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Optimization for Shipping Logistics Paths Based on Evolutionary Ant Colony Algorithm: Improvement and Application of Dual Population Mechanism

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To improve the efficiency of shipping logistics, reduce transportation costs, and minimize energy consumption, this study introduces a dual population mechanism to improve the conventional ant colony algorithm and applies it to optimizing shipping logistics paths. Firstly, the shipping logistics network is abstracted as a set of nodes and edges in graph theory, simplifying the complex logistics network structure and providing a framework and theoretical basis for subsequent ant colony algorithm applications. Then, objective functions are set from four aspects: minimizing logistics transportation expenses, minimizing logistics transportation time, minimizing carbon emissions, and maximizing path reliability to guide the algorithm in searching for the optimal solution. Finally, a dual population mechanism is introduced, utilizing two independent ant populations for parallel search. Population 1 adopts an elite ant strategy to achieve fast convergence, while Population 2 uses an enhanced sub path evaluation mechanism to explore new solution spaces and help the population escape from local optima. By using the path contribution evaluation mechanism, better paths can be selected to obtain the optimal shipping logistics path. According to the simulation results, it can be seen that the total transportation time of this method is 41 days throughout the entire experimental cycle, saving 9 days and 7 days respectively compared to the two existing methods; The total transportation expenses of this method is 1250000 USD, saving 170000 USD and 130000 USD respectively compared to the two existing methods; The total carbon emissions of this method are 11800 tons, saving 1700 tons and 1400 tons respectively compared to the two existing methods. It can be seen that this method outperforms existing methods in terms of total transportation time, total transportation expenses and total carbon emissions, indicating that this method effectively achieves the design expectations.

Povzetek: Prispevek uvaja izboljšan evolucijski algoritem dveh populacij mravelj za optimizacijo pomorskih logističnih poti, ki zmanjša stroške, čas in emisije ter poveča zanesljivost poti.

1 Introduction

In today's globalized economic landscape, shipping and logistics play a crucial role. The vast majority of global trade relies on shipping for the transportation of goods, which connects major economies and trade centers around the world [1]. According to statistics, over 80% of global trade goods are transported by sea, which indicates the core position of shipping logistics in international trade. Therefore, the efficiency of shipping logistics directly affects the operational efficiency of the global economy and trade costs.

However, traditional shipping logistics path planning has many problems. On the one hand, due to the lack of precise data analysis and real-time information, route selection is often fixed and conservative [2]. This may result in ships encountering unnecessary detours, congestion, or adverse weather conditions during navigation, thereby increasing transportation time and costs. On the other hand, traditional path planning takes less into account environmental factors, and the high-energy consumption of navigation not only increases operating costs, but also puts significant pressure on the marine environment.

Given the shortcomings of traditional shipping logistics paths, researching optimization methods for shipping logistics paths has important practical significance. By utilizing advanced information technology, big data analysis, and intelligent algorithms, dynamic planning and real-time adjustment of shipping routes can be achieved [3]. This can not only improve the efficiency of shipping logistics, reduce transportation costs, but also reduce energy consumption and environmental pollution.

Therefore, based on the consideration of fuel supply strategy in reference [4], a transportation fleet path optimization method was designed. After in-depth research on the uniqueness of grain shipping and the characteristics of changes in oil prices at fuel supply ports over time and place, this method explores the relationship between oil prices and supply quantities at fuel supply ports, as well as the interaction between average oil prices at fuel supply ports and port service fees. Then, based on the transportation characteristics of the grain fleet, the selection of fuel supply ports, specific fuel supply quantities, and ship navigation routes were selected as key decision-making factors, and a path model integrating integer programming was constructed accordingly. However, although this method considers fuel supply strategies, it may be conservative in path selection and may not fully consider time efficiency. In order to reduce fuel costs or port service fees, longer shipping routes or more transit ports may be chosen, thereby increasing the total transportation time. In reference [5], a navigation vessel diversion path planning method was designed for peak maritime traffic periods. This method first sets a comprehensive objective function aimed at minimizing the length of the voyage, improving navigation safety, and ensuring smooth navigation. Then, the grid method is used to reproduce the ship operation status during the peak period of maritime traffic. Finally, using an improved genetic algorithm, the optimal ship diversion path planning scheme was searched globally. With the help of nonlinear programming techniques, the local optimal solution of the model was further solved, thereby accurately determining the optimal ship diversion path. Although this method aims to minimize the length of the voyage, it may not have taken into account other cost factors such as fuel costs, port charges, etc. In addition, due to the relatively single objective function, it may not be possible to achieve optimal total transportation expenses. On the basis of considering carbon emissions, a method for optimizing oil tanker route scheduling was designed in reference [6]. A green scheduling optimization model for shuttle oil tankers was designed in this method, with the core objective of minimizing the overall cost of shipping. This cost structure includes both traditional fixed transportation costs and variable costs closely related to carbon emissions, reflecting considerations for environmental benefits. In addition, the model not only focuses on optimizing the navigation route planning of shuttle oil tankers, but also finely adjusts the composition and configuration of shuttle oil tanker fleets, thus achieving dual optimization from fleet design to navigation paths. Although this method has included carbon emission costs as part of variable costs, there may still be other cost factors that have not been fully considered or the weighting settings are unreasonable. In addition, with changes in market conditions such as fluctuations in fuel prices, port fee adjustments, etc., this method may need to be continuously updated and adjusted to adapt to new cost structures.

Based on the above analysis, with the goal of improving shipping logistics efficiency, reducing transportation costs, and decreasing energy consumption, this study designs a shipping logistics path optimization method based on evolutionary ant colony algorithm. The design concept of this method is as follows:

(1) Abstracting the shipping logistics network as a directed weighted graph in graph theory, where nodes represent ports, edges represent transportation paths, and weights include distance, time, cost, etc. Build a mathematical model based on the Traveling Salesman Problem (TSP) to adapt to the dynamic changes in shipping logistics demand.

(2) Design objective functions from four aspects: minimizing logistics transportation expenses, minimizing logistics transportation time, minimizing carbon emissions, and maximizing path reliability. Set port capacity constraints, time window constraints, fuel consumption constraints, port congestion constraints, etc. to ensure the feasibility and practical operability of the path.

(3) To improve the search efficiency and global optimization ability of the algorithm, and avoid getting stuck in local optima, a dual population mechanism is introduced. For population 1, the elite ant strategy is adopted to quickly converge to the local optimal solution; For population 2, a strengthened sub path evaluation mechanism is adopted to explore new solution spaces and escape from local optima. On this basis, a path contribution evaluation mechanism is designed to compare the optimal paths of two populations and select the path with higher contribution as the global optimal solution. The dual population mechanism increases the diversity and comprehensiveness of the search, and the path contribution evaluation mechanism further improves the quality of the global optimal solution.

(4) Use the improved ant colony algorithm to solve the objective function. Initialize ant colony algorithm parameters, construct a directed weighted graph, and perform parallel search to generate two candidate paths. Update pheromones based on elite ant strategy and strengthened sub path evaluation mechanism, calculate path contribution, and screen for better paths. Iterate the search until the global optimal path is no longer updated, and output the optimal path that satisfies the multi-objective function. This process achieves efficient and accurate path optimization through parallel search and pheromone update mechanisms, significantly improving the convergence speed and solution quality of the algorithm.

2 Design of optimization methods for shipping logistics paths

2.1 Analysis of TSP problems in shipping logistics

In the field of path selection and planning, TSP is a classic combinatorial optimization problem [7], which can be described as: given a series of cities and the distance between each pair of cities, solving the shortest path to visit each city once and return to the starting city.

Therefore, this study first abstracts the shipping logistics network as a set of nodes and edges in graph theory. Use nodes to represent key locations of logistics ports, edges to represent transportation paths, and analyze their TSP mathematical models. This step not only simplifies the structure of complex logistics networks, but also provides a clear framework and theoretical basis for the subsequent application of ant colony algorithms, making path optimization problems easier to analyze, solve, and verify. At the same time, this abstract method has high flexibility and scalability, and can adapt to the dynamic changes and multi-objective optimization requirements in shipping logistics.

Set up a directed weighted graph $G(V,D)$, as shown in Fig. 1.

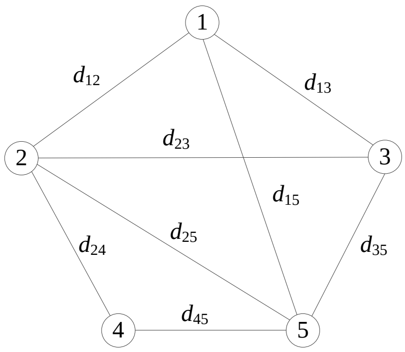


Figure 1: Structure diagram of directed weighted graph (taking a directed weighted graph with 5 vertices as an example)

Among them:

Using different cities (logistics ports) as vertices, obtain a vertex set $V=\{1,2,\cdots,i,\cdots,j,\cdots,n\}$;

Take the line connecting city i and city j as the weighted edge, and the set of edges is $D=\{d_{ij}\,|i,j\in n\}$.

Shipping logistics networks typically involve multiple ports, multiple modes of transportation, and complex constraints [8]. Through graph theory abstraction, they can be simplified into a computable mathematical model for subsequent analysis and optimization.

Then, assuming the existence of $s_{ij}=\begin{cases}1, & i \text{ is directly connected to } j\\ 0, & \text{others}\end{cases}$, TSP mathematical model of shipping logistics can be expressed in the following form:

$$M=\min\left(\sum_{i,j=1}^{n} d_{ij}s_{ij}\right)$$
$$\text{s.t.}\begin{cases}\sum_{i=1}^{n} s_{ij}=\sum_{j=1}^{n} s_{ij}=1\\ \sum_{i,j\in S} s_{ij}=|S|\end{cases} \tag{1}$$

In Equation (1), S represents a subgraph of G; $|S|$ represents the number of cities in S.

The TSP problem requires finding a path that passes through all nodes and has the minimum total cost, which is highly consistent with the goal of optimizing shipping logistics paths. In shipping logistics, it is usually necessary to plan a path from the starting point to the destination, passing through multiple ports, while minimizing transportation costs, time, or carbon emissions. The above TSP model can well describe this requirement.

On this basis, due to the complexity of logistics in reality, the application of TSP needs to fully consider travel time and cost. Therefore, this study extended the dynamic TSP model. Set up rolling time-domain optimization in TSP problem, decompose global path planning into multiple time windows, re optimize local paths based on the latest data within each window, adjust subsequent paths every 3 hours according to updated weather and port status, and enhance dynamic response capability.

2.2 Objective function and constraint setting for optimizing shipping logistics paths

In the research of optimizing shipping logistics paths, the design of the objective function is crucial. The objective function aims to quantify the performance indicators of the optimized path to guide the algorithm in searching for the optimal solution. Therefore, based on the characteristics of optimizing shipping logistics paths, this study sets objective functions from four aspects: minimizing logistics transportation expenses, minimizing logistics transportation time, minimizing carbon emissions, and maximizing path reliability.

(A) Minimizing logistics and transportation expenses

Reducing transportation expenses is one of the core goals of shipping and logistics enterprises, which directly affects their profitability and market competitiveness [9]. The objective function aims to minimize the total transportation expenses in shipping logistics, including fuel costs, port costs, ship maintenance costs, labor costs, etc. By optimizing the route and selecting the lowest cost route and transit port, the operating expenses of shipping and logistics enterprises can be reduced.

Shipping and logistics transportation expenses mainly include five parts: fuel expenses, port fees, loading and unloading fees, carbon emission expenses, and surcharges. Therefore, the objective function is established as follows:

$$F_1=\min(A_1+A_2+A_3+A_4+A_5) \tag{2}$$
$$\min\left(\begin{array}{l}\sum_{i,j\in V} C_{ij}f_1t_{ij}P+\sum_{i,j\in V}\sum_{j\in N} C_j f_2 t_j P+sO_j+\\ \sum_{j=1}^{n}(L_j+U_j)+\sum_{i,j\in V} C_{ij}f_1t_{ij}kc+\sum_{j\in N} C_j\varepsilon_j\end{array}\right)$$

In Equation (2), $C_{ij}=\begin{cases}1,\ \text{if Choose the route from port } i \text{ to } j\\ 0,\ \text{otherwise}\end{cases}$ represents the path selection coefficient; $C_j=\begin{cases}1,\ \text{if select port } j \text{ as the port of call}\\ 0,\ \text{otherwise}\end{cases}$ represents the port selection coefficient; The meanings of the remaining parameters are as follows: A_1, A_2, A_3, A_4, A_5 respectively represent fuel expenses, port fees, loading and unloading fees, carbon emission expenses, and surcharges; V represents a collection of shipping networks, $i, j \in V$; f_1 and f_2 respectively represent the daily fuel consumption of shipping vessels in sailing and berthing states; P represents fuel price; N represents the set of n ports (i.e. cities in the directed weighted graph) that can be docked in the entire shipping network; t_j represents the berthing time of shipping vessels at port j ; s represents the number of times fuel is replenished; O_j represents the operational cost incurred by the shipping vessel for refueling at port j ; L_j and U_j respectively represent the allowable container loading and unloading capacity at port j ; t_{ij} represents the transportation time from Port i to Port j ; k represents the carbon emission tax rate; c represents the carbon emission factor; ε_j represents the additional fee for shipping vessels at port j .

Set the following constraints for the objective function of minimizing logistics transportation expenses:

(1) The actual cargo volume of containers between ports shall not exceed the maximum loading capacity of the sea vessel, that is:

$$\text{s.t. } Q_{ij} \le H_{\max}, \forall i, j \in V \tag{3}$$

In Equation (3), Q_{ij} represents the container freight volume between ports i and j ; $H_{\max}$ represents the maximum container capacity of the shipping vessel.

(2) Ensure that the total container load at all ports matches the total unloading volume, that is:

$$\text{s.t. } \sum_{i=1}^{n} L_i C_{ij} = \sum_{i=1}^{n} U_i C_{ij}, \forall i, j \in \{0,1,2,\cdots,n\} \tag{4}$$

(3) The maximum number of times a port can be visited is once, that is:

$$\text{s.t. } 0 \le C_j \le 1 \tag{5}$$

(4) The number of ports of call selected shall not exceed the required total, that is:

$$\text{s.t. } \sum_{j=1}^{n} C_j \le \kappa_V \tag{6}$$

In Equation (6), κ_V represents the maximum number of ports that can be docked.

(5) Ensure the conservation of container loading and unloading volume at each dock [10], that is:

$$\begin{aligned}&\text{s.t.}\\ &\sum_{i=1}^{n} Q_{ij} = U_j\\ &\sum_{j=1}^{n} Q_{ij} = U_i\end{aligned} \tag{7}$$

(6) Ensure that the total freight volume meets the minimum required freight volume, that is:

$$\begin{aligned}&\text{s.t.}\\ &\sum_{i=1}^{n}\sum_{j=1}^{n} Q_{ij} \ge Q\\ &\sum_{j=1}^{n} Q_{ij} = U_i\end{aligned} \tag{8}$$

In Equation (8), Q represents the minimum container freight volume required to achieve the predetermined revenue.

(7) The decision variable conforms to the 0-1 constraint, that is:

$$\begin{aligned}&\text{s.t.}\\ &C_{ij}, C_j \in \{0,1\}\end{aligned} \tag{9}$$

(8) Minimize logistics transportation time

Shortening transportation time can meet customers' demand for timeliness, reduce the uncertainty of goods in transit, and improve the turnover rate of ships [11]. Therefore, the objective function aims to minimize the total transportation time in shipping logistics, including sailing time, port waiting time, loading and unloading time, etc. By optimizing the route and selecting the shortest route and transit port, logistics efficiency can be improved.

Based on the above analysis, the objective function for minimizing logistics transportation time is established as follows:

$$F_2 = \min\left(\sum_{a=1}^{A} t_{sail,a} + \sum_{j=1}^{n} t_{wait,j} + \sum_{k=1}^{K} t_{load/unload,k}\right) \tag{10}$$

In Equation (10), $t_{sail,a}$ represents the sailing time of segment a ; $t_{wait,j}$ represents the waiting time at port j ; $t_{load/unload,k}$ represents the time of the k -th loading and unloading; A , K represent the number of flight segments and the number of loading and unloading times.

To minimize the objective function of logistics transportation time, the following constraints are set:

(1) Port capacity constraints:

s.t.

$$\sum_{j} t_{wait,j} \leq \text{Capacity port } j \quad (11)$$

In Equation (11), $\text{Capacity port } k$ represents the maximum processing capacity or capacity of port j. This constraint ensures that the cumulative waiting time for each port does not exceed its processing capacity.

(2) Time window constraint: The goods need to arrive at a certain port within a specific time window [12], that is:

s.t.

$$t_{arrival,j} \in \left[\text{TimeWindowStart}_j, \text{TimeWindowEnd}_j\right] \quad (12)$$

In Equation (12), TimeWindowStart_j and TimeWindowEnd_j represent the start and end times of the time window for port j, respectively. This constraint requires that the goods arrive at port j within the specified time window.

2.3 Minimize carbon emissions

Reducing carbon emissions is an important goal of green logistics, and this objective function aims to minimize the total carbon emissions in shipping logistics to reduce the impact on the environment. Carbon emissions are usually related to fuel consumption and route distance. By optimizing routes and selecting routes and transit ports with the lowest carbon emissions, green logistics can be achieved [13].

Based on the above analysis, the objective function for minimizing carbon emissions is established as follows:

$$F_3 = \min\left(\sum_{i,j=1}^{n} e_{ij} C_{ij}\right) = \min\left(\sum_{i,j=1}^{n} \sum_{a=1}^{A} c_{fuel,a} d_a C_{ij}\right) \quad (13)$$

In Equation (13), e_{ij} represents the carbon emissions from port i to port j, which are usually related to fuel consumption and route distance; $c_{fuel,a}$ represents the carbon emission coefficient per unit distance of the segment route a; d_a represents the distance of the segment route a.

For the objective function of minimizing carbon emissions, fuel consumption constraints are set, requiring that fuel consumption cannot exceed the fuel reserve of the vessel, that is:

s.t.

$$\sum_{a=1}^{A} \text{FuelConsumption}\left(d_a, c_{fuel,a}\right) \leq \text{TotalFuelReserve} \quad (14)$$

In Equation (14), $\text{FuelConsumption}\left(d_a, c_{fuel,a}\right)$ represents the fuel consumption of route segment a; TotalFuelReserve represents the total fuel reserve of the vessel. This constraint ensures that the total fuel consumption does not exceed the vessel's fuel reserve [14].

2.4 Maximizing path reliability

Improving path reliability can ensure timely arrival of goods, reduce unexpected losses during transportation, and enhance customer trust [15]. Therefore, the objective function aims to maximize the reliability of the shipping logistics path, that is, the probability that the path can be smoothly executed in practical operations. Reliability is usually affected by factors such as weather, port congestion, and route safety. By optimizing the route and selecting the most reliable route and transit port, transportation risks can be reduced.

Based on the above analysis, the objective function for maximizing path reliability is established as follows:

$$F_4 = \max\left(\prod_{i,j=1}^{n} r_{ij}^{C_{ij}}\right) \quad (15)$$

In Equation (15), r_{ij} represents the path reliability from port i to port j.

Set the following constraints for the objective function of maximizing path reliability:

(1) Considering the impact of port congestion on reliability, the port congestion constraints are set as follows [16]:

s.t.

$$P_{\text{reliable},j} \geq P_{\text{congestion},j} \quad (16)$$

In Equation (16), $P_{\text{reliable},j}$ represents the reliability probability of port j; $P_{\text{congestion},j}$ represents the reliability probability of port j being affected by congestion. This constraint ensures that the reliability probability of port operations is not lower than the probability allowed by congestion conditions.

(2) No sub loop constraint:

s.t.

$$u_i u_j + nC_{ij} \leq n-1 \quad (17)$$

In Equation (17), u_i and u_j represent auxiliary variables used to eliminate sub loops.

In summary, the objective function for optimizing shipping logistics routes is as follows:

$$F = \omega_1 F_1 + \omega_2 F_2 + \omega_3 F_3 + \omega_4 F_4 \quad (18)$$

In Equation (18), ω_1, ω_2, ω_3 and ω_4 are the weight values of the four objective functions respectively.

The process of setting weight factors is as follows: Firstly, due to the different units and magnitudes of each target, normalization is required first. Map each target value to the interval of 0, 10, and 1 through linear transformation to eliminate dimensional differences. Then, based on the actual needs of shipping companies and external constraints, initial weights are assigned as 0.4, 0.3, 0.2, and 0.1, respectively. On this basis, the Analytic Hierarchy Process (AHP) and expert evaluation are combined to construct a matrix for comparing the importance of objectives. For example, expenses are more important than time (2:1 ratio), time is more important than carbon emissions (1.5:1 ratio), and carbon emissions are more important than reliability (1.2:1 ratio). Finally, through matrix consistency testing (consistency ratio CR<0.1), the weights of each target were calculated, and the final weights were obtained as 0.30, 0.30, 0.20, and 0.20 respectively.

2.5 Optimization for shipping logistics routes based on evolutionary ant colony algorithm

Based on the objective function obtained above, the improved ant colony algorithm is used to solve and obtain the optimal shipping logistics path.

Evolutionary design and application of ant colony algorithm

In the context of shipping logistics, each logistics port is like a city in TSP. Shipping vessels need to visit different ports in sequence for cargo loading and unloading operations, and usually hope to complete all port visits with the optimal path [17, 18].

However, as the number of cities increases, the search space of TSP grows exponentially, which makes it difficult for ant colony algorithms to traverse all possible paths in a limited time, and is susceptible to the accumulation of pheromones during the search process, leading to premature convergence to local optimal solutions. In response to this issue, this study proposes improvements to the ant colony algorithm. The improvement ideas are as follows:

(1) Introduce the idea of dual population and use two independent ant populations for parallel search. Population 1 adopts the elite ant strategy to update pheromones, quickly converges using existing information, and obtains the shortest path of TSP; Population 2 adopts a strengthened sub path evaluation mechanism to update pheromones, and jumps out of local optimal solutions by exploring new solution spaces to obtain the shortest path of TSP;

(2) Comparing the two shortest paths obtained above, using the path contribution evaluation mechanism to update the pheromones of the two populations again, the final TSP solution is obtained, which is the optimal shipping logistics path.

Dual population ant colony algorithm based on path contribution evaluation

Based on the TSP mathematical model established in Section 2.1, the ant colony algorithm is used to solve for the shortest path that traverses all cities (logistics ports) and returns to the starting point. The process is as follows:

Assuming the number of ants is m. At time t, the probability of state transition for ant a moving from city i to city j is $q_{ij}^{a}(t)$:

$$q_{ij}^{a}(t)=\begin{cases}\dfrac{\left[\alpha p_{ij}(t)\right]\left[\beta v_{ij}(t)\right]}{\sum\limits_{k\in V_a}\left[\alpha p_{ik}(t)\right]\left[\beta v_{ik}(t)\right]}, & \text{if } j\in V_a\\ 0, & \text{if } j\notin V_a\end{cases} \tag{19}$$

In Equation (19), V_a represents the set of cities that ant a can select in the future; $p_{ij}(t)$ represents pheromone; $v_{ij}(t)$ represents the visibility of the path; α and β respectively represent the heuristic factors of $p_{ij}(t)$ and $v_{ij}(t)$; k represents any other city except for cities i and j [19].

The update equation for pheromones is:

$$p_{ij}(t+1)=\sum_{a=1}^{m}\Delta p_{ij}^{a}+(1-\gamma+\zeta)\,p_{ij}(t) \tag{20}$$

In Equation (20), in the current loop, Δp_{ij}^{a} represents the pheromone left by ant a on path $i\to j$; γ represents the residual factor of $h_{ij}(t)$ [20]; ζ represents the pheromone decay rate.

Usually, α, β, and ζ significantly affect the performance of algorithms. Therefore, this study conducted empirical research. This study set three sets of experimental parameters:

The first set of parameters: $\alpha=1.5, \beta=2.0, \zeta=0.3$. Under this setting, the algorithm is more inclined to explore new paths in the early stages (due to the larger value of β), but the pheromone decay is relatively slow, which helps maintain the pheromone concentration of the better paths explored in the early stages.

The second set of parameters: $\alpha=2.5, \beta=1.5, \zeta=0.5$. At this point, the algorithm focuses more on utilizing existing information (with a larger value of α), but the pheromone decay is faster, which may lead to premature convergence to the local optimal solution.

The third set of parameters: $\alpha=2.0, \beta=2.0, \zeta=0.4$. This is a compromise setting aimed at balancing exploration and utilization while maintaining a moderate rate of pheromone decay. Therefore, this set of values was adopted in this study.

However, as analyzed earlier, the search space of TSP is positively correlated with the number of cities, which makes it difficult for ant colony algorithm to traverse all paths in a limited time, and the convenient process is easily affected by the accumulation of pheromones, resulting in premature convergence of the algorithm and difficulty in obtaining the optimal path for the entire site. To address this issue, this study introduces the dual ant colony algorithm, which utilizes two independent ant populations for parallel search when solving the TSP mathematical model. Population 1 adopts the elite ant strategy, focusing on utilizing existing information to quickly converge. Population 2 adopts a strengthened sub path evaluation mechanism, focusing on exploring new solution spaces. This dual population mechanism increases the diversity and comprehensiveness of the search, helping the population to escape from local optima and obtain an optimal path that traverses all cities and returns to the starting point.

For population 1, adopting the elite ant strategy and improving the updating method of pheromones, the equation is as follows:

$$p_{ij}\left(t+1\right)=\lambda p_{ij}\left(t\right)+\Delta p_{ij}^{*}+\sum_{a=1}^{m}\Delta p_{ij}^{a} \tag{21}$$

In Equation (21), Δp_{ij}^{*} represents the pheromone increment of elite ants on path $i\rightarrow j$.

The calculation equations for Δp_{ij}^{a} and Δp_{ij}^{*} are as follows:

$$\Delta p_{ij}^{a}=\begin{cases}\dfrac{\eta}{d_a}, & \text{if } a \text{ passes through path } i\rightarrow j \text{ in the current loop}\\ 0, & \text{if } a \text{ does not pass through path } i\rightarrow j \text{ in the current loop}\end{cases}$$
$$\Delta p_{ij}^{*}=\begin{cases}m^{*}\times\dfrac{\eta}{d_{best}}, & \text{if path } i\rightarrow j \text{ belongs to the optimal solution}\\ 0, & \text{if path } i\rightarrow j \text{ does not belong to the optimal solution}\end{cases} \tag{22}$$

In Equation (22), m^{*} represents the number of elite ants; η represents the strength of pheromones; d_a represents the length of the movement path of ant a; d_{best} represents the path length of the optimal solution for TSP.

For population 2, a strengthened sub path evaluation mechanism is used to update pheromones, ensuring accurate partitioning of the contribution of different sub paths when solving TSP and improving the quality of TSP solutions.

After introducing the enhanced negative feedback mechanism, the equation for calculating the state transition probability of population 2 is:

$$q_{ij}^{a}\left(t\right)=\frac{\alpha p_{ij}\left(t\right)\times\beta v_{ij}\left(t\right)\times I_{\delta}\left(1-\delta_{ij}\left(t\right)\right)}{\sum_{k\in V_a}\alpha p_{ij}\left(t\right)\times\beta v_{ij}\left(t\right)\times I_{\delta}\left(1-\delta_{ij}\left(t\right)\right)} \tag{23}$$

In Equation (23), $\delta_{ij}\left(t\right)$ represents a negative feedback pheromone; I_{δ} represents the heuristic factor of $\delta_{ij}\left(t\right)$.

In the enhanced negative feedback mechanism, the increment of sub path length pheromone is introduced to obtain the enhanced sub path evaluation mechanism. The updated values $\Delta p_{ij}\left(t\right)$ and $\Delta\delta_{ij}\left(t\right)$ of positive and negative feedback pheromones are improved, and the improvement amounts of both are as follows:

$$\begin{cases}\Delta p'_{ij}\left(t\right)=\dfrac{\eta}{d_{best}}\times\left(1-\varepsilon\times\dfrac{d_{ij}}{d_{best}}\right)\\ \Delta\delta'_{ij}\left(t\right)=\dfrac{\eta}{d_w}\times\left(1+\varepsilon\times\dfrac{d_{ij}}{d_w}\right)\end{cases} \tag{24}$$

In Equation (24), ε represents the amplification factor of the path factor; d_w represents the worst path within the current loop; μ represents the path magnification factor.

Optimization Solution of TSP

In order to enable two ant populations to discover more potential high-quality solutions and ultimately find higher quality TSP solutions, two paths are obtained for the two populations, and a path contribution evaluation mechanism is introduced to screen for the better path.

The calculation equation for path contribution degree C is as follows:

$$C=\frac{d_a}{d_{best}} \tag{25}$$

Analyzing the complexity of pheromone updates in the above process, it is mainly reflected in the following aspects: Firstly, the mechanism introduces a dual population strategy, where population 1 adopts the elite ant strategy and population 2 adopts the enhanced sub path evaluation mechanism. This parallel search method significantly increases the exploration space of the algorithm, but also brings about the complexity of pheromone updates. Population 1 and Population 2 need to maintain their respective pheromone matrices and update them according to their respective strategies during the iteration process, which increases the consumption of computing resources; Secondly, the update of pheromones not only depends on the path length of the current ant, but also considers parameters such as the proportion of elite ants and the amplification factor of path factors. The introduction of these parameters makes the pheromone update formula more complex, but also improves the algorithm's global search ability and ability to escape from local optima; In addition, the real-time data-driven pheromone reset mechanism enables the algorithm to dynamically adjust the distribution of pheromones according to changes in the external environment, further increasing the complexity and adaptability of the algorithm. However, it also puts higher demands on the real-time performance and data accuracy of the algorithm.

In summary, using the dual population ant colony algorithm based on path contribution evaluation to solve the mathematical model of TSP, the specific steps are as follows:

Step 1: Parameter initialization;

Step 2: In the directed weighted graph, randomly select two cities as the starting points for populations A and B;

Step 3: For groups 1 and 2, calculate the state transition probability of ant a using Equations (19) and (23) respectively, and store the unselected cities in the set of candidate cities;

Step 4: Improve population 1 through elite ant strategy and improve population 2 through strengthened sub path evaluation mechanism. Store the optimal solutions and corresponding path lengths d_1 and d_2 for the two populations in the current loop separately;

Step 5: Update pheromones for two populations using Equations (21) and (24) respectively;

Step 6: By collecting port congestion index (number of waiting ships in anchorage, utilization rate of loading and unloading equipment), meteorological and sea condition data (wind speed, wave height), and fuel price fluctuation data, a dynamic factor matrix is formed. When the dynamic factor of a certain flight segment exceeds the preset threshold, the local pheromone reset is immediately triggered, and the pheromone is updated again using Equations (21) and (24);

Step 7: Using the evaluation criteria for path contribution, compare and analyze d_1 and d_2, and select the path with higher contribution as the global optimal path length d_{best};

Step 8: Analyze whether d_{best} continues to update. Continue updating, jump back to step 2; If no longer updated, output the optimal solution of TSP. d_{best} is the shortest path connecting all cities in the directed weighted graph.

The specific way in which the improved ant colony algorithm jumps out of local optima is as follows:

(1) Parallel search and independent evolution: The dual population mechanism introduces two independent ant populations for parallel search. This parallelism enables the algorithm to simultaneously explore multiple potential optimal solutions in the solution space, thereby increasing the likelihood of discovering the global optimal solution. Two populations adopt different strategies for evolution. Population 1 adopts the elite ant strategy, focusing on utilizing existing information to quickly converge; And population 2 adopts a strengthened sub path evaluation mechanism, focusing on exploring new solution spaces. This independence ensures that each population can explore deeply within its specific search area, reducing dependence on the search process of other populations.

(2) Elite Ant Strategy and Rapid Convergence: Population 1 adopts the Elite Ant Strategy, which updates pheromones by retaining and utilizing the optimal solution (Elite Ant) in each iteration. This strategy helps Population 1 to quickly converge to a local optimal solution, especially when there are clearly advantageous regions in the solution space. Meanwhile, the continuous exploration of population 2 provides an opportunity for the algorithm to escape from local optima.

(3) Enhanced sub path evaluation mechanism and global exploration: Population 2 adopts an enhanced sub path evaluation mechanism to update pheromones by calculating the contribution of sub paths. This mechanism enables population 2 to explore unknown regions in the solution space more deeply, thereby discovering new potential optimal solutions. When population 1 falls into a local optimum, population 2 uses its global exploration ability to discover a new path to the global optimum. This ability is achieved through a strengthened sub path evaluation mechanism, which can accurately assess the contribution of different sub paths and update pheromones accordingly, guiding ants to evolve towards a better path.

(4) Path contribution evaluation mechanism and global optimal selection: By comparing the path contribution of two populations, the algorithm selects the path with higher contribution as the global optimal solution. This mechanism ensures that the algorithm always evolves towards the global optimal solution during the convergence process, rather than staying at a local optimal solution.

(5) Real time data-driven pheromone reset mechanism: The algorithm also introduces a real-time data-driven pheromone reset mechanism. When real-time data (such as port congestion index, meteorological and sea condition data, fuel price fluctuation data, etc.) undergoes significant changes, this mechanism can adjust the distribution of pheromones in a timely manner, guiding ants to explore new paths. This dynamic adaptability enables the algorithm to quickly respond to changes in the external environment, thereby avoiding getting stuck in local optima caused by environmental changes.

2.6 Optimization of shipping logistics routes

Using the improved ant colony algorithm mentioned above, solve the objective function in Equation (18) to obtain the optimal shipping logistics path. The solving process is as follows:

Step 1: Parameter initialization.

Initialize various parameters in ant colony algorithm, including ant count, initial pheromone value, pheromone residual factor, pheromone volatilization factor, heuristic factor, elite ant count, amplification factor of path factor, maximum iteration times, etc.

Step 2: Build a directed weighted graph $G(V,D)$.

Construct a directed weighting graph based on the actual situation of the shipping logistics network. Using nodes in the graph to represent key locations of logistics ports, edges to represent transportation paths, and the weights of edges to be quantified based on factors such as distance, time, and cost. Due to the focus on factors such as distance, time, cost, and carbon emissions in this study, these factors were comprehensively considered and used as weights for the edges.

Step 3: Build a solution space.

Based on the characteristics of the shipping logistics network, considering factors such as the location of logistics ports, transportation distance, transportation time, transportation expenses, carbon emissions, and path reliability, a solution space is constructed that includes all possible paths. This solution space will serve as the search range for ant colony algorithm.

Step 4: Select the starting point.

In the directed weighted graph $G(V, D)$, arbitrarily select two cities (logistics ports) as the starting points for population 1 and population 2.

Step 5: Calculate the state transition probability of ants.

For each ant in population 1 and population 2, calculate the state transition probability $q_{ij}^{a}(t)$ using Equations (19) and (23) based on the current port and the set of candidate ports.

Step 6: Calculate the objective function value.

For each path generated by an ant in the current iteration, calculate its corresponding objective function value F according to Equation (18).

Step 7: Update the pheromone.

After each iteration, update the pheromone concentration on the path based on the ant's movement path and objective function value [21]. For population 1, according to Equation (21), the elite ant strategy is adopted to improve the updating method of pheromones, resulting in $p_{ij}(t+1)$; For population 2, according to Equation (24), a strengthened sub path evaluation mechanism is used to update the pheromones, obtaining the updated values $\Delta p_{ij}(t)$ and $\Delta\delta_{ij}(t)$ of positive and negative feedback pheromones, in order to ensure accurate division of the contribution of different sub paths in the solving process.

Step 8: Calculate the path contribution degree.

After each iteration, calculate the path contribution C of the two paths obtained from the two populations according to Equation (25), select the better path, and further adjust the pheromone concentration accordingly.

Step 9: Update the global best path.

Compare the contribution of two paths obtained from two populations, select the path with higher contribution as the global best path, and update the length of the global best path.

Step 10: Iterative search.

Repeat steps 3 to 7 for multiple iterations of the search. In each iteration, ants are guided to find a better path in the directed weighted graph based on the current pheromone concentration and state transition probability.

Step 11: Determine the termination condition.

Determine whether the global optimal path length d_{best} has been updated. If no longer updated, the shortest path connecting all cities within $G(V, E)$; Otherwise, return to step 3 to continue iterating.

Step 12: Output the optimal path.

After the algorithm stops, output the optimal shipping logistics path. The path should meet the objective function requirements of minimizing logistics transportation expenses, minimizing logistics transportation time, minimizing carbon emissions, and maximizing path reliability. At the same time, the path can be further optimized and adjusted according to actual needs.

3 Simulation experiment and result analysis

To verify the feasibility of the optimization method for shipping logistics paths based on evolutionary ant colony algorithm designed above, the following simulation experiments are designed.

3.1 Simulation experiment design

Before the experiment, the following designs were developed for two populations:

Population 1 uses the Elite Ant System for pheromone updates. In this population, the number of ants is 100, the proportion of elite ants is 0.3, the pheromone importance factor is 2.5, the heuristic function importance factor is 5.0, the pheromone intensity is 100, the proportion of elite ants is 0.3, and the pheromone volatilization rate is 0.25.

The sub path length threshold for population 2 is 5, the sub path contribution weight is 0.75, the negative feedback heuristic factor is 1.2, and all other parameters are the same as population 1.

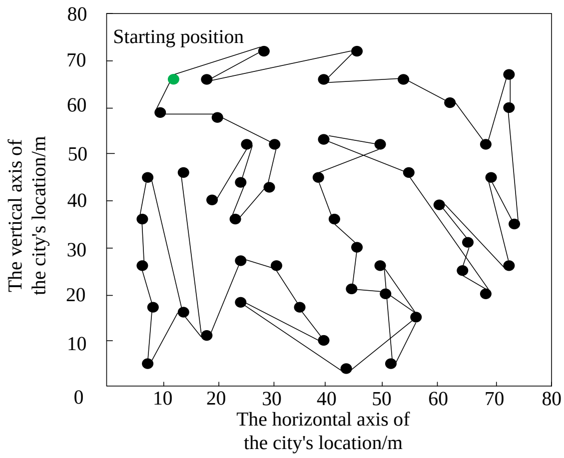
The parameter difference between the two populations is not randomly set, but a targeted design to meet their division of labor goals: Population 1 achieves rapid convergence through high heuristic weights, elite retention, and low pheromone volatilization; Population 2 achieves global search through sub path evaluation, negative feedback mechanism, and local exploration weights. Therefore, in addition to sampling the same parameter settings as population 1, additional sub path length thresholds and sub path contribution weights were set for population 2.

Assuming there are 50 cities (logistics ports), construct a directed weighted graph based on their geographical locations and transportation conditions.

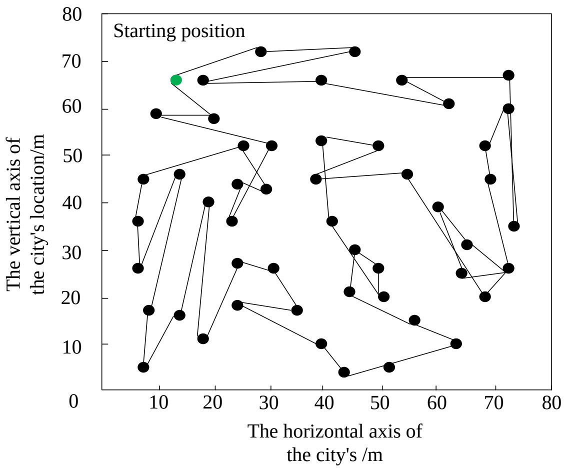
Using the method of this paper for solution analysis, the solution path analysis results are shown in Fig. 2.

From the analysis of Fig. 2, it can be seen that although both population 1 and population 2 can be used to solve the path scheme, after using the dual population ant colony algorithm, the path does not overlap or repeat. The solution path lengths for different algorithms are shown in Table I.

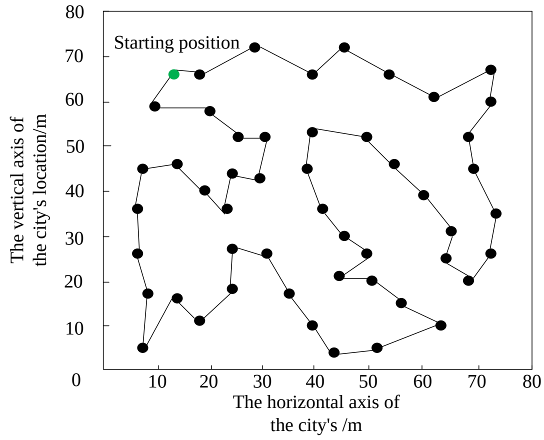
Based on the comprehensive analysis of Fig. 2 and Table I, it can be seen that the path length obtained by using only Population 1 or Population 2 is relatively long, while the path length obtained by using the dual population ant colony algorithm is significantly shorter, indicating the effectiveness of the improved ant colony algorithm proposed in this paper.



(a) Analysis results of solving population 1



(b) Analysis results of solving population 2



(c) Analysis and solution results of dual population ant colony algorithm

Figure 2: The solution result of the algorithm

Table 1: The path length for solving different algorithms

Algorithm	The length of the path/$\times 10^6$ nautical mile	Pheromone level
Population 1	468	85.0
Population 2	523	70.2
Dual population ant colony algorithm	407	95.3

On this basis, the convergence curves of using only population 1, only population 2, and the dual population ant colony algorithm are shown in Fig. 3. By comparing the optimal path cost during the iteration process of different algorithms, the efficiency of different algorithms is compared.

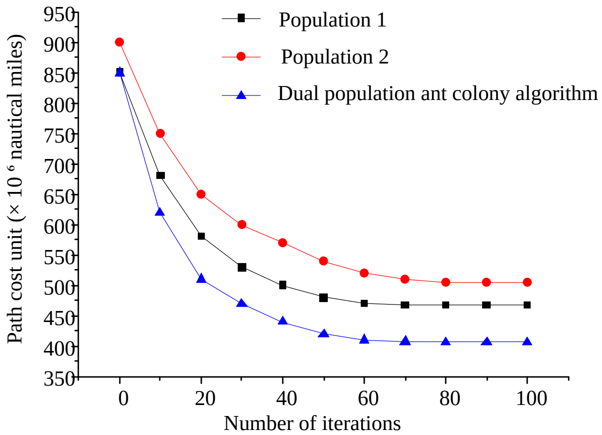


Figure 3: Comparison of optimal path costs in different algorithm iterations

Observing Fig. 3, it can be seen that the dual population algorithm has the advantage of parallel search, and its initial value is similar to that of population 1. Population 1 rapidly declines (first 30 iterations) but subsequently falls into local optima; Population 2 has a slow convergence rate, but continues to explore new solutions and has not reached the global optimum. The dual population algorithm combines fast convergence and continuous exploration to ultimately achieve the optimal value, and the convergence speed is significantly faster than that of a single population. After 50 iterations, the dual population algorithm is approaching the final solution, while there is still a significant gap between the individual populations. After 80 iterations, all algorithms tend to stabilize, and the dual population mechanism exhibits global optimality.

3.2 Comparative analysis of application effects

Design of simulation experiment environment

The experimental simulation starts from port A in China and ends at port R in the United States, passing through 16 dockable ports from B to Q. These ports are distributed in different countries and regions, representing key nodes in the shipping logistics path. Among them, C, H, M, and P are ports that must be stopped.

By optimizing the path, we aim to minimize transportation costs, minimize transportation time, minimize carbon emissions, and maximize path reliability.

Design of simulation experiment parameters

The ship and navigation parameters are set as follows: the ship type is a Cape of Good Hope container ship, the ship load is 150000 tons, the ship speed is 15 nautical miles per hour, and the daily navigation distance is 360 nautical miles.

The fuel consumption parameters are set as follows: the container ship used for simulation belongs to the Cape of Good Hope ship type, with an average load of 150000 tons. The daily fuel consumption during ship navigation is 48.5 tons/day, and the daily fuel consumption during berthing is 3.81 tons/day. Calculate $965 per ton of fuel based on the average fuel cost in 2024. In the simulation experiment, the ship is set to refuel at least once, with priority given to docking or anchoring for refueling.

The container and port operation parameters are set as follows: the maximum container capacity is 15000 TEU, and the ratio of 20 size to 40 size containers is 1:1. Due to the inconsistent operating cost standards of various ports, for the convenience of calculation, the simulation experiment is estimated using the average value. The individual operating cost for a 20-size container is $45, and for a 40-size container it is $65

The carbon emissions and environmental parameters are set as follows: the carbon tax rate is set at an estimated intermediate value of $42.75/ton, and the carbon conversion factor for ship navigation fuel consumption is determined to be 3.25, which is used to calculate carbon emissions.

The environmental parameters are set as follows: In order to simulate the impact of maritime weather on shipping logistics, the experiment introduced weather condition parameters. Assuming there are varying degrees of sea conditions during the experiment, such as light waves, medium waves, large waves, etc., each sea condition will have different impacts on the vessel's sailing speed, fuel consumption, and safety reliability. The specific parameter settings are as follows:

Light waves: reduced sailing speed by 5%, increased fuel consumption by 2%, and reduced path reliability by 1%.

Mid wave: reduced sailing speed by 10%, increased fuel consumption by 5%, and reduced path reliability by 3%.

Big waves: reduced sailing speed by 15%, increased fuel consumption by 10%, and reduced path reliability by 5%.

The weather conditions will be randomly assigned to different flight segments to simulate the changes in sea conditions that may be encountered during actual navigation.

The additional fee and other parameter settings are as follows: The simulation experiment simulation additional fee mainly includes security fees, text fees, etc. There is not much difference in charges among major ports, so the standard is set at $102 per port. When constructing a directed weighting graph, distance, time, and cost (including fuel costs, port operation fees, carbon emission reductions, etc.) are comprehensively considered as the weights of edges. In addition, port loading and unloading delays are common uncontrollable factors in shipping logistics. To simulate this situation, the experiment set loading and unloading delay parameters. The specific parameter settings are as follows:

Normal loading and unloading: Complete loading and unloading operations according to the scheduled time.

Minor delay: loading and unloading time extended by 10%.

Serious delay: loading and unloading time extended by 30%.

Loading and unloading delays will be randomly assigned to different ports to simulate the delay situations that may be encountered in actual port operations. The setting of these parameters will help to more accurately evaluate the feasibility and reliability of different paths in actual shipping.

Path description

To avoid the singularity of experimental results, method of reference [4] and method of reference [5] were compared and validated against method of this paper in the same environment. Below are three methods for generating shipping logistics paths.

(A) The shipping logistics path generated by the method of this paper is as follows:

Path description:

Port A (starting point) → Port B (short stay) → Port C (stop, supply) → Port D (no stay) → Port E (short stay) → Port F (no stay) → Port G (no stay) → Port H (stop, supply) → Port I (short stay) → Port J (no stay) → Port K (short stay for equipment inspection) → Port L (no stay) → Port M (stop, supply) → Port N (no stay) → Port O (short stay) → Port P (stop, supply) → Port Q (no stay) → Port R (end point)

The duration of stay at each port is shown in Table II.

Table 2: Duration of stay at each port (method of this paper)

Port	Duration of stay
C	The vessel stays for 24 hours for cargo loading, unloading, and replenishment.
H	The vessel stays for 48 hours for deep replenishment and equipment maintenance.
M	The vessel stays for 36 hours for cargo transfer and necessary inspections.
P	The ship stays for 24 hours for final replenishment and cargo sorting.
Other ports	The average stay time does not exceed 12 hours.

Supply situation: Fuel, fresh water, and food supplies are provided at the four stopover ports of C, H, M, and P. Partial supply will be provided as needed at some temporary ports of stay (such as B, E, I, K, O).

(B) The shipping logistics path generated by method of reference [4] is as follows:

Path description:

Port A (starting point) → Port C (stopover, supply) → Port D (short stay) → Port E (no stay) → Port F (short stay) → Port G (no stay) → Port H (stopover, supply) → Port I (short stay) → Port J (stopover, unplanned supply) → Port K (no stay) → Port L (short stay) → Port M (stopover, supply) → Port N (no stay) → Port P (stopover, supply) → Port Q (no stay) → Port R (end point).

The duration of stay at each port is shown in Table III.

Table 3: Duration of stay at each port (method of reference [4])

Port	Duration of stay
C	The ship stays for 24 hours.
H	The ship stays for 36 hours.
J	The vessel is not scheduled to stay for 24 hours for replenishment (due to the inability to dock at the original planned port).
M	The ship stays for 24 hours.
P	The ship stays for 36 hours.
Other ports	The average stay time does not exceed 12 hours.

Supply situation: Supply will be conducted at ports C, H, M, and P. Due to unplanned stops at J port, supply costs have increased.

(C) The shipping logistics path generated by method of reference [5] is as follows:

Path description:

Port A (starting point) → Port B (short stop) → Port C (stop, supply) → Port D (no stop) → Port E (short stop) → Port F (stop, non essential supply) → Port G (no stop) → Port H (stop, supply) → Port I (no stop) → Port J (short stop) → Port K (stop, supply) → Port L (no stop) → Port M (stop, supply) → Port N (short stop) → Port O (no stop) → Port P (stop, supply) → Port R (end point).

The duration of stay at each port is shown in Table IV.

Table 4: Duration of stay at each port (method of reference [5])

Port	Duration of stay
C	The ship stays for 36 hours.
F	The vessel is not required to stay for 12 hours for replenishment.
H	The ship stays for 24 hours.
K	The ship stays for 24 hours for equipment inspection.
M	The ship stays for 36 hours.
P	The ship stays for 24 hours.
Other ports	The average stay time does not exceed 12 hours.

Supply situation: Supply will be conducted at ports C, H, K, M, and P. The non essential stay at Port F increases the cost and time of supply.

The difference between the necessity and non necessity of different methods for port stay in the above results is due to their optimization objectives and dynamic response capabilities. The necessary stops (C, H, M, P ports) are set as mandatory constraints by the experiment, and all methods must be followed. Non essential stops may arise due to different algorithm designs: this method dynamically avoids inefficient ports and reduces redundant stops through multi-objective optimization (minimizing expenses, time, carbon emissions, and maximizing reliability) and real-time pheromone reset mechanism; Reference [4] focuses on fuel cost as the core objective and relies on static models. When the original planned port is unavailable, it is forced to detour (such as J port) and increase non essential stops; Reference [5] focuses on the shortest distance and safety, ignoring the overall cost, resulting in suboptimal path selection (such as non essential supplies at F port). The method of this paper significantly reduces unnecessary stops due to its ability to balance multiple objectives and dynamic adjustments, while the comparative method performs poorly in terms of transportation efficiency, cost, and environmental friendliness due to its single objective or rigid model, making it difficult to balance complex constraints.

Comparative analysis

According to the above generated path optimization scheme, the total transportation time, total transportation expenses, and total carbon emissions after applying different methods were compared, and the results are shown in Table V.

Table 5: Comparison table of results

	Total transportation time/day	Total transportation expenses/USD	Total carbon emissions/ton
Method of this paper	41	1250000	11800
Method of reference [4]	50	1420000	13500
Method of reference [5]	48	1380000	13200

By comparing the paths generated by the three methods, it can be seen that the total transportation time of this method is 41 days throughout the entire experimental cycle, saving 9 days and 7 days respectively compared to the two existing methods; The total transportation expenses of this method is 1250000 USD, saving 170000 USD and 130000 USD respectively compared to the two existing methods; The total carbon emissions of this method are 11800 tons, saving 1700 tons and 1400 tons respectively compared to the two existing methods. It can be seen that Method of this paper outperforms Method of Reference [4] and Method of Reference [5] in terms of total transportation time, total transportation expenses, and total carbon emissions. The method of this paper effectively improves the global optimization capability of path optimization by introducing a dual population mechanism and a path contribution evaluation mechanism. Although the method of reference [4] considers fuel supply strategies, its path selection is relatively conservative, resulting in higher total transportation time and expenses. The method of reference [5] is designed for peak periods of maritime traffic, but its path optimization objective is relatively single and fails to comprehensively consider factors such as transportation costs and carbon emissions, resulting in slightly inferior performance compared to the method of this paper.

On this basis, 30 independent experiments were conducted on different methods in the same simulation environment, and the following indicators were recorded for each experiment: total transportation time, total transportation expenses, and total carbon emissions. Calculate the mean and 95% confidence interval (CI) of each method indicator, as shown in Table VI.

Table 6: Confidence interval validation

	Total transportation time (Mean ± CI)/day	Total transportation expenses (Mean ± CI)/USD	Total carbon emissions (Mean ± CI)/ton
Method of this paper	41±1.2	1,250,000±25,000	11,800±300
Method of reference [4]	50±2.1	1,420,000±35,000	13,500±450
Method of reference [5]	48±1.8	1,380,000±30,000	13,200±400

Compare the mean difference between the method proposed in this study and two comparison methods, and verify its significance (with a significance level of α =0.05).

Total transportation time: t=6.34, p<0.001 (significantly better than both methods)

Total transportation expenses: t=5.89, p<0.001 (significantly better than both methods)

Total carbon emissions: t=4.76, p<0.001 (significantly better than both methods)

Statistical tests show that the improvement of the method of this study in transportation time, cost, and carbon emissions is statistically significant (p<0.001). The confidence intervals are non overlapping, further supporting the stable advantage of our method on multiple objectives.

4 Discussion

An in-depth analysis of the experimental results is conducted, and the advantages and disadvantages of the two traditional methods are shown in Table VII.

Table 7: The advantages and disadvantages of traditional methods

Method	Method of reference [4]	Method of reference [5]
Advantage	Consider fuel supply strategy: Conduct in-depth research on the characteristics of grain shipping and the changes in fuel supply port oil prices over time and place, explore the relationship between fuel supply port oil prices and supply quantities, average oil prices and port service fees, and make fuel supply strategies more in line with actual operational situations, which can help reduce fuel costs. Constructing a path model that integrates integer programming: selecting fuel supply port selection, fuel supply quantity, and ship navigation route as key decision-making elements, the constructed model can comprehensively consider multiple factors and provide more comprehensive decision-making basis for path optimization.	Setting a comprehensive objective function: aimed at minimizing the length of the voyage, improving navigation safety, and ensuring smooth navigation, it helps to find relatively good ship diversion paths in complex maritime traffic peak environments, ensuring safe and smooth shipping operations. Multiple algorithms are used to solve the problem: the grid method is used to reproduce the ship operation status during peak maritime traffic hours, the improved genetic algorithm searches for the optimal ship diversion path planning scheme on a global scale, and the nonlinear programming technique further solves the local optimal solution, improving the accuracy and effectiveness of the solution.
Disadvantage Disadvantages	Conservative route selection: In order to reduce fuel	Single objective function: The objective function mainly

in total transportation time	costs or port service fees, longer routes or more transit ports may be chosen, which increases the total transportation time. Lack of consideration for time efficiency: Insufficient consideration of time efficiency has resulted in an inability to effectively balance transportation time and cost during path optimization.	focuses on the length of the voyage, navigation safety, and stability, without fully considering time efficiency, which may result in longer transportation time. Unbalanced transportation time and other factors: During the optimization process, transportation time was not well balanced with other factors that may affect transportation efficiency.
Disadvantages in total transportation expenses	Incomplete consideration of cost factors: Although fuel supply strategies have been considered, excessive emphasis on fuel and port service fees in route selection may overlook other potential cost factors, resulting in suboptimal total transportation expenses. Failure to conduct comprehensive cost optimization: Failure to conduct comprehensive optimization from the perspective of overall transportation costs may result in higher costs in certain situations.	Not considering cost factors comprehensively: The objective function is relatively single and does not take into account other cost factors such as fuel costs and port charges, which may result in suboptimal total transportation expenses. Lack of cost optimization mechanism: There is no effective cost optimization mechanism established in the method, which cannot reduce transportation costs as a whole.
Disadvantages in total carbon emissions	The impact of route selection: longer routes will increase the distance traveled by ships, thereby increasing fuel consumption and leading to an increase in total carbon emissions. Lack of carbon emission considerations: The methods did not specifically optimize for carbon emissions, and carbon emission factors were not fully considered in path selection and transportation decisions.	The impact of route length: Although minimizing the length of the route can reduce certain costs, longer routes will increase the distance traveled by ships, increase fuel consumption, and lead to an increase in total carbon emissions. Lack of carbon emission optimization objectives: Carbon emissions were not included as one of the optimization objectives in the method, and carbon emission factors were not fully considered in path planning.

The method of this paper introduces a dual population mechanism to improve the conventional ant colony algorithm and applies it to optimize shipping logistics paths, effectively solving multiple key problems of traditional methods. On the one hand, conventional ant colony algorithms are prone to getting stuck in local optima in complex shipping networks and are sensitive to initial parameters. The improved algorithm enhances global search capability and parameter robustness through a dual population mechanism, reducing the risk of getting stuck in local optima and improving the adaptability and stability of the algorithm. On the other hand, traditional algorithms usually focus on single objective optimization, which makes it difficult to balance multiple objectives such as logistics transportation expenses, transportation time, carbon emissions, and path reliability. The improved algorithm sets up a multi-objective function to achieve trade-offs and coordination between various objectives, and can generate multiple Pareto optimal solutions, providing decision-makers with more comprehensive path selection and meeting the needs of different scenarios. In addition, the shipping logistics network structure is complex, and the improved ant colony algorithm abstracts it as a set of nodes and edges in graph theory, simplifying the network structure and providing a clear search framework for the algorithm, improving its efficiency and feasibility.

However, although the method of this paper has shown significant advantages in transportation time, cost, and carbon emissions, there are still significant bottlenecks in its computational complexity. As the number of port nodes increases, the algorithm needs to maintain pheromone matrices and parallel search mechanisms for two independent populations, resulting in exponential growth in memory usage and computational complexity. Especially when dealing with multi-objective optimization involving time window constraints, port capacity limitations, etc., the algorithm requires a large number of iterations to balance the weight relationships between different objective functions, which reduces the feasibility of real-time dynamic path adjustment. In addition, algorithms are sensitive to parameter settings, such as pheromone volatilization factor, elite ant ratio, and other key parameters that need to be finely tuned for different shipping scenarios, otherwise it may lead to premature convergence of population 1 or low exploration efficiency of population 2. The setting of threshold parameters in the path contribution evaluation mechanism also lacks universal standards, which may lead to path evaluation bias in extreme weather or sudden port closures and other abnormal situations.

Another potential issue is that the improved ant colony algorithm based on the method of this paper has a strong dependence on the quality of input data. When there is noise or update delay in basic data such as distance between ports and fuel prices, the "optimal path" generated by the algorithm may have significant deviations in actual execution. For example, in the experiment, it is assumed that the operating costs of each port are estimated using the average value, but in reality, the difference in charging standards between different ports may be as high as 30%, which will directly affect the accuracy of achieving the goal of minimizing transportation costs. In addition, although the dual population mechanism improves the global search capability, the pheromone synchronization mechanism between the two populations may cause unstable convergence speed of the algorithm, especially when dealing with ultra large scale networks with more than 100 nodes, the computation time may exceed the time window limit of shipping scheduling. These limitations indicate that this method is more suitable as an offline planning tool, leveraging its advantages in scenarios with high data quality and sufficient computing resources.

In addition, in the real-time data fluctuation environment, the method based on evolutionary ant colony algorithm adopted in this study demonstrates certain dynamic adaptability by introducing real-time data-driven pheromone reset mechanism and path contribution evaluation mechanism. When real-time data (such as port congestion index, meteorological and sea condition data, fuel price fluctuation data, etc.) undergoes significant changes, these pheromones reset mechanisms can adjust the distribution of pheromones in a timely manner, guide ants to explore new paths, and to some extent cope with the uncertainty brought by data fluctuations. However, excessive or frequent fluctuations in real-time data may also have a negative impact on the performance of this method. For example, sudden changes in extreme weather conditions may lead to a significant increase in port loading and unloading delays or forced route adjustments, requiring algorithms to respond quickly and re plan their routes. In this case, the convergence speed and solution quality of the algorithm may be affected to some extent. However, overall, this method exhibits certain dynamic adaptability and robustness under real-time data fluctuations, but further optimization and testing are still needed to improve its stability and performance under extreme or frequent fluctuations. In addition, continuous monitoring and adjustment of algorithm parameters can also help improve its performance under real-time data fluctuations.

5 Conclusion

This study used an improved ant colony algorithm to solve the optimization problem for shipping logistics paths. The method designed in this study not only considers the advantages of traditional ant colony algorithm, but also improves the search efficiency and global optimization ability of the algorithm by introducing dual population mechanism and path contribution evaluation mechanism. The final optimal shipping logistics path can effectively reduce transportation costs, shorten transportation time, reduce carbon emissions, and improve the reliability of the path in practical applications, providing a scientific and efficient path planning solution for shipping logistics enterprises.

In the next stage of research, it may be considered to integrate the results of this study with AIS data. AIS data can provide real-time information on route congestion, weather, and sea conditions. However, in integration, AIS data streams require low latency processing, which requires algorithms to support incremental updates rather than full iteration. Based on your experience, it is necessary to further optimize the algorithm iteration frequency (such as reducing it from hourly level to minute level) and enhance noise robustness.

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Appendix

Pseudocode for the iterative process of the evolutionary ant colony algorithm

```
Input: Directed weighted graph G, parameters
Output: Global optimal path P_global

Initialize:
  - Pheromone matrices for Population 1 and 2
  - Heuristic matrix based on edge weights (distance, cost, etc.)
  - Global best path P_global ← null
  - Dynamic data monitoring module (port congestion, weather, fuel prices)

For iter in 1 to max_iter:
  // Parallel search for two populations
  For each population k in {1, 2}:
    For each ant m in population k:
      P_m ← ConstructPath
      Calculate objective function using Eq. (18)
    End For

    // Update pheromones for each population
    If k == 1:
      Update using Elite Strategy (Eq. 21-22):
     Else:
      Update using Enhanced Subpath Evaluation (Eq. 24):
    End If

    // Store local best paths
    P_k_best ← SelectBestPath(population k)
  End For

  // Path Contribution Evaluation (Eq. 25)
  For each path in {P_1_best, P_2_best}:
    Calculate contribution_score
  End For

  // Update global best path
  P_candidate ← argmax(contribution_score(P_1_best), contribution_score(P_2_best))
  If F(P_candidate) < F(P_global) or P_global == null:
    P_global ← P_candidate
  End If

  // Real-time Data-Driven Pheromone Reset
```

```
    For each edge (i, j) in G:
        If dynamic_factor(i, j) > threshold (e.g., congestion,
weather risk):
            Reset to initial values
        End If
    End For

    // Termination Check
    If no improvement for 10 consecutive iterations:
        Break
    End If
End For

Return P_global

Function ConstructPath:
    Initialize path P with random start node
    While not all nodes visited:
        Next node selection using state transition probability:

        Add next node to P
    End While
    Return P
```