Z_1 + Z_2 + Z_3 + Z_4 + Z_5 \tag{9}$$

3.2. Cold Chain Logistics Route Optimization Model Based on Elite Strategy and Adaptive Mechanism

GA possesses strong search capability and can process multiple candidate solutions simultaneously, making it a good solution to the optimization problem of CCL vehicle delivery paths. The implementation process of GA requires first choosing a coding method to construct chromosome individuals and forming a fixed number of initial populations. Then, it uses the set FF as the goal for directed selection to select outstanding individuals. Next, it utilizes a certain adaptive probability for undirected crossover and mutation operations to evolve excellent individuals into the next generation. In the process of continuous updating and iteration, the algorithm will find the individual with the strongest adaptability (Huang *et al.*, 2020). The basic GA process is shown in Figure 2.

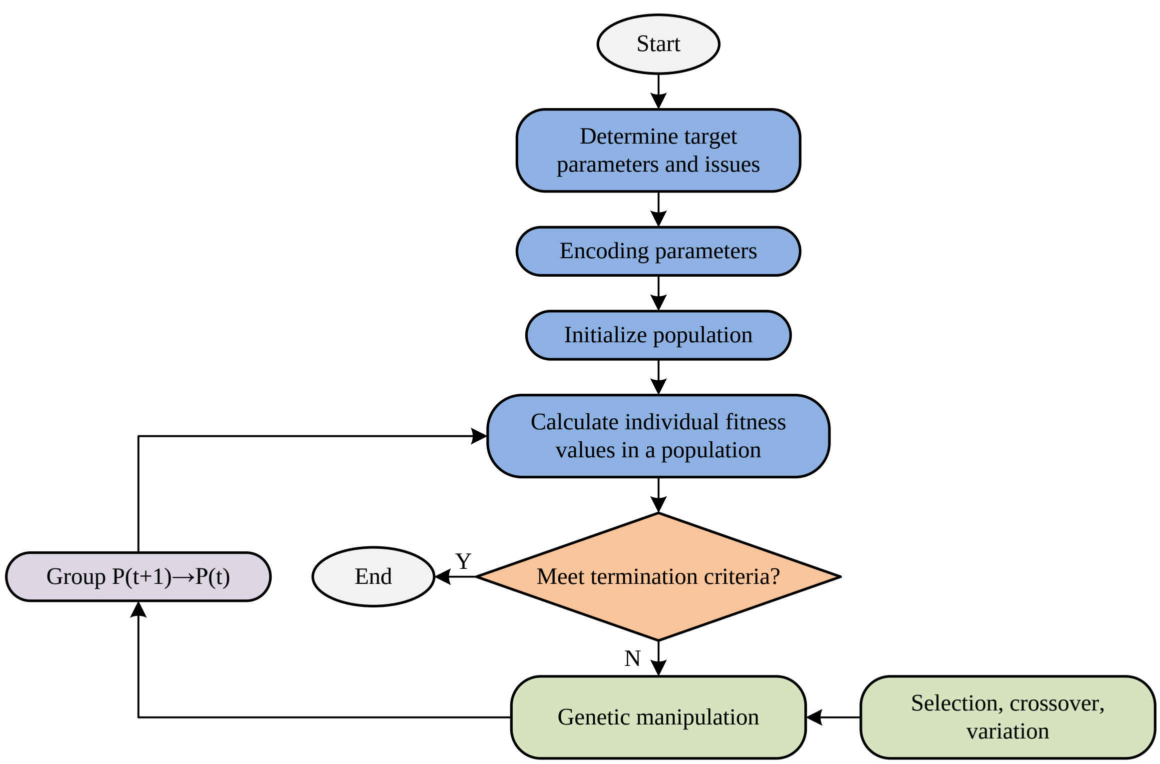


Figure 2. Basic GA process

For GA, encoding is the process of mapping feasible solutions in the problem space onto chromosomes in the genetic space. The widely used encoding methods currently include floating-point encoding, binary encoding, symbol encoding, gray encoding, etc.

Natural number encoding can directly encode feasible solutions in the problem space, making the encoded meaning clearer; this reduces the complexity of the algorithm and makes it more efficient to run (Yang, 2022). The optimization problem of CCL vehicle delivery paths studied involves 3 DC and 22 customer points. To encode the solution space, this study utilizes the natural number encoding method.

In the early, it is necessary to have a population formed by an initial population of individuals that can meet the set conditions. In the problem space, it can be understood as the solution set formed by N initial solutions. The size of the population is determined by the actual situation of the iteration task carried out by the population, and the quantity does not change during the iteration process, and the size is fixed and unchanging. The size of the population has an impact on the efficiency and accuracy of the algorithm. Thus, establishing an optimal population size is vital for resolving the problem of premature convergence in the algorithm.

The FF is mainly used in GA to evaluate an individual's adaptability to the living environment and reflect their level of superiority and inferiority. The design of the FF is usually associated with the objective function, as its selection directly influences the convergence of the algorithm. To enhance the accuracy of the calculation results, it is usually possible to make reasonable and effective range modifications to the objective function to obtain a FF. This prevents issues with individual deception caused by improper function design in the early stages of evolution (Yang 2022). The commonly used scaling methods are shown in Table 2.

Table 2. Common scaling methods

Transformation method	Representation	Value	Illustration
linear transformation	$f' = af + b$	$a = 1, b = -f_{min}$	ξ is a smaller number that can increase population diversity
		$a = -1, b = f_{max}$	
Dynamic transformation	$f' = a^k f + b^k$	$a^k = 1, b^k = -f_{min}^{k^k}$	k is the iterative algebra, ξ^k is the selection pressure for regulation
		$a = -1, b^k = -f_{max}^{k^k}$	
Power function transformation	$f' = f^{\alpha}$	α >1, high selection pressure	α is a parameter used to adjust the selection pressure
		α <1, low selection pressure	
Exponential transformation	$f' = e^{-\beta f}$	The smaller the β, the more inclined the selection is towards individuals with higher fitness	β >0

In this process, dynamic linear transformation is often employed to solve non-negative selection problems. In addition to linear transformation, pressure adjustment parameters can also be introduced to adjust the selection pressure, thereby increasing the diversity of solutions and improving the reproductive opportunities of individuals. By designing a FF reasonably and adjusting selection pressure, the search performance of GA can be improved, and the accuracy of calculation results can be enhanced.

In GA, selection refers to selecting appropriate selection strategies, directly selecting chromosomes with excellent genes from the current population as parent chromosomes and passing them on to the next generation. The criteria for the selection step are mainly based on the fitness value of the individual. The fitness value is used to measure the degree of fitness of an individual to solve a specific problem, and the higher the fitness, the more likely an individual is to be selected. In the selection step, it is also necessary to consider the balance between population diversity and convergence. In order to maintain the diversity of the population, individuals with high fitness but also with certain differences can be selected to enter the next generation. At the same time, in order to avoid the algorithm falling into the local optimal solution, it is also necessary to consider the convergence of the algorithm, that is, whether the optimal solution of the problem can be found within a limited number of iterations. Therefore, factors such as individual fitness value, population diversity and algorithm convergence should be considered comprehensively in the selection step to develop a suitable selection strategy. This study utilizes the elite selection method, which involves initially choosing individuals from the population based on the roulette wheel selection strategy. Then, the individuals with the highest levels of fitness are directly selected to enter the next generation. This method can prevent the destruction of excellent genes in the population, effectively preserving and propagating outstanding individuals. In GA, the performance of chromosomes is mainly reflected in its fitness, that is, the degree of adaptation of chromosomes to solve specific problems. Chromosomes with high fitness have better problem-solving abilities and are, therefore, more likely to be selected as parent chromosomes during selection.

In the iterative process of GA, crossover refers to the replacement or recombination of a portion of genes on the chromosomes of two-parent individuals with a certain probability of crossover Pc, resulting in the generation of new individuals. The crossing is an important operation for optimizing population genes and enhancing the global optimization ability of algorithms, and it is also one of the differences between GA and other biomimetic algorithms. The design of crossover operations mainly involves the mode and probability of crossover (Wang *et al.*, 2022). The study adopts a two-point crossover approach, as shown in Figure 3. The crossover probability value typically falls in the [0.4, 0.99] range.

Another important operation in GA is mutation. In GA, mutation is an operation performed on individuals within an existing algebraic population. Determine whether an individual meets the mutation conditions by setting the corresponding mutation probability P. When an individual meets the mutation conditions, one or some genes in their chromosomes will undergo changes. Mutation operation can ensure the diversity of the population, especially in the later of population evolution, as its appearance can effectively suppress the premature problem of the algorithm. Like crossover operations, mutation operations also need to consider the mode and probability of mutation (Zou *et al.*, 2020). The study adopts reverse mutation, a frequently used mutation operation within GA, which offers several advantages. Increased diversity. Reverse mutation can randomly select a continuous segment of genes in an individual's gene sequence for inversion operations, thereby breaking the original sequence and introducing new gene combinations. This can increase the diversity of the population, avoid falling into local optima, and improve the exploration ability of the algorithm. Local search capability can be enhanced with reverse mutation operations that make local adjustments to individuals in a population and rearrange gene sequences. By inverting a small gene sequence, it is possible to better adapt to the current environment and improve individual fitness. This can help the algorithm perform more fine-grained searches in the solution space and improve its local search ability. The mutation effect is strong. Reverse mutation is a strong mutation operation that can alter an individual's gene combination to a greater extent. Compared to other mutation operations, such as point mutation, reverse mutation can introduce new gene combinations more effectively, helping to jump out of local optima. The principle of reverse mutation is shown in Figure 4. Typically, the mutation probability value ranges between 0.005 to 0.01.

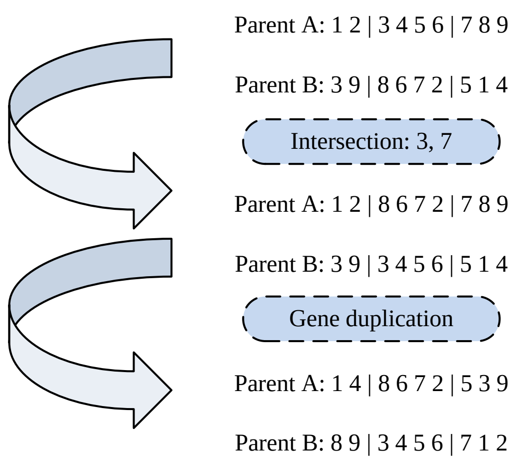


Figure 3. Two-point crossover

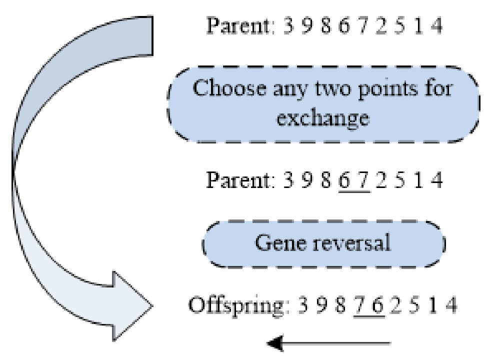


Figure 4. Reverse mutation

The FF is a standard for evaluating an individual's adaptability to the living environment, and its formulation directly affects the convergence of GA. In this study, a dynamic linear transformation was employed to create the FF, and its transformation formula is shown in Equation (10).

$$f' = a^k f + b^k \tag{10}$$

The model constructed through research needs to solve for the minimum value, with a =-1, to obtain Equation (11).

$$b^k = f_{max}^{k^k} \tag{11}$$

The FF is shown in Equation (12).

$$f' = f_{max}^{k^k} \tag{12}$$

In Equation (12), f is the objective function; f' is the FF; f_{max}^{k} is the maximum objective function value of generation k; ξ^{k} is the selected pressure for regulation; Its value is shown in Equation (13).

$$\xi^{k}=\begin{cases}M, k=0\\ \xi^{k-1}*r, k>0, (r\in[0.9,0.999])\end{cases} \tag{13}$$

M is the total number of logistics centers; r is a constant, with a value range of [0.9, 0.999]. By adjusting M and r to control the size of ξ^{k}, the diversity of solutions is enriched, and the opportunity for individual reproduction is increased. In the early of population evolution, the selection pressure should be adjusted to a smaller value to ensure a wide search range, and in the later stage, the selection pressure should be adjusted to a larger value to ensure that excellent individuals enter the next generation.

In order to prevent the loss of excellent genes within the population in offspring, the study introduces the Elite Preservation Strategy in conventional GA to ensure the preservation of the optimal genes. In this way, during the population iteration process, the optimal gene will not cross or mutate, but will be directly copied to the next generation to maintain the global convergence ability of the algorithm. This strategy can prevent simple selection operations from harming individuals with superior genes, thus enhancing the convergence speed of the algorithm. Therefore, in the multi-objective optimization PP model utilizing the improved GA, a preservation strategy for elites will be introduced. This strategy will ensure the transmission and maintenance of optimal solutions within the population, leading to the discovery of the optimal or suboptimal solution.

A simple selection operation followed by crossover and mutation may destroy the original individuals with good genes, resulting in the transmission of good genes in the population, thus reducing the rate of convergence. To counter the loss of excellent genes in offspring, this study introduces a strategy for elite conservation by way of the roulette wheel method. In the selection operation in view of the roulette wheel, the optimal gene does not participate in crossover and mutation, but is transmitted to the next generation through direct replication, ensuring better global convergence ability of the algorithm. In the iterative process of the population, if each individual uses the same probability of crossover and mutation, it will have an unfair impact on the individual (Kukreja *et al.*, 2020). The study introduced an adaptive crossover mutation strategy in the designed algorithm, dynamically adjusting the size of crossover probability Pc and mutation probability Pm in view of fitness values to better balance the relationship between search range, randomness, and diversity and improve the exploration ability and convergence of the algorithm. The relevant calculation for the probability of adaptive CM is shown in Equations (14) and (15).

$$Pc=\begin{cases}\dfrac{k_1(f_{\max}-f')}{f_{\max}-f_{avg}}, & f'\geq f_{avg}\\ k_2, & f'<f_{avg}\end{cases} \tag{14}$$

$$Pm=\begin{cases}\dfrac{k_3(f_{\max}-f')}{f_{\max}-f_{avg}}, & f'\geq f_{avg}\\ k_4, & f'<f_{avg}\end{cases} \tag{15}$$

In Equations (14) and (15), f' serves as the larger fitness among the two individuals selected in the crossover operation; f_{avg} serves as the average fitness of the population; f_{max} represents the maximum fitness in the population. k_1, k_2, k_3, and k_4 are constants between (0, 1). The research has made different settings on the encoding, fitness function, save strategy, mutation strategy, and stop rule of GA compared to conventional GA. Natural number encoding was used, and a custom-designed fitness function was implemented. In terms of preservation strategy, the elite preservation strategy was used, and in terms of mutation strategy, the adaptive cross-mutation strategy was used. At the same time, two stopping rules were combined as the stopping rules for this study. The improved GA process is shown in Figure 5.

In the hybridization step, research will utilize adaptive genetic strategies for crossover and mutation operations. Firstly, compare individuals with less excellent fitness values to determine whether they are worth participating in crossover and variation. This step aims to retain individuals with higher fitness values and enhance the quality of the new population through screening. For individuals with poor fitness they are directly eliminated and do not participate in subsequent crossover and mutation operations. This can reduce the number of low-quality individuals in the population and focus on more potential solutions. The remaining individuals are combined using the calculation formulas for adaptive crossover and mutation probabilities mentioned earlier. The probability formula will adjust dynamically based on an individual's fitness, with those possessing higher fitness being more likely to participate in crossover and mutation while individuals with lower fitness have correspondingly reduced chances. This can enhance the information transmission between outstanding individuals in the population and improve the algorithm's global search ability. Finally, by inserting the combined individuals into a new population, the next generation population is formed. In this way, continuous iteration and crossover and mutation operations based on adaptive genetic strategies will gradually gather excellent individuals in the new population, while individuals with poor fitness will be eliminated, thereby driving the algorithm to search for better solutions. Through the above adaptive genetic strategy, individuals with higher fitness can be chosen for crossover and mutation, preserving exceptional genes and enhancing population quality.

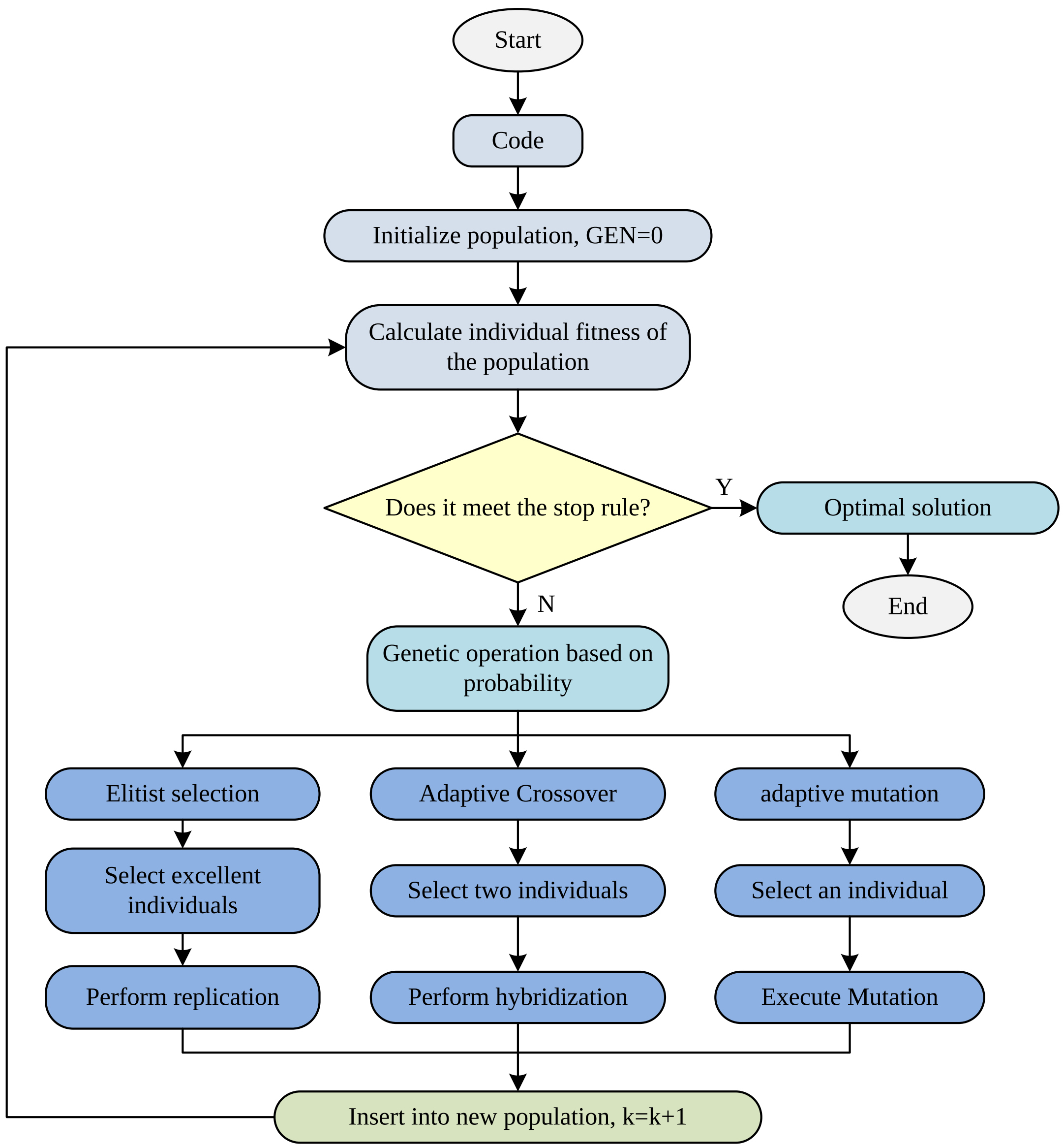


Figure 5. Improved GA process

The limits of cold chain transportation in research are difficult to measure but still present. Strict requirements must be met to ensure the quality and safety of goods during transportation, especially perishable products, which need to be transported under specific temperature and humidity conditions to avoid damage or contamination. These quality and safety requirements are difficult to fully quantify, but they are crucial for the success of CCL. Environmental factors in the transportation environment of CCL are extremely important. Environmental factors, including temperature, humidity, and air pressure, are vital for transporting and storing goods. However, these factors vary depending on the type of product, which makes them dynamic. In addition, climate and seasonal changes can also have an impact on the CCL, requiring adaptive and flexible solutions. Resource constraints require appropriate equipment, personnel, and financial support for CCL. For example, the availability and adaptability of cold storage, RT, transportation equipment, etc., play an important role in the effectiveness of CCL. These resource constraints are factors that cannot be ignored in CCL and are difficult to fully quantify. CCL is limited in several ways, including by quality and safety requirements for products, environmental factors, transportation time windows, and resource constraints. These limitations need to be comprehensively considered and combined with quantifiable cost factors to establish a comprehensive CCL model in order to achieve effective optimization of CCL transportation and distribution paths.

4. ALGORITHM PERFORMANCE TESTING AND PATH OPTIMIZATION MODEL EXAMPLE ANALYSIS

This study first used the Schaffer function to conduct experimental analysis on the performance of the improved GA and then applied the CCL distribution path optimization model in view of the improved GA to an example for instance analysis; it determines the optimal solution of the model by continuously running it 10 times; The various costs were compared before and after algorithm improvement.

4.1. Improving GA Performance Testing

For testing the performance of the improved GA, the Schaffer function was used to evaluate the algorithm and compare the results with the basic GA. The Schaffer function is a function that exists in a two-dimensional space with countless local minimum points. Its global minimum point is unique, with a minimum value of 0 at (0, 0) and strong oscillation, which hinders global optimization search. The iterative diagram of the improved GA designed to solve this function is illustrated in Figure 6.

In Figure 6(a), variables are initially distributed relatively scattered when the number of iterations is 5. However, variables gradually concentrate as the number of iterations increases. Figure 6(d) shows that when the quantity of iterations is 150, variable points achieve the best concentration effect. Through analysis, it can be seen that the improved GA has excellent convergence. The convergence comparison between the improved GA and the basic GA designed in the study is shown in Figure 7.

Convergence and rate of convergence of algorithms are two different concepts. Convergence refers to whether the algorithm can gradually approach or achieve the required result during the execution of the algorithm. A convergent algorithm is able to find a solution in a limited number of steps. If an algorithm doesn't converge, it means that it can't find a solution or it can't stop during infinite execution. The rate of convergence refers to the degree of improvement at each step of the algorithm as it approaches the solution. Algorithms that converge faster are able to approach the solution in fewer iterative steps, while algorithms that converge slower require more steps to approach the solution. Thus, convergence is concerned with whether the algorithm can find a solution, while the speed of convergence is concerned with how efficiently the algorithm can find a solution. Figure 7 shows that the improved GA has better performance in convergence and rate of convergence than the basic GA. Even in the case of a large number of local optima in the Schaffer function, the improved GA can still find better optimization results. This improvement is primarily attributed to the integration of more intelligent methods, including adaptive CM and elite preservation. Through these improved strategies, the improved GA can more effectively search for the global optimal solution when solving complex optimization problems. It can quickly converge and avoid falling into local optima, leading to optimal solutions for practical applications.

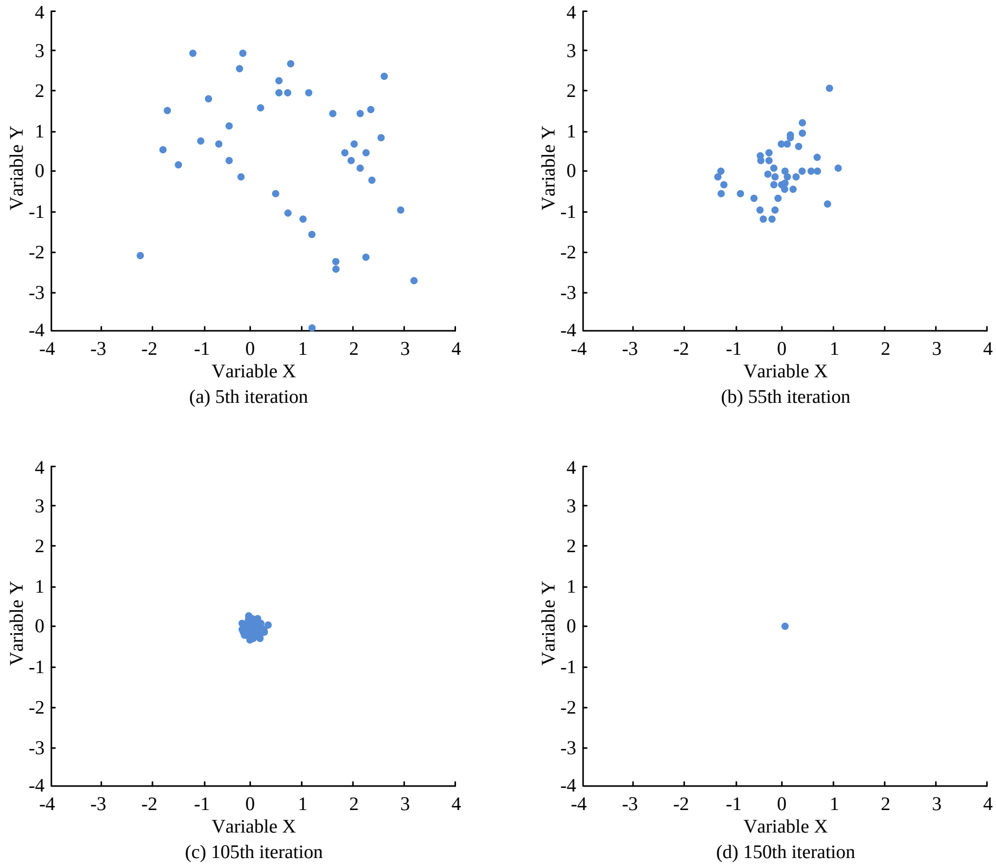


Figure 6. Schaffer function iteration diagram

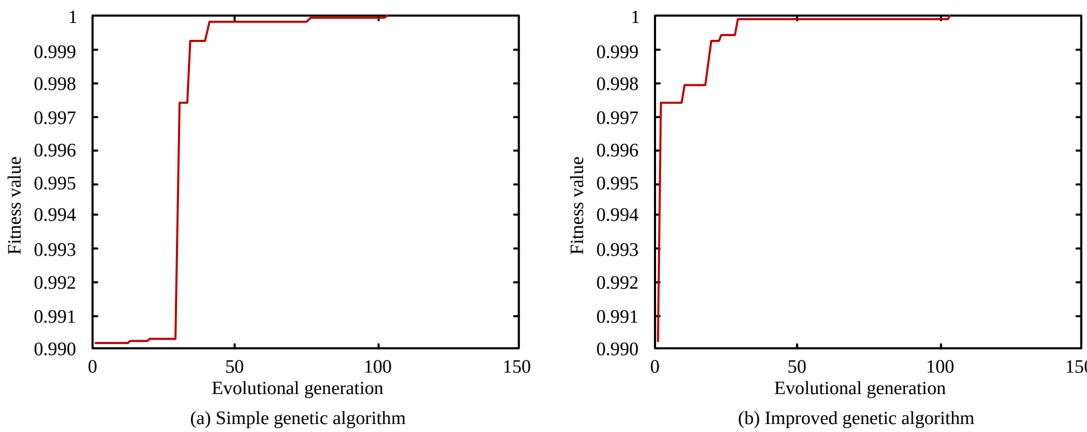


Figure 7. Fitness evolution curve

4.2. Application Analysis of CCL Delivery Path Optimization Model in View of GA

The main business scope of S Food Frozen Company includes cold chain foods such as fresh fruits, vegetables, seafood, and cold fresh meat. S Company has 18 DC throughout the province and has established long-term supply and marketing partnerships with 152 large and small supermarkets. These DC are distributed throughout the province and provide distribution services in view of the areas they radiate. For cold chain foods that require full low-temperature control during the supply and marketing process, S Company adopts a three-level distribution layout. The company has established a large-scale cold fresh meat processing workshop in the provincial capital city, so the first level DC will be built there. The first-level DC transports goods to second-level DCs located in different cities. These DCs are equipped with cold storage facilities for temporary storage. Finally, the product is directly delivered from the DC to the third-tier sales point for sale. This layout method forms a two-layer distribution network to meet the distribution needs of cold chain food. It marks each customer point on the map, as shown in Figure 8.

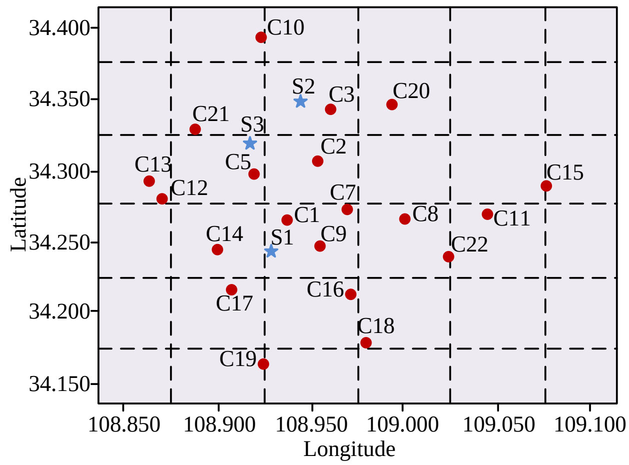


Figure 8. Customer distribution coordinates

In this distribution network, the DC is $S_i(i = 1,2,3)$, and the customer point is $C_i(i = 1,2,\cdots,22)$; when planning the delivery route, it ensures that the k -th RT departs from DC S_i and returns to DC S_i after completing the delivery task. The relevant information of the customer point is shown in Table 3.

Table 3. Relevant data of customer points

Customer number	Requirement q/t	Coordinate		Unloading time T/min	Time window	
		X	Y		ET	LT
C1	2.2	108.9375	34.2653	22	6:00	9:00
C2	2.1	108.9528	34.3065	20	5:30	8:00
C3	1.5	108.9604	34.3431	14	6:30	8:30
C4	1.8	108.9436	34.3485	18	5:30	9:00
C5	2.0	108.9203	34.2971	20	6:00	8:30
C6	1.6	108.9686	34.2741	15	5:30	8:30
C7	2.5	108.9693	34.2742	28	6:00	9:00
C8	1.2	108.9998	34.2662	13	7:00	9:30
C9	2.0	108.9552	34.2463	21	6:00	8:30
C10	1.8	108.9232	34.3934	18	5:00	7:30
C11	1.6	109.0445	34.2681	16	6:30	9:00
C12	2.0	108.8705	34.2806	20	7:00	9:00
C13	2.2	108.8641	34.2924	23	6:00	9:30
C14	1.3	108.8997	34.2442	12	6:30	8:30
C15	1.9	109.0763	34.2878	15	6:00	9:30
C16	2.5	108.9713	34.2133	24	5:30	9:00
C17	1.2	108.9078	34.2165	11	5:00	8:30
C18	1.8	108.9787	34.1776	18	6:30	9:00
C19	1.4	108.9246	34.1634	14	6:00	8:30
C20	1.1	108.9928	34.3458	13	7:00	8:30
C21	1.0	108.8876	34.3284	11	6:30	8:00
C22	1.2	109.0239	34.2403	10	7:00	8:30

The price of goods for the distribution task in the study is 15000 yuan/ton; the unit FC is 350 yuan; the unit transportation cost is 3 yuan, and the transportation speed is 55 km/h. The attenuation coefficient of the freshness of goods is 0.45%; the advance PCO is 150 yuan/hour; the delay PCO is 300 yuan/hour; The fuel consumption rate is 0.18 % when there is no load and 0.41 % when there is a full load. The refrigerant consumption coefficient during transportation is 5 yuan/hour, and the refrigerant consumption coefficient for loading and unloading goods is 12 yuan/hour. The carbon tax is 20 yuan/ton; the carbon emission coefficient is 3.0959kg • CO2/kg, and the oil price is 8.12 yuan/liter. In this study, the following parameter values were set. The population size NP =150, the probability of genetic generation gap $Ggap$ =0.8, the maximum number of genetic iterations is 500, parameter k_1 =0.5, parameter k_2 =0.8, parameter k_3 =0.005, parameter k_4 =0.05. Due to the strong randomness of GA, they exhibit different results each time they run to find the optimal solution, although the resulting values are infinitely close to the optimal solution. To determine the optimal solution, the study adopted a method of continuous operation for 10 times and selected the best result as the optimal solution of the model. The results of the optimal operation are shown in Figure 9.

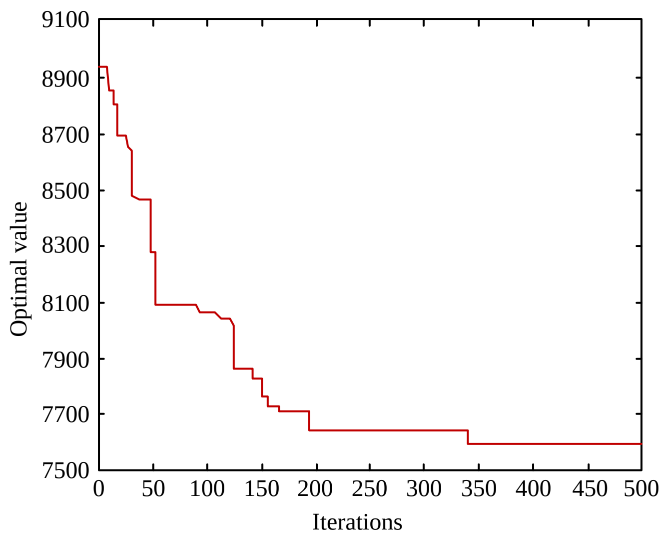


Figure 9. Iterative graph of improved GA

The iteration results in Figure 9 indicate that the iteration curve shows a sharp downward trend in the initial stage. This trend can be attributed to the low adaptability of individuals within the initial population and the high fluctuation of feasible solutions. As the population iterates and updates, the magnitude of the curve's decline gradually slows down, approaching the optimal solution, and finally, a relative optimal solution appears in the 341 generation, at which point the individual's fitness is the highest. The delivery path before and after algorithm optimization is shown in Figure 10.

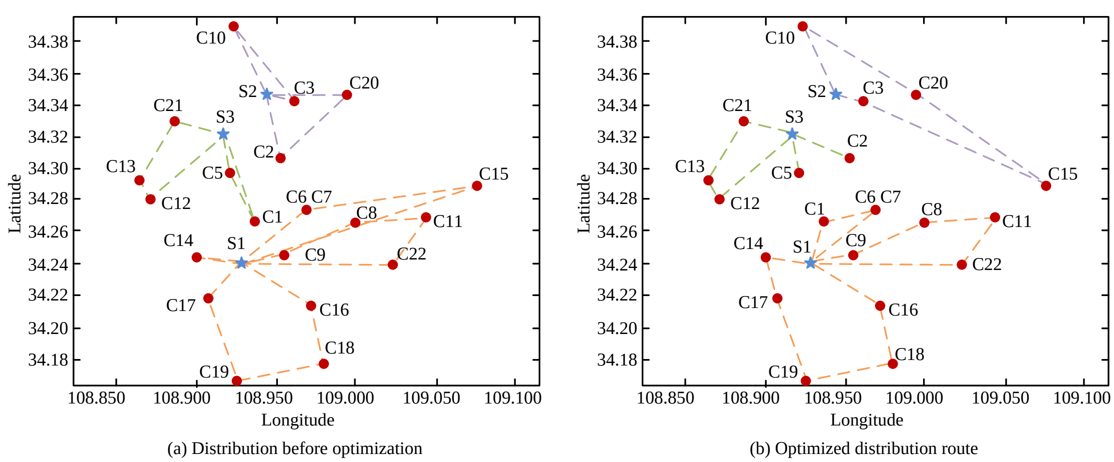
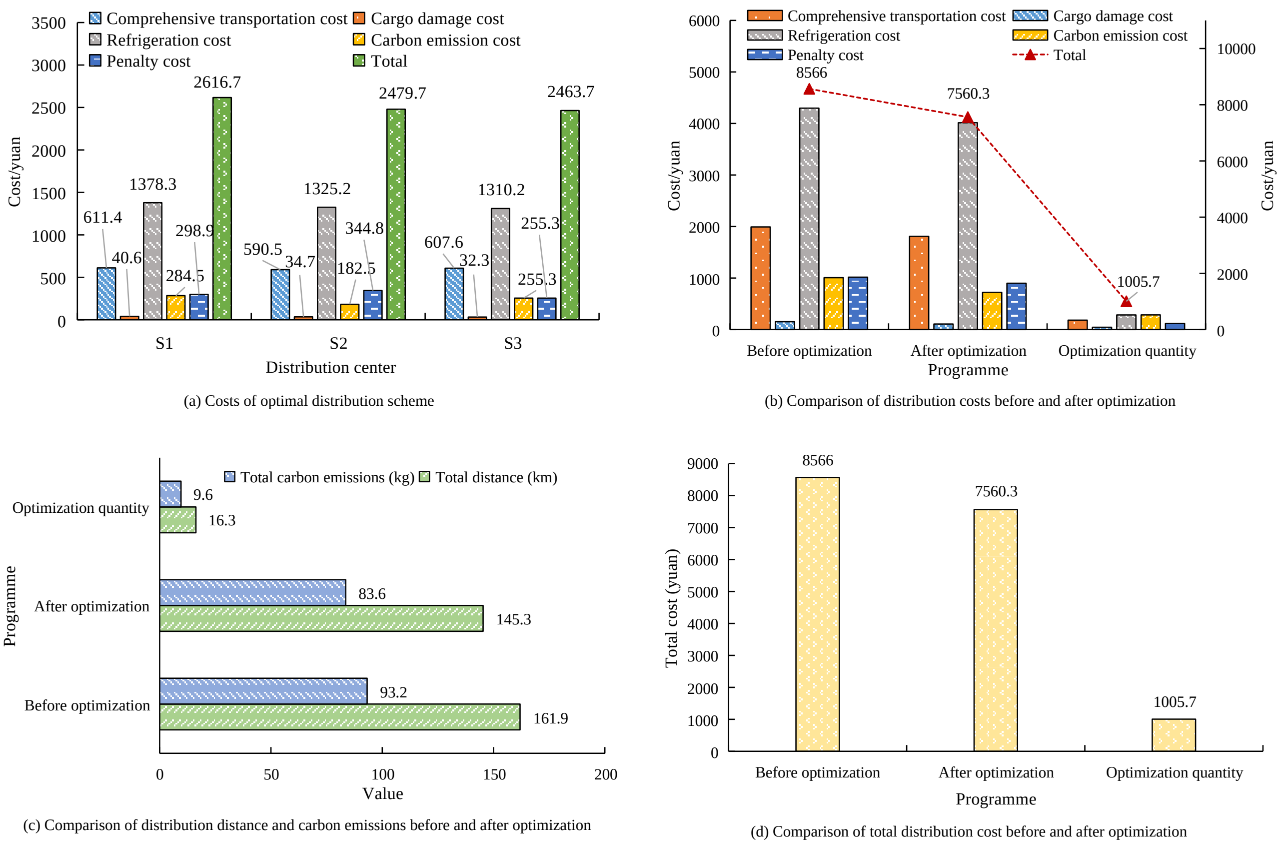


Figure 10. Distribution route before and after optimization

By observing the distribution paths before and after optimization in Figure 10, it can be seen that the customer points served by each DC have changed. For example, customer point C1 is changed from the original DC S2 to the distribution network of S1; customer point C2 is changed from the original DC S2 to the distribution network of S3, and customer point 15 is changed from the original DC S1 to the distribution network of S3. By optimizing the layout of the distribution network and adjusting the distribution routes of each DC, the LC CCL path with the lowest distribution cost was obtained. The comparison of the costs before and after the optimization is shown in Figure 11.



(a) Costs of optimal distribution scheme

(b) Comparison of distribution costs before and after optimization

(c) Comparison of distribution distance and carbon emissions before and after optimization

(d) Comparison of total distribution cost before and after optimization

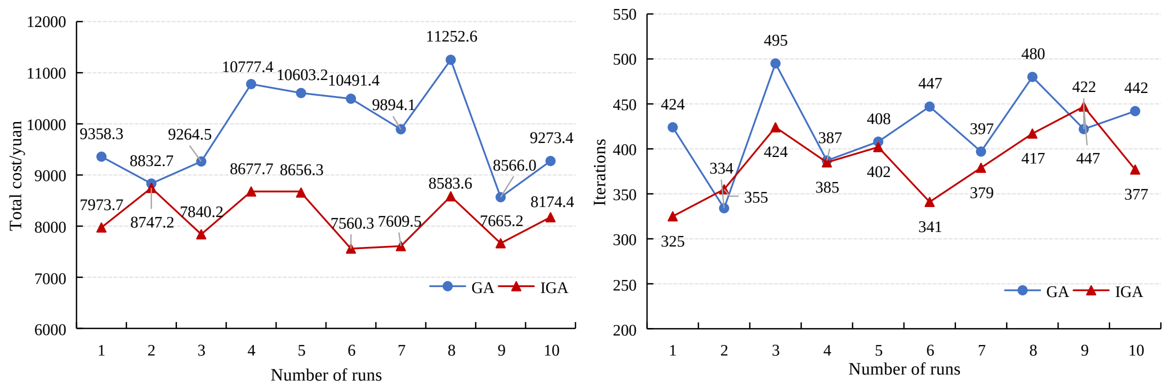
Figure 11. Comparison before and after optimization

Figure 11 shows that from the perspective of delivery costs, the optimized delivery plan has a significant improvement in total delivery costs, with a significant decrease in total delivery costs compared to before optimization. The total delivery cost was reduced from 8566.0 yuan to 7560.3 yuan, resulting in a total savings of 1005.7 yuan. Among other delivery indicators, the total delivery distance has been reduced by 16.7 km, and the total carbon emissions have been reduced by 9.6kg.

In summary, all results before and after optimization have been improved, achieving the goal of maximizing economic and environmental benefits.

The simulation results of the basic GA and the improved GA after 10 runs were compared using various data in the example. The comparison of the results of running the two algorithms 10 times is shown in Figure 12.

Figure 12 shows that the basic GA has a minimum total cost of 8566.0 yuan compared to the improved GA's minimum total cost of 7560.3 yuan. In terms of average total cost, the average total cost of the simple GA is 9381.4 yuan, while the average total cost of the improved GA is 8184.78 yuan. The analysis showcases that the improved GA possesses better performance in searchability and rate of convergence. This algorithm exhibits better optimization ability for path optimization problem-solving. The optimized delivery route chosen by S Frozen Food Company will improve the company's delivery efficiency, effectively control carbon emission costs, minimize the environmental impact of the delivery process, and achieve the unity of economic and environmental benefits.



(a) Total cost comparison

(b) Comparison of iteration times

Figure 12. Comparison of the results of two algorithms running for 10 times

5. CONCLUSION

The study aims to optimize the CCL distribution path problem by proposing an enhanced GA. This algorithm introduces elite preservation strategy and adaptive CM strategy, constructs a CCL distribution path optimization model by comprehensively considering various costs and constraints, and solves it using an improved GA. The experiment reveals that the enhanced GA outperforms the standard one in terms of convergence and convergence rate. From the iteration results, it can be observed that the iteration curve shows a sharp downward trend in the initial stage. As the population iterates and updates, the magnitude of the curve's decline gradually slows down, approaching the optimal solution, and ultimately, a relatively optimal solution appears in the 341 generation. Comparing the delivery costs of the two algorithms, the optimization model in view of the improved algorithm can significantly reduce the total delivery cost from 8566.0 yuan to 7560.3 yuan. In addition, the total delivery distance has been reduced by 16.7 km, and the total carbon emissions have been reduced by 9.6kg. Comparing the average total cost of the two algorithms, the improved GA is 8184.78 yuan, while the basic GA is 9381.4 yuan. The comprehensive analysis demonstrates that the improved GA performs better in terms of searchability and convergence rate. This algorithm exhibits better optimization ability for solving path optimization problems; the optimized delivery route will improve delivery efficiency, effectively control carbon emission costs, reduce the impact of the delivery process on the environment, and achieve the unity of economic and environmental benefits. Due to the complexity of vehicle path optimization and algorithm programming, the experimental consideration of randomness in practical applications is not sufficient. In terms of the constraints of the model, relevant research should further consider the distribution problem of multi-vehicle transportation, considering factors such as unforeseen traffic accidents, road congestion, and other variables. Based on the above research conclusions, this study provides some distribution strategies for CCL distribution operators in reality. Firstly, it is route optimization. Based on an improved GA, the distribution path is optimized to ensure that the total distribution cost and distance are reduced while considering various costs and constraints. This will effectively improve delivery efficiency. Secondly, environmentally friendly delivery: By decreasing carbon emissions, optimal route planning can be implemented to decrease the distance and duration of vehicle travel, ultimately reducing the environmental impact. This will give your distribution business a positive image in terms of environmental protection. Then, there is the consideration of multi-vehicle transportation, and further consideration is given to the distribution problem of multi-vehicle transportation. According to actual needs, allocation is made based on different logistics needs and vehicle types to optimize transportation efficiency and costs. Finally, it is necessary to flexibly respond to unexpected situations, consider the impact of sudden traffic accidents, road congestion, and other situations on the delivery process, and make adjustments and re planning based on real-time conditions to avoid delivery delays and additional costs. Considering these proposed strategies can help CCL operators improve their distribution efficiency, reduce costs and environmental impact, and respond to different situations in a flexible manner, leading to the achievement of economic and environmental benefits. In recent years, CCL has become increasingly important in China. However, against the backdrop of rapid market demand growth, China still faces some bottlenecks that need to be overcome. Researchers have found that the transportation industry has the highest carbon emissions among various industries, while logistics and distribution fuel consumption accounts for 34% of the industry's total consumption, with carbon dioxide emissions reaching 18.9%. Therefore, from the overall perspective of the cold chain logistics system, the vast majority of carbon dioxide emissions come from the distribution process. This is mainly because the delivery process needs to maintain a low temperature level to ensure that product quality and damage rate meet the requirements. Compared to general logistics, low-temperature conditions inevitably consume more energy. In the context of carbon peaking and carbon neutrality, there is a certain contradiction between the development of the logistics industry and carbon emissions. Therefore, the industry must shift towards LC, continuously promote emission reduction and consumption reduction, and strive for an LC transformation and development. It is essential to optimize the cold chain logistics transportation structure and establish a new development system centered on LC logistics for the industry's long-term and healthy growth. Based on the development background of cold chain logistics and LC economy, research was conducted on vehicle path optimization problems, and the constructed model and algorithm were applied to practical cases. The study results were used to propose a research method that combines the actual background of cold chain logistics with vehicle path optimization problems. In theory, research has promoted academic understanding in the field of cold chain logistics by combining path optimization problems with cold chain logistics. When studying the vehicle routing problem of LC cold chain logistics, a reasonable model and solution method were proposed considering the characteristics of transportation costs, time window requirements, refrigeration equipment, cargo damage rate, and carbon emission costs. This provided an effective theoretical framework for optimizing paths in real-world scenarios. In practice, studying the optimization problem of cold chain logistics paths can ensure the safety and quality of cold chain products, improve enterprise economic efficiency, and provide reference for other enterprises in similar industries. In addition, optimizing vehicle routes can also help alleviate the greenhouse effect, reduce carbon dioxide emissions, promote resource-saving business models, enhance the public image of enterprises, and contribute to the sustainable development of society. This study holds crucial academic and practical value for advancing the growth of the cold chain logistics sector and addressing related issues.

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