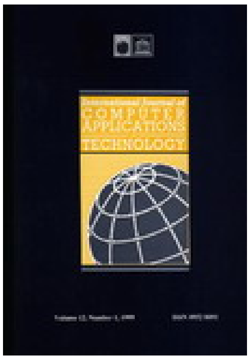

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Study on 'Road to Waterway' model for medium to long-distance cargo transportation considering transportation efficiency

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Abstract: This paper studies a 'Road to Waterway' model for medium and long-distance cargo transportation with consideration of transport efficiency. First, addressing the time-sensitive requirements of high-value-added cargo transportation faced by multimodal operators, a 'Road to Waterway' model for medium and long-distance transportation is developed. Second, through cost analysis that quantifies various expenses while establishing objective functions and constraints, the model ensures reasonable transportation mode selection, transit connections and flow balance. Finally, employing genetic algorithms to generate initial solutions and maintain population diversity, combined with ant colony algorithm's positive feedback mechanism for optimal solution search, the model demonstrates significantly improved solving efficiency and time performance. Experimental results indicate a stable on-time arrival rate exceeding 97.7% and cost savings reaching 9.3%.

Keywords: transportation efficiency; medium to long distance; freight transportation; 'Road to Waterway' model.

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1 Introduction

With the continuous development of China's economy and optimisation of industrial layout, the demand for medium and long-distance freight transportation is showing a rapid growth trend (Zheng et al., 2022). The current high proportion of road transportation has led to a series of prominent problems: high transportation costs, with data showing that road transportation costs are more than 30% higher than waterway transportation (Hu et al., 2021). Energy consumption continues to rise, with road transportation consuming 5 to 7 times more energy per unit than water transportation. Environmental pollution is becoming increasingly severe, with carbon emissions from road freight accounting for over 40% of the total transportation sector (Lu et al., 2021). At the same time, significant progress has been made in the construction of inland waterway networks, and the navigation conditions of main waterways such as the Yangtze River Golden Waterway have continued to improve, creating a good foundation for the development of waterway transportation (Guo et al., 2023). However, the industry still faces key challenges such as insufficient optimisation of transportation structure, poor connection of multimodal transport and bottlenecks in water transportation timeliness. In this context, it is urgent to establish a scientific 'revolving water' transportation decision-making model, systematically evaluate the economic and feasibility of transportation mode conversion and provide decision support for promoting the green and low-carbon development of the logistics industry (Liu, 2023).

Duan and Li (2022) proposed a 'Road to Waterway' method for cargo transportation based on an improved immune optimisation algorithm, which uses a three parameter Weibull distribution model to characterise the dynamic deterioration and loss of goods during cold chain transportation, and constructs a transportation optimisation framework aimed at minimising overall transportation costs. By improving the immune optimisation algorithm with the dual search mechanism of particle swarm optimisation, the solving efficiency of the algorithm has been accelerated. Although the study used a three parameter Weibull distribution model to characterise the dynamics of item deterioration and loss, the impact of external environmental factors involved in cold chain transportation, such as temperature fluctuations, humidity changes and transportation equipment performance, on item deterioration may far exceed the assumptions of the model. Yang et al. (2024) proposed a 'Road to Waterway' method for cargo transportation based on an improved sand cat swarm optimisation algorithm, and develops a logistics integrated intermodal transportation system model. Based on the intelligent optimisation strategy of sand cat swarm, the initial layout of sand cat individuals is optimised using random scattering method and *K*-means clustering technology, while incorporating the principles of particle collaborative operation and random walking path planning. Although research has proposed a 'Road to Waterway' method for cargo transportation based on improved sand cat swarm optimisation algorithm and integrated multiple optimisation strategies, its effectiveness and superiority in practical logistics scenarios have not been verified through actual cases or comparative experiments with other optimisation algorithms such as genetic algorithm, ant colony algorithm, etc. Zhang and Han (2023) proposed a 'Road to Waterway' model method for cargo transportation based on multi-objective fuzzy chance constraint planning, and constructed a multi-objective fuzzy random constraint model. The constant crossover and mutation rates directly affect the convergence performance of the algorithm. To solve this problem, an adaptive mechanism was combined with the non-dominated sorting genetic algorithm NSGA-II, and the effectiveness of the model and algorithm was verified by comparing it with DOCPLEX and the standard NSGA-II. Although a multi-objective fuzzy random constraint model was constructed and optimised using adaptive mechanisms and non-dominated sorting genetic algorithm NSGA-II, the setting of fuzzy chance constraints may be too idealised and fail to fully consider the complex uncertainties and dynamic changes in actual highway waterway intermodal transportation, such as transportation delays, weather effects, equipment failures, etc.

In response to the problems in existing research methods, this paper conducts a study on the 'Road to Waterway' model of medium to long-distance cargo transportation considering transportation efficiency. The detailed research framework of this model is as follows:

1) A multi-objective optimisation framework was constructed by integrating transportation costs, time value and carbon emission costs through the system. This model innovatively introduces a quantitative mechanism for the decay of the time value of goods, incorporating the economic losses of high efficiency sensitive goods into the path decision-making system, making up for the shortcomings of traditional transportation optimisation that only focuses on explicit costs, and providing a more comprehensive theoretical support for the comprehensive cost evaluation of multimodal transportation.

2) The model has significant practical application value in constraint condition design. By strictly limiting the selection of a single transportation method for adjacent nodes, imposing hard constraints on transit operation time and implementing flow balance rules, the integrity of cargo transportation is ensured, and the fine matching of road and waterway transportation resources is achieved. This modelling approach that balances system feasibility and operational standardisation is particularly suitable for addressing the multiple demands of timeliness, economy and environmental friendliness for high-value goods in medium to long-distance transportation.

3) The proposed genetic ant colony hybrid algorithm generates high-quality initial solutions and maintains population diversity through genetic algorithms, effectively overcoming the low efficiency caused by the lack of pheromones in the early stages of traditional ant colony algorithms. The algorithm utilises the global

search capability of genetic algorithm to quickly locate the advantageous regions in the solution space, and then achieves precise optimisation through the positive feedback mechanism of ant colony algorithm, significantly improving the accuracy and convergence speed of the solution. The innovative binary encoding scheme and dynamic termination conditions not only ensure the complete expression of transportation paths and modes, but also achieve seamless integration of the two algorithms, providing an efficient intelligent decision-making tool for optimising medium and long-distance multimodal transportation paths.

2 The 'Road to Waterway' model for medium to long-distance cargo transportation

Figure 1 illustrates a multimodal transport structure comprising key stakeholders: shippers and consignees as demand endpoints, diverse transport providers (road carriers, shipping lines, terminal operators) executing segmented operations with coordinated stage transitions, government regulators (customs, quarantine, maritime safety administrations) overseeing the supply chain and intermodal organisers performing system integration through route design, resource coordination and risk assumption (Xu and Rong, 2022).

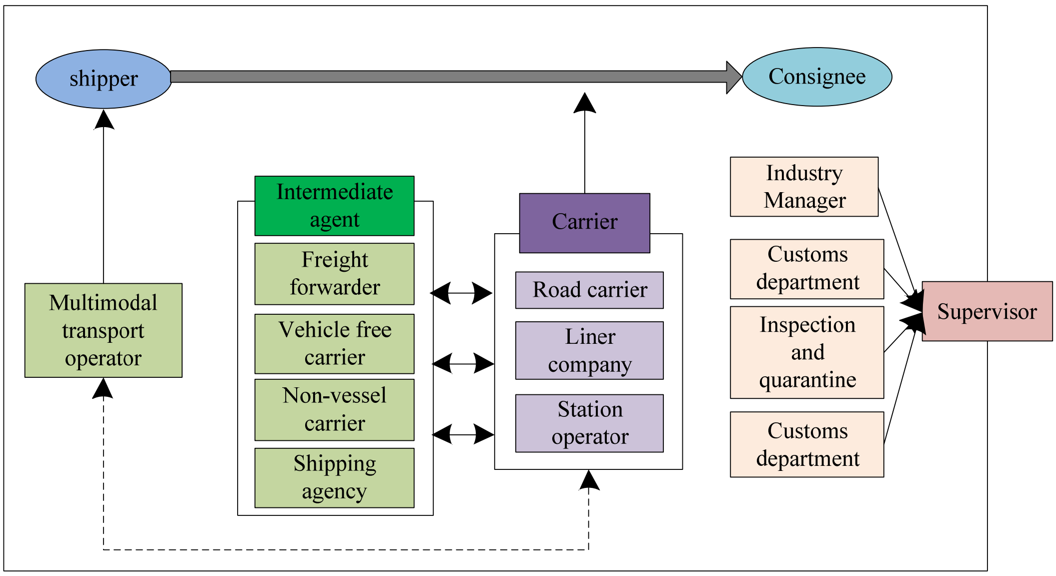
A multimodal transport operator has taken over a shipment of goods that are highly sensitive to both time and value. These goods need to be transported through a comprehensive transportation path $G(N, A, K)$ that integrates roads and waterways, passing through multiple transfer points (quantity N) from the starting station O until reaching the destination D. In this process, A represents the set of transportation routes connecting any two stations, while K encompasses a variety of available transportation modes. It is worth noting that the transportation distance, time, cost and carbon emissions between any two stations may vary depending on the selected transportation method. Given that fluctuations in actual demand have affected the choice of waterway transportation for high-value time sensitive goods, resulting in significant differences in the time value loss of various transportation routes, it is necessary to develop a 'Road to Waterway' model for medium to long-distance cargo transportation (Goldman and Trevisan, 2024). This model aims to find the waterway transportation solution with the lowest comprehensive cost composed of transportation costs, cargo time costs and carbon emission costs. At the same time, it is necessary to consider the fixed operating time constraints of the transit station transportation mode and the hard time constraints of the destination transportation time, to ensure that the selected path meets both cost and time standards. For the convenience of model construction, the following prerequisites are preset:

1) During the transportation and transit of goods, their integrity must be maintained and they cannot be split or transported in batches. Only a single transportation method can be selected between adjacent stations to complete the transportation task.

2) For each node, its available transportation options are limited to a maximum of two: road or waterway, excluding options for railway, air and pipeline transportation.

3) The transfer stations and their optional logistics methods have sufficient cargo handling capabilities to meet various transportation needs.

Figure 1 Schematic diagram of multimodal transport participants (see online version for colours)



During business operations, upon receiving a shipper's transportation request, the multimodal transport operator develops a customised transportation plan based on specific requirements and available resources for shipper review. Mutual agreement leads to contract signing, wherein the shipper fully delegates transportation operations to the operator who assumes complete responsibility. Post-contract execution, the operator directly or via agents establishes segmented transportation contracts with carriers according to the approved plan (Kammammettu et al., 2024). Throughout transportation execution, the operator supervises strict contract compliance by carriers and agents to ensure successful task completion, while these parties maintain contractual obligations to the operator.

2.1 *Optimisation of multimodal transportation routes*

2.2 *Multiple cost constraints*

(1) *Transportation cost*: The logistics cost mainly consists of two parts: the cumulative transportation costs between nodes and the total transit costs incurred by switching transportation modes at nodes. The calculation formula is expressed as:

$$C_y = Q \cdot \left(\sum_{i,j \in N} \sum_{k \in K} c_{ij}^k \cdot d_{ij}^k \cdot x_{ij}^k + \sum_{i \in N} \sum_{k,l \in K} c_i^{kl} \cdot y_i^{kl} \right) \tag{1}$$

In the formula, i and j represent city nodes; k, l means of transportation, $K = \{k,l \mid k,l = 1,2\}$,1 - road, 2 - water; C_y stands for transportation cost; Q represents the demand for goods; c_{ij}^k represents the unit transportation cost of the *k*-th mode of transportation; d_{ij}^k represents the distance between nodes i and j for selecting the *k*-th mode of transportation; c_i^{kl} represents the unit transit cost converted from transport mode k to transport mode l at node i; x_{ij}^k represents the decision variable, which means that the transport mode k between nodes i and j is 1, otherwise it is 0. y_i^{kl} represents the decision variable, which means that the transformation from the k mode of transport to the l mode of transport at node i is 1, otherwise it is 0.

(2) *Time value cost of goods*: The time value cost of goods quantifies value depreciation during logistics processes caused by temporal factors, primarily through transportation duration that progressively diminishes original economic worth. This metric captures commodity value attenuation in supply chains. Road transport offers superior timeliness but incurs elevated costs and carbon emissions; conversely, waterway transport demonstrates lower timeliness yet provides substantial economic and environmental advantages. Transportation duration directly influences time value costs: time-sensitive commodities with higher depreciation rates favour road transport, while low-sensitivity goods with reduced temporal demands prefer waterways. A 'Road-to-Waterway' optimisation model enables quantitative analysis of timeliness-cost relationships, facilitating transportation route selection that balances economic and environmental objectives.

The calculation formula for the time value cost of goods is:

$$C_h = Q \cdot \lambda \cdot G \cdot \frac{T_Z}{24} \tag{2}$$

In the formula, λ refers to the average proportion of daily value reduction; G is the original economic value of the goods themselves; T_Z is the total time it takes for the goods to travel from the starting point to the destination.

The calculation formula for T_Z is:

$$\begin{aligned} T_Z &= t_{ij}^k + t_c^k + w_i^k \\ &= \sum_{i,j \in N} \sum_{k \in K} \left\{ \frac{d_{ij}^k}{\overline{v}_k} \cdot x_{ij}^k + Q \cdot t_i^{kl} \cdot y_i^{kl} + \left(w_{i1}^k + w_{i2}^k \right) \cdot x_{ij}^k \right\} \end{aligned} \tag{3}$$

In the formula, t_{ij}^k is used to describe the total time it takes for goods to be transported; t_c^k refers to the time required for goods to switch between different modes of transportation; w_i^k represents the cumulative dwell time of transportation mode k at node i; $\overline{v}_k$ is the average transportation speed of transportation mode k; t_i^{kl} represents the transit time for each transition from transportation mode k to transportation mode l at node i (Shi et al., 2021).

The total waiting time w_i^k is influenced by both the arrival time of the goods at the node and the departure time of subsequent transportation vehicles, and can be further divided into connecting waiting time and departure waiting time. Its mathematical expression is as follows:

$$w_{i1}^k = \begin{cases} \varphi_i^{\min} - S_i, \; S_i < \varphi_i^{\min} \\ 0, \varphi_i^{\min} \le S_i \le \varphi_i^{\max} \\ \varphi_i^{\min'} - S_i, \; \varphi_i^{\max} < S_i < \varphi_i^{\min'} \end{cases} \tag{4}$$

$$w_{i2}^k = \begin{cases} \varphi_i^{\max} - Q \cdot t_i^{kl} - \varphi_i^{\min}, S_i < \varphi_i^{\min} \\ \varphi_i^{\max} - S_i - Q \cdot t_i^{kl}, \varphi_i^{\min} \le S_i \le \varphi_i^{\max} \\ \varphi_i^{\max'} - Q \cdot t_i^{kl} - \varphi_i^{\min'}, \varphi_i^{\max} < S_i < \varphi_i^{\min'} \end{cases} \tag{5}$$

In the formula, w_{i1}^k and w_{i2}^k represent the arrival and departure times of transportation mode k at node i, respectively; $\varphi_i^{\min}$ and $\varphi_i^{\max}$, respectively represent the specific times when transportation mode k arrives at node i and leaves node i; $\varphi_i^{\min'}$ and $\varphi_i^{\max}$, respectively refer to the specific time when the next train of transportation mode k arrives at node i and departs from node i; S_i represents the actual time point when the goods arrive at node i.

According to the above analysis, the total dwell time of goods at the node can be expressed by the following formula:

$$w_i^k = \begin{cases} \varphi_i^{\max} - Q \cdot t_i^{kl} - S_i, S_i < \varphi_i^{\min} \\ \varphi_i^{\max} - S_i - Q \cdot t_i^{kl}, \varphi_i^{\min} \le S_i \le \varphi_i^{\max} \\ \varphi_i^{\max'} - Q \cdot t_i^{kl} - S_i, \varphi_i^{\max} < S_i < \varphi_i^{\min'} \end{cases} \tag{6}$$

(3) *Carbon emission cost*: Regarding the issue of carbon emissions, the core lies in measuring the total amount of carbon dioxide released during transportation and transit loading and unloading processes. The specific calculation method is as follows:

$$C_t = Q \cdot \left(\sum_{i,j \in N} \sum_{k \in K} e_{ij}^k \cdot d_{ij}^k \cdot x_{ij}^k + \sum_{i \in N} \sum_{k,l \in K} \mu_i^{kl} \cdot y_i^{kl} \right) \tag{7}$$

In the formula, e_{ij}^k refers to the carbon dioxide emissions per unit distance of transportation mode k operating between nodes i and j; μ_i^{kl} represents the amount of carbon dioxide released per unit operation when node i switches transportation mode k to l.

2.3 Objective function construction

In summary, the mathematical expression of the objective function of the 'Road to Waterway' model for cargo transportation determined by demand can be expressed as:

$$\min Z = \min\left(C_y + C_h + C_t\right) \tag{8}$$

The constraint conditions are as follows:

$$\sum_{k \in K} x_{ij}^k \le 1, \forall i, j \in N; \forall k \in K \tag{9}$$

$$\sum_{k,l \in K} y_i^{kl} \le 1, \forall i, j, n \in N; \forall k, l \in K \tag{10}$$

$$x_{ij}^k + x_{jn}^l \ge 2 y_i^{kl}, \forall i, j, n \in N; \forall k, l \in K \tag{11}$$

$$\sum_{i \in N} \sum_{k \in K} x_{ij}^k - \sum_{i \in N} \sum_{k \in K} x_{ji}^k = \begin{cases} -1, j = O \\ 0, j \ne O, D \\ 1, j = D \end{cases} \tag{12}$$

$$x_{ij}^k, y_i^{kl} \in \{0,1\}, \forall i, j \in N; \forall k, l \in K \tag{13}$$

$$S_i \ge 0, \forall i \in N \tag{14}$$

Among the above constraints, formula (9) stipulates that the transportation of goods between adjacent nodes can only be carried out using a single method; formula (10) indicates that only one mode of transportation can be selected at node i, including maintaining the original mode or switching to another mode; formula (11) ensures seamless connection between different modes of transportation and guarantees the continuity of the transportation process; formula (12) reflects the traffic balance limitation of intermediate nodes; formula (13) limits the decision variable to 0 or 1; formula (14) imposes explicit constraints on the range of variable values.

3 Model solving of genetic ant colony algorithm

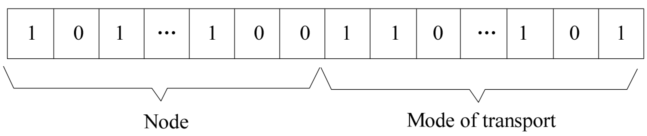
Ant colony optimisation achieves optimisation goals through simulated ant communication mechanisms, demonstrating advantages in positive feedback and distributed global optimisation, though initial-stage pheromone deficiency may reduce solving efficiency. Genetic algorithms employ clear global search logic but exhibit limited feedback utilisation, with solution space constraints leading to ineffective iterations that hinder accuracy improvement speed.

The hybrid algorithm compensates for individual shortcomings by combining strengths through sequential evaluation of individual order values, with the top 20% selected for initial solution generation leveraging genetic algorithms' random search, fast convergence and global optimisation capabilities. To maintain population diversity, a subset of individuals is randomly selected from the remaining 80% to form the initial pheromone distribution for ant colony optimisation. The subsequent solution phase employs ant colony optimisation's positive feedback mechanism and high-precision characteristics, while carefully calibrated genetic algorithm iteration counts prevent premature termination or excessive computation. This synergistic approach significantly enhances solution efficiency and time performance by fully exploiting both algorithms' complementary advantages (Lohmann et al., 2022; Nguyen and Sakurai, 2024).

Randomly select transit nodes and transportation modes, generate waterway transfer paths, calculate their function values and sort them, select the top 20% of individuals to perform genetic operations and randomly generate *n* individuals from the bottom 80% to enter the next generation. The specific implementation steps of genetic algorithm are as follows:

Step 1 (Encoding): A binary system identifies each node and transportation method (detailed identification rules appear in Figure 2). Each chromosome contains two modules: in the site module, 0 and 1 indicate node bypass status; in the transportation route module, 0 and 1 correspond to road and waterway transportation methods, respectively.

Figure 2 Schematic diagram of chromosome encoding



Step 2 (Select): In order to ensure the smooth transmission of high-quality information to subsequent populations while maintaining the diversity of the gene pool, a roulette wheel screening mechanism is used for individual selection. The mathematical expression for its selection probability is as follows:

$$p(i) = \frac{f_{it}(i)}{\sum_{i=1}^{n} f_{it}(i)} \tag{15}$$

Step 3 (Cross over): To preserve optimal individuals in subsequent iterations and prevent failure to achieve global optimisation, a single-point crossover strategy is implemented by exchanging specific segments with selected parent individuals to generate new transportation plans. The single-point crossover schematic appears in Figure 3.

Figure 3 Schematic diagram of single point intersection

1	0	1	⋯	1	0	0	1	0
1	1	0	⋯	0	1	0	1	0

1	⋯	1	1	0
0	⋯	1	0	1

↓

1	0	1	⋯	1	0	0	1	0
1	1	1	⋯	0	1	0	1	0

0	⋯	1	0	1
0	⋯	1	1	0

Step 4 (Mutation): Using a single point mutation strategy, genes are modified with a specific probability in randomly selected individuals to generate new individuals.

To ensure seamless integration between genetic algorithm and ant colony optimisation, the genetic algorithm iteration process incorporates three control mechanisms: maximum iteration limit, population evolution rate monitoring, and offspring evolution rate threshold setting. When the population evolution rate remains below the minimum threshold within preset iterations – indicating substantially reduced optimisation efficiency– the system automatically terminates genetic algorithm execution and initiates ant colony optimisation.

Step 1 (Parameter initialisation): The new solution generated by genetic algorithm and the randomly generated solution jointly construct the pheromone matrix of the ant colony. At time point t, the amount of pheromones retained between nodes is represented by $\tau_{ij}(t)$. In the initial state, the set values of pheromones are:

$$\tau_{ij} = \tau_c + \tau_{g+r} \tag{16}$$

In the formula, τ_c represents a fixed value set based on a specific problem; τ_{g+r} refers to the pheromone value converted from the previous generation of individuals.

Step 2: Assign m ants to n nodes and have m ants randomly select a node as the next target for movement, as shown in:

$$p_{ij}^k = \begin{cases} \dfrac{\left[\bar{\tau}_{ij}\right]^\alpha \left[\eta_{ij}\right]^\beta}{\sum\left[\bar{\tau}_{ij}\right]^\alpha \left[\eta_{ij}\right]^\beta}, j \in tabu_k, \\ 0, \qquad j \in tabu_k \end{cases} \tag{17}$$

In the formula, η_{ij} represents heuristic information, reflecting the tendency of ants to move from position i to position j; α represents the influence of residual pheromones at positions i and j; β represents the weight of heuristic information; $tabu_k$ refers to the restriction list.

Step 3: Update the pheromone, requiring only the current optimal solution to be updated within a week. The path trajectory update rule is:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}^{best} \tag{18}$$

$$\Delta\tau_{ij}^{best} = \begin{cases} \dfrac{1}{C^{best}}, (i, j) \in T^{best} \\ 0, \qquad other \end{cases} \tag{19}$$

In the above formula, ρ represents the increase in pheromones and C^{best} represents the length of the optimal iterative path.

Output the best result and its corresponding objective function value, with the set maximum number of iterations as the end condition, and terminate the calculation when the algorithm reaches the maximum number of iterations.

The unique contribution of genetic algorithm in this study is reflected in the innovative integration of node selection and transportation mode decision-making through binary encoding, the use of roulette wheel selection mechanism to balance the preservation of high-quality genes and population diversity, and the single point crossover strategy effectively avoiding the loss of global optimal solutions. By dynamically monitoring the evolution rate, seamless integration with ant colony algorithm is achieved, and limiting the maximum number of iterations not only prevents invalid calculations but also ensures the quality of the initial solution. This design fully leverages the global search advantage of genetic algorithms and provides high-value initial pheromone distributions for subsequent ant colony algorithms. Its encoding structure and termination condition settings significantly improve the collaborative efficiency of the hybrid algorithm.

4 Test experiment

4.1 Experimental environment and data

In order to verify the effectiveness of the 'Road to Waterway' model for medium to long-distance highway freight transportation, a specific testing environment was constructed. The transportation route runs from Wuhan Port to Nanjing Port, with a distance of about 800 kilometres. The cargo consists of 100 tons of electronic products and a volume of 500 cubic metres. The road transportation distance is 200 kilometres, and the waterway transportation distance is 600 kilometres. Road transportation uses heavy-duty trucks with a load capacity of 20 tons per vehicle, requiring 5 vehicles to transport at a speed of 80 kilometres per hour. The fuel consumption is 30 litres per 100 kilometres, and the fuel price is 7 yuan per litre. The total economic cost of road transportation (only including fuel costs) is about 2100 yuan, and the carbon emissions are 504 kg CO_2. Waterway transportation uses inland vessels with a carrying capacity of 1000 tons, a speed of 12 knots, a fuel consumption of 50 tons/day (shared according to the actual proportion of transported goods), a fuel price of 3000 yuan/ton, a transportation time of 27 hours, an economic cost of 16875 yuan and a carbon emission of 450 kg CO_2. By comparison, waterway transportation takes longer, but has economic advantages in large-scale cargo transportation and lower carbon emissions.

In practical applications, the selection of road or waterway transportation requires comprehensive consideration of factors such as cargo characteristics, transportation distance, timeliness requirements and economic costs. For medium to long-distance large-scale cargo transportation, the 'Road to Waterway' model is a more economical and environmentally friendly choice, especially suitable for goods with lower timeliness requirements, while road transportation is more suitable for scenarios with higher timeliness requirements.

Assuming the population size of the genetic algorithm is set to 400, the path intersection probability is set to 0.85, the transition point mutation probability is set to 0.05 and the maximum iteration is 300 times. Set the number of ants to 400, the pheromone volatilisation rate to 0.15, the pheromone enhancement coefficient to 1.0, the heuristic information importance to 2.0 and the maximum iteration count to 300.

4.2 *Test plan and indicators*

Compare the method proposed in this paper with the methods in Duan and Li (2022) and Yang et al. (2024), using on-time delivery rate and cost savings rate as testing indicators.

- *On time arrival rate*: refers to the proportion of goods that successfully arrive at the destination according to the scheduled time requirements within a certain period of time. It reflects the timeliness and reliability of the transportation system, and is an important indicator for evaluating whether the transportation mode meets customer needs.
- *Cost saving rate*: refers to the proportion of transportation cost reduction achieved by transferring some or all of the goods from road transportation to waterway transportation. It reflects the economic advantages of waterway transportation over road transportation and is an important indicator for evaluating whether the transfer of transportation modes has economic benefits.

4.3 *Analysis of test results*

4.3.1 *On-time arrival rate*

The on-time arrival rate serves as a key indicator for measuring transportation system timeliness and reliability, directly impacting customer satisfaction and logistics efficiency. Testing enables quantitative comparison of timeliness differences between road and waterway transportation, providing data-driven support for transportation mode selection. Additionally, on-time arrival rate analysis helps identify transportation bottlenecks and risk factors (e.g., weather conditions, traffic congestion, port efficiency), thereby facilitating transportation plan optimisation and resource allocation. The on-time arrival rate test results for the three methods appear in Table 1.

Table 1 On-time arrival rate

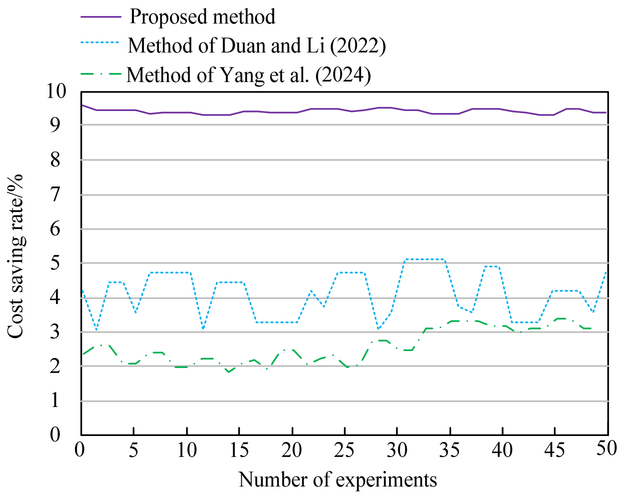
Number of tests	*On-time arrival rate/%*		
	Proposed method	*Duan and Li (2022) method*	*Yang et al. (2024) method*
5	98.2	85.3	76.8
10	97.9	80.1	72.5
15	98.5	88.7	79.4
20	98.1	82.6	74.1
25	97.8	79.3	70.9
30	98.4	87.2	78.5
35	98.2	81.4	73.6
40	98.3	84.9	75.2
45	97.7	78.8	69.7
50	98.6	89.1	79.8

From the 50th test data in Table 1, it can be seen that our method significantly outperforms the methods in Duan and Li (2022) and Yang et al. (2024) in terms of on-time arrival rate. The on-time arrival rate of this method consistently remains above 97.7%, with a maximum of 98.6%, demonstrating extremely high stability and reliability. In contrast, the on-time arrival rate of the Duan and Li (2022) method fluctuates greatly, ranging from 78.8 to 89.1%, and the overall level is significantly lower than that of the method proposed in this paper. The on-time arrival rate of the method in Yang et al. (2024) is lower, ranging from 69.7 to 79.8%, with a more significant difference compared to the method proposed in this paper. For example, in the 5th test, the on-time arrival rate of our method was 98.2%, while the methods in Duan and Li (2022) and Yang et al. (2024) were 85.3% and 76.8%, respectively; In the 50th test, our method achieved 98.6%, while the methods in Duan and Li (2022) and Yang et al. (2024) only achieved 89.1% and 79.8%, respectively. These data indicate that the method proposed in this paper has significant advantages in improving on-time arrival rates, better meeting the requirements of timeliness, and providing reliable technical support for the optimisation of transportation systems. This is because the method proposed in this article achieves dynamic resource allocation and precise time control in transportation path planning through intelligent algorithm fusion and multi-objective collaborative optimization mechanism, thereby maintaining a high on-time performance of over 97% in complex logistics scenarios. The dual optimisation of genetic algorithm and ant colony algorithm not only ensures the global search capability but also strengthens the local convergence efficiency, enabling the transportation scheme to adaptively adjust node connection and flow allocation, fundamentally solving the problem of time fluctuation caused by fixed path planning in traditional methods.

4.3.2 *Cost saving rate*

The cost-saving rate serves as a core indicator for measuring economic benefits in transportation mode shifts, directly reflecting waterway transportation's cost advantage over road transport. Testing quantitatively compares total cost differences between the two modes, providing decision-makers with a scientific basis for evaluating mode shift feasibility. Cost-saving rates for the three methods are presented in Figure 4.

Figure 4 Cost savings rate (see online version for colours)



Observing the cost saving rate results shown in Figure 4, it can be seen that under 50 testing experiments, the cost saving rate of our method reached 9.3%, while the cost saving rates of the methods in Duan and Li (2022) and Yang et al. (2024) were the highest at around 5% and 3%, respectively. The advantage of this method in terms of cost savings indicates that it has higher efficiency and economy in optimising transportation costs. This is because the method proposed in this article utilises a collaborative optimisation mechanism of genetic algorithm and ant colony algorithm to accurately quantify the implicit cost factors of multimodal transportation while ensuring transportation efficiency, achieving dynamic optimal allocation of water and land transportation resources, and systematically reducing transit losses and empty load rates, achieving a stable cost savings rate of 9.3%.

5 Conclusion

This study focuses on improving on-time delivery rates and cost-saving rates in medium-to-long-distance transportation while exploring the optimisation model for shifting road freight to waterways. By constructing a model framework that comprehensively considers transportation efficiency, cost and environmental impact, dual optimisation of path selection in terms of cost and time is achieved. Detailed cost analysis not only quantifies various expenses but also ensures model rationality in transportation mode decision-making, transit connection, and flow balance through objective functions and constraint conditions. Furthermore, the hybrid optimisation strategy combining genetic and ant colony algorithms significantly enhances model-solving efficiency and performance. Experimental verification shows the method achieves an on-time arrival rate exceeding 97.7% and a cost-saving rate of 9.3%. Future research will focus on continuous model improvement to better serve medium-to-long-distance transportation optimisation practices.

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Declarations

All authors declare that they have no conflicts of interest.

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