Research on Optimization of Delivery Vehicle Pathways Considering Carbon Emissions and Soft Time Windows

Xun Zhang and Cunhua Qian*

Nanjing University of Technology, Nanjing, Jiangsu, 211816, China

*qch64317@njtech.edu.cn

Abstract. Aiming to reduce the total cost of logistics distribution, this paper constructs a mathematical model for multi-vehicle route optimization with time window constraints. The objective is to minimize the comprehensive total cost, which includes fixed vehicle costs, transportation costs, carbon emission costs, and time penalty costs. In terms of algorithm design, this study enhances heuristic functions and state transition probabilities, optimizes the global pheromone update strategy, and introduces a chaotic disturbance mechanism to improve the ant colony algorithm. Finally, MATLAB software is used for empirical analysis to compare the optimized ant colony algorithm with the traditional ant colony algorithm. The results indicate that, compared to the basic ant colony algorithm, the improved ant colony algorithm reduces delivery distance by 7.2% and total delivery cost by 17.5%, thereby verifying the effectiveness of the proposed method. Moreover, the paper analyzes how delivery costs and carbon emissions change with fluctuations in carbon tax prices.

Keywords: Research on path optimization; Carbon emissions; Soft time window; Improving Ant Colony Algorithm

1 INTRODUCTION

As China enters a new stage of high-quality development, the market size of the logistics industry is expected to continuously expand. However, it faces challenges such as high transportation costs, insufficient efficiency, and isolated information systems. To address these issues and enhance competitiveness, logistics enterprises need to undergo strategic transformation and upgrades, utilizing advanced technologies to optimize operations and reduce costs. Additionally, in response to global carbon emission concerns, China has implemented carbon reduction policies. The logistics sector must also prioritize environmental protection by optimizing delivery routes and reducing carbon emissions to promote sustainable development.

Regarding the current research on Vehicle Routing Problems considering carbon emissions and time windows, it has been found that the academic community has extensively explored this area and made numerous optimization attempts in VRP solution strategies. Xiang et al. proposed a meta-heuristic algorithm that solves dynamic vehicle routing problems within the framework of ant colony optimization by incorporating a

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demand coverage diversity adaptive method, enabling the optimizer to effectively respond to new customer requests that arise dynamically during route execution[1]. Li et al. developed a multi-site green vehicle routing problem and applied an improved ant colony optimization algorithm, effectively addressing the logistics challenge of maximizing revenue while minimizing costs, time, and emissions[2]. Ng et al. introduced two new artificial bee colony algorithms that solve dynamic vehicle routing problems, significantly reducing the risk of delayed deliveries caused by traffic congestion and enhancing the flexibility and robustness of route optimization[3]. Chiabwoot improved the ant colony algorithm by introducing path elimination techniques and pheromone resetting techniques to address routing problems involving multiple pickup trucks and delivery vehicles with time windows, enhancing the algorithm's performance in handling infeasible paths and local optima issues, and showcasing the potential application of the improved ant colony algorithm in complex logistics and distribution domains[4]. Ozgur developed a genetic algorithm that incorporates niche techniques and constraint-handling methods, effectively solving the green vehicle routing problem characterized by multi-site, multi-route, heterogeneous fleets, and split delivery features[5].

Given these considerations, this paper constructs a Vehicle Routing Problem model aimed at minimizing the total costs while considering carbon emissions and time window constraints. This research innovates the traditional ant colony algorithm, including adjustments to the heuristic function and state transition probabilities, optimization of the global pheromone update strategy, and the introduction of a chaos perturbation mechanism. These enhancements enrich the application of the ant colony algorithm in the field of route optimization and better align with national objectives for carbon neutrality and peak carbon emissions, as well as the practical needs of businesses.

2 PROBLEM DESCRIPTION AND MODEL ESTABLISHMENT

2.1 Problem Description

This model addresses a logistics issue where a fleet composed of various types of vehicles performs delivery tasks from a single distribution center to numerous customer nodes. In the set scenario, the geographical locations and demand volumes of all customer nodes are known. Different types of vehicles have varying load capacities and cost characteristics. Each vehicle departs loaded with known goods, completes deliveries, and returns to the distribution center. According to regulations, each vehicle can only serve a fixed route, and each customer node is served by only one vehicle. Given the time window constraints at each customer node, failure to complete delivery within these windows results in additional time penalty costs.

2.2 Model Assumptions

(1) The demand for customer orders is one-time and complete; that is, orders cannot be divided into multiple parts to be delivered by different vehicles in separate batches. Instead, they must be entirely delivered by a single vehicle in one go.

(2) Customer demand volumes are accurately known prior to delivery and remain unchanged throughout the delivery process, requiring vehicles to load goods based on these known quantities.

(3) During delivery, it is assumed that all vehicles travel at a constant speed and only stop at delivery points as necessary to load and unload goods.

(4) The distribution center has an adequate supply of goods, enabling vehicles to load freely according to demand volumes without being affected by shortages or stocking times.

(5) Vehicles of the same type have uniformity in load capacity and energy consumption, meaning each vehicle type has the same parameters in terms of carrying capacity and fuel efficiency.

(6) External factors that might affect delivery efficiency and costs, such as drivers' driving behaviors, actual road conditions, and weather conditions, are not considered during the delivery process.

2.3 Model Establishment

Symbols And Parameters. The following symbols and their definitions are provided: U0={0,1,2,…,n} represents the set of customer points and the distribution center, where i represents the distribution center; U1={1,2,3,…,n} represents the set of customer points; K={1,2,3,…,mc+md} represents the set of all vehicles; Kc={1,2,3,…,mc}represents the set of light-duty fuel vehicles; Kd={me+1,…,mc+md} represents the set of medium-duty fuel vehicles; Wc represents the maximum load capacity of light-duty fuel vehicles; Wd represents the maximum load capacity of medium-duty fuel vehicles; qi represents the demand at customer point i; dij represents the delivery distance between node i and node j; Wijkc represents the load carried by light-duty fuel vehicles from node i to node j; Wijkd represents the load carried by medium-duty fuel vehicles from node i to node j; ρ1 represents the fuel consumption per unit distance when light-duty fuel vehicles are unladen; ρ2 represents the fuel consumption per unit distance when light-duty fuel vehicles are fully laden; ρ3 represents the fuel consumption per unit distance when medium-duty fuel vehicles are unladen; ρ4 represents the fuel consumption per unit distance when medium-duty fuel vehicles are fully laden; ti represents the arrival time of vehicles at node i; tij represents the travel time of vehicles between node i and node j; tsi represents the service time at node i; [ETi，LTi] represents the desired service time window at customer point i; tik represents the arrival time of vehicle k at customer point i; c1 represents the fixed usage cost of light-duty fuel vehicles; c2 represents the fixed usage cost of medium-duty fuel vehicles; c3 represents the fuel price; c4 represents the variable cost of light-duty fuel vehicles; c5 represents the variable cost of medium-duty fuel vehicles; λ_1 represents the unit penalty cost for early arrival; λ_2 represents the unit penalty cost for late arrival; v represents the vehicle speed; μ represents the fuel carbon emission coefficient; ω represents the carbon tax; x_{ijk} is a 0-1 variable, indicating whether the transportation vehicle k has passed through the road section from customer point i to j; y_{ik} is a 0-1 variable, indicate whether customer point i is served by vehicle k.

Mathematical Model.

$$\begin{aligned} minC = {} & c_1 \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K_c} x_{ijk} + c_2 \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K_d} x_{ijk} + c_4 \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K_c} d_{ij}x_{ijk} \\ & + c_5 \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K_d} d_{ij}x_{ijk} \\ & + \omega\left(\theta \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K_c} x_{ijk}\, d_{ij}\, f_{ijk} + \mu \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K_d} x_{ijk}\, d_{ij} f_{ijk}\right) \\ & + \lambda_1 \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K} x_{ijk} max\{ET_i - t_i, 0\} \\ & + \lambda_2 \sum_{i\in U_0}\sum_{j\in U_0}\sum_{k\in K} x_{ijk} max\{t_i - LT_i, 0\} \end{aligned} \tag{1}$$

$$\sum_{i\in U_0}\sum_{k\in K_c} x_{ijk} + \sum_{i\in U_0}\sum_{k\in K_d} x_{ijk} = 1, \forall j \in U_0 \tag{2}$$

$$\sum_{i\in U_0}\sum_{k\in K} x_{ijk} = \sum_{i\in U_0}\sum_{k\in K} x_{jik}\,, \forall j \in U_0 \tag{3}$$

$$\sum_{i\in U_0}\sum_{k\in K} x_{i0k} = \sum_{j\in U_0}\sum_{k\in K} x_{0jk} \tag{4}$$

$$\sum_{i\in U_0}\sum_{j\in U_0} y_{ik} q_j \le W_c\,, \forall k \in K_c \tag{5}$$

$$\sum_{i\in U_0}\sum_{j\in U_0} y_{ik} q_j \le W_d\,, \forall k \in K_d \tag{6}$$

$$t_i + t_{ij} + t_{si} = t_j\,, \forall i, j \in U_o \tag{7}$$

$$EETi \le t_i \le LLTi,\ \forall i \in U_o, k \in K \tag{8}$$

$$x_{ijk} \in \{0,1\}, i, j \in U_0, k \in K \tag{9}$$

In the model, Equation (1) represents the objective function, which aims to minimize the total distribution cost, the cost mainly consists of fixed costs, transportation costs, carbon emission costs, and penalty costs. Equation (2) ensures that each customer is serviced exactly once by one type of vehicle. Equation (3) stipulates that after servicing a demand point, a vehicle must leave that point. Equation (4) requires that each vehicle returns to the distribution center after completing its tasks. Equations (5) and (6) specify that the load of fuel vehicles during delivery should not exceed their rated capacity. Equation (7) ensures the continuity of the delivery process. Equation (8) ensures that service times fall within the designated time windows. Finally, Equation (9) defines the range of values for the decision variables.

3 ALGORITHM DESIGN

Ant Colony Optimization (ACO), as a leading intelligent heuristic search technology, has demonstrated significant results in various fields, particularly in handling Vehicle Routing Problems (VRP). The algorithm effectively plans optimal routes from starting points to destinations and exhibits remarkable stability. However, ACO also faces several limitations, such as tendencies to converge prematurely, become trapped in local optima, and experience slow optimization speeds and low efficiency. To overcome these challenges, this paper introduces innovative improvements in heuristic function and state transition rules, global pheromone update strategies, and the incorporation of chaos perturbation mechanisms.

3.1 Improved Heuristic Function and State Transition Probability

In the Ant Colony Optimization algorithm, the heuristic information initially considers only the distance between the current and potential customer points, which can leave ants directionless during the early stages of the search. To address this, the improved heuristic additionally considers the distance between the chosen customer point and the target customer point. The improved heuristic information is represented as Equation (10).

$$\eta_{ij} = \frac{1}{\omega_1 d_{ij} + \omega_2 d_{jG}} \tag{10}$$

In the equation, d_{ij} represents the distance from the i-th customer point to the j-th customer point, and d_{jG} represents the distance from the candidate j-th customer point to the target customer point G. The distance weighting coefficients are ω_1 and ω_2, with $\omega_1 + \omega_2 = 1$.

Given the context of this paper, which includes considerations of deviation from time window penalties and carbon emission costs, differing from traditional routing optimization problems, the model aims to more accurately simulate the decision-making process of actual vehicle distribution. The model incorporates factors related to the time window widths between customers i and j, as well as carbon emission factors, leading to the following improved state transition probability formula:

$$P_{ij}^{k} = \begin{cases} \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}(1/width_{ij})^{\gamma}(1/Z_{ij})^{\varphi}}{\sum_{j\in allowed_k}(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}(1/width_{j})^{\gamma}(1/z_{ij})^{\varphi}}, j \in allowed_k \\ 0 \qquad j \notin allowed_k \end{cases} \tag{11}$$

In the formula: τ_{ij} represents the pheromone level between nodes i and j; α is the pheromone importance factor in the ant colony algorithm, where a larger value indicates that ants are more likely to choose paths with higher pheromone concentrations;

η_{ij} is the heuristic information between nodes i and j; β, γ, and φ are factors indicating the importance of the heuristic function in the ant colony algorithm; $width_{ij} = LT_i - ET_i$ represents the width of the time window for the customer, where a tighter window indicates a more urgent need, giving priority to servicing such customers;Z_{ij} is the amount of carbon emissions produced by the delivery vehicle from customer point i to j on the route, with smaller values indicating lower carbon emissions generated by the path.

3.2 Global Pheromone Update Strategy

When the algorithm iterates a certain number of times and the quality of the solution no longer improves, it may indicate that a global optimum has been reached or that the algorithm is trapped in a local optimum. To address this, this paper proposes an improved pheromone update strategy. The main adjustments include reducing the retention of pheromones and accelerating their evaporation rate. These changes can effectively disperse the concentration of pheromones, increasing the opportunities for the algorithm to explore unknown paths, thereby enhancing the performance of the ant colony algorithm in global search. The improved pheromone update mathematical expression is as follows:

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \Delta\tau_{ij}{}^{*} \tag{12}$$

$$\Delta\tau_{ij}{}^{*} = \frac{Q}{L_{best}} \tag{13}$$

In the formula: $\Delta\tau_{ij}(t)$represents the concentration of pheromones on the path from node i to node j during the t-th iteration; ρ describes the evaporation rate of pheromones on the path after each iteration; $\Delta\tau_{ij}{}^{*}$ represents the amount of pheromones released by the ant that finds the optimal path between two customer points i and j during the current iteration; Q is a constant that denotes the total amount of pheromones released by an ant upon completing one cycle; L_{best} is the total length of the path covered by the ant that finds the best path during the iteration cycle.

3.3 Chaos Perturbation Mechanism

Chaos is a deterministic yet non-periodic behavior characterized by excellent randomness and ergodic properties. By leveraging these characteristics of chaos, it is possible to effectively disrupt pheromone trails, enabling the algorithm to explore a more extensive solution space. The specific methods for generating chaos perturbation are as follows:

$$F_{ij}(t+1) = \sigma F_{ij}(t) * [1 - F_{ij}(t)] \tag{14}$$

In the formula, $F_{ij}(t)$ represents the chaotic variable, and σ is a control variable with a typical range of values between 3.5 and 4.0.

Additionally, this paper introduces chaos perturbation during the pheromone update phase after the ants complete a round of search. This approach is designed to enhance the exploratory and random aspects of the search process, thereby preventing the algorithm from prematurely converging to local optima. The pheromone update expression, after introducing chaos perturbation, is as follows:

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \Delta\tau_{ij}{}^{*} + \xi F_{ij}(t) \tag{15}$$

In the formula, ξ is an adjustable coefficient.

3.4 Improved Ant Colony Algorithm Implementation Steps

The specific steps of the improved ant colony algorithm are as follows:

Step 1: Initialize algorithm parameters, setting initial parameters such as α, β, γ, and φ; import information for each customer point, set the current iteration $iter = 0$, and the maximum number of iterations $iter_{max}$.

Step 2: Initialize a taboo list to ensure that each delivery vehicle (viewed as an ant) starts from the distribution center. The taboo list is used to record visited customer points to avoid repeated service.

Step 3: While adhering to time and load restrictions, ants choose the next point to visit based on the updated state transition probability formula, and mark this point as visited, adding it to the taboo list.

Step 4: If a current delivery vehicle cannot meet another customer point's requirements (such as time windows or exceeding load capacity), it will return to the distribution center. Subsequently, update the taboo list and repeat the selection process until all customer points are covered, and all given constraints are satisfied.

Step 5: Calculate the objective function (lowest total cost) to determine the best route solution for this iteration and record it.

Step 6: Adjust the pheromone intensity on each path according to specific pheromone update rules.

Step 7: After each iteration, calculate and evaluate the newly obtained feasible solution, then compare it with the best feasible solution obtained in previous iterations. If the new solution is superior, update the current record of the best solution. To avoid the algorithm getting stuck in local optima and to maintain the dynamism of the search, if the feasible solution remains unchanged for five consecutive iterations, a chaos perturbation strategy will be employed.

Step 8: Check if the algorithm meets the termination condition $iter \geq iter_{max}$. If it does, output the optimal solution; otherwise, clear the taboo list and jump to execute Step 2.

4 INSTANCE VERIFICATION

4.1 Basic Data

The algorithm running environment in this article is Windows 10, 64 bit system, and MATLAB 2023a software. The study focuses on a distribution center located in a specific area, tasked with delivering products to 25 customer points. The distribution center is equipped with more than ten delivery vehicles. The locations and demand volumes of the distribution center and customer points are detailed in Table 1 below. The specific address information of the distribution center and the 25 stores is shown in Figure 1.

Table 1. Customer demand information table

Number	x	y	time window	service time
Distribution Center	11.1	29.4		
1	11.4	35.1	9:00-11:30	10
2	7.0	24.1	8:30-10:30	20
3	1.4	19.4	9:15-11:30	10
4	0.0	23.3	9:00-17:00	15
5	4.4	6.2	10:00-12:00	10
6	17.9	18.2	10:00-18:00	15
7	6.1	15.7	9:30-17:00	25
8	9.0	7.8	9:20-11:50	10
9	10.8	12.6	8:00-11:00	20
10	17.0	9.1	11:00-13:00	20
11	17.0	5.5	9:15-11:15	15
12	24.8	5.2	11:00-13:00	25
13	24.4	9.0	9:00-17:00	15
14	33.6	9.0	8:30-17:30	20
15	29.2	10.3	10:00-12:00	25
16	29.8	15.3	9:00-17:00	10
17	29.1	19.8	9:30-12:30	20
18	24.3	22.9	8:00-10:00	15
19	40.0	10.7	9:30-18:00	15
20	17.2	30.4	11:00-13:00	20
21	32.4	29.4	9:00-17:00	20
22	38.8	31.0	9:30-11:00	10
23	39.5	17.6	9:00-11:30	20
24	35.4	23.7	9:30-18:00	20
25	25.6	32.8	14:00-18:00	15

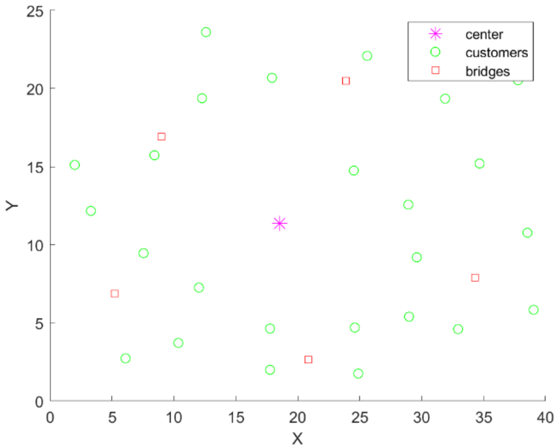
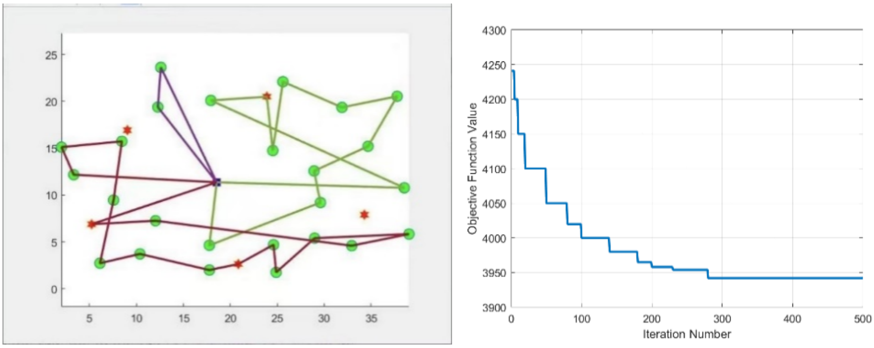


Fig. 1. Customer Center and Store Coordinate Map

Other parameter settings: The fixed cost for vehicles is set at 200 yuan. The variable cost for light-duty fuel vehicles is 5 yuan per kilometer, and for medium-duty fuel vehicles, it is 6 yuan per kilometer. The vehicles travel at a speed of 50 kilometers per hour. The rated carrying capacity of light-duty fuel vehicles is 1.5 tons, while that of medium-duty fuel vehicles is 2.5 tons. The penalty cost for early delivery is 20 yuan, and for late delivery, it is 40 yuan. The fuel consumption of light-duty fuel vehicles is 0.15 liters per kilometer when unladen and 0.3 liters per kilometer when fully laden. For medium-duty fuel vehicles, the consumption is 0.2 liters per kilometer when unladen and 0.4 liters per kilometer when fully laden. Additionally, a carbon tax of 0.05 yuan per kilogram is applied.

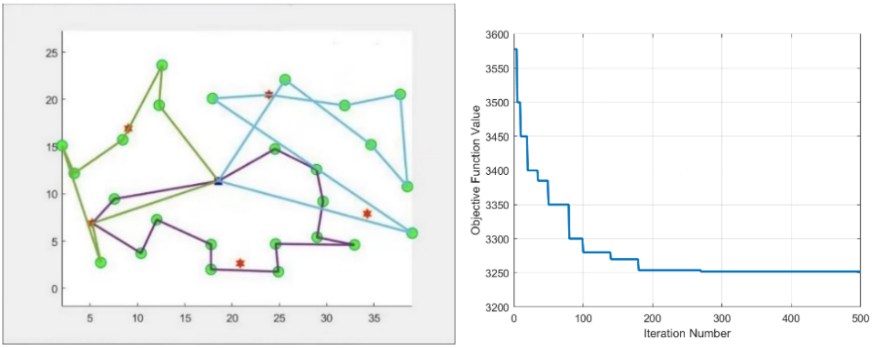
4.2 Comparative Analysis

For the aforementioned instance, the model was executed ten times in MATLAB, and the best result from these runs was selected as the optimal solution for the model. This solution is recorded along with the distribution route maps generated by both the basic ant colony algorithm and the improved ant colony algorithm. The specific details are illustrated in Figures 2 and Figures 3.



a Vehicle delivery route diagram b Ant colony algorithm iteration curve chart

Fig. 2. Schematic diagram of running results before algorithm optimization



a Vehicle delivery route diagram b Ant colony algorithm iteration curve chart

Fig. 3. Schematic diagram of running results after algorithm optimization

The costs of the solutions generated by the basic ant colony algorithm and the improved ant colony algorithm are compared. Given that this paper primarily considers the impacts of time windows and carbon emissions on route optimization, the comparison is conducted from several perspectives as shown in Table 2.

Table 2. Result comparison table

Algorithm	Total Driving Distance(km)	Total Cost (CNY)	Carbon Emission Cost (CNY)	Penalty Cost (CNY)
Basic Ant Colony Algorithm	389.24	3941.87	8.83	213.84
Improved Ant Colony Algorithm	361.35	3252.78	6.84	139.55

From the analysis of multiple graphs, it is evident that in terms of iteration numbers, the ant colony algorithm before optimization begins to converge around the 280th iteration, while after optimization, it starts converging around the 180th iteration. The optimized ant colony algorithm demonstrates a more stable convergence process, faster convergence speed, and higher efficiency. The improved ant colony algorithm and the basic ant colony algorithm achieved minimum delivery distances of 361.35 km and 389.24 km, and minimum total delivery costs of 3252.78 CNY and 3941.87 CNY, respectively, representing reductions of 7.2% and 17.5%. Based on these results, the improved ant colony algorithm provides more optimal delivery solutions for solving the Vehicle Routing Problem with multiple vehicle types.

4.3 Carbon Emission Price Sensitivity Analysis

In the model solution discussed in this paper, the preliminary carbon tax price was set at 0.05 CNY/kg. To further analyze the impact of different carbon tax levels on the results, this study conducted 10 simulation solutions for each of the following carbon tax prices: 0.03 CNY/kg, 0.06 CNY/kg, 0.08 CNY/kg, and 0.1 CNY/kg. The optimal results for each scenario are recorded and detailed as follows Table 3 and Figures 4:

Table 3. Table of Solution Results for Different Carbon Taxes

Carbon Tax (CNY/kg)）	Total Cost (CNY)	Carbon Emissions (kg)
0.03	3218.53	139.17
0.05	3252.78	136.89
0.06	3282.74	134.48
0.08	3361.28	132.52
0.1	3452.52	131.76

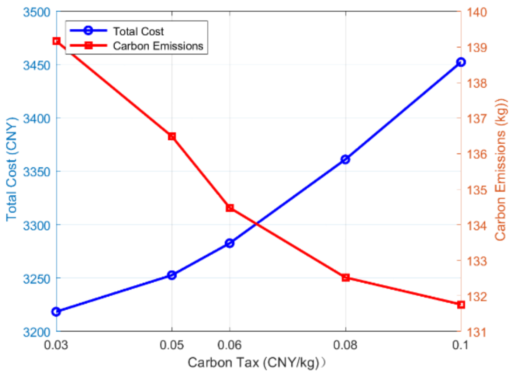


Fig. 4. Solution Results for Different Carbon Taxes

According to the analysis of the charts, it is evident that as the carbon tax price increases, the total cost of delivery also rises accordingly. However, carbon emissions decrease as the carbon tax price increases, but the proportion of reduction diminishes with higher tax rates. This phenomenon suggests that governments can effectively reduce carbon dioxide emissions by increasing the carbon tax rate. Nevertheless, such control must be confined within certain limits. Once these limits are exceeded, the effectiveness may not be as significant, and it could lead to increased total delivery costs for businesses, thereby diminishing their incentive to implement low-carbon delivery strategies.

5 CONCLUSION

Under the drive of the "dual carbon" goals, the development philosophy of balancing economic growth with environmental protection is increasingly becoming a focus across all industries. This paper constructs a low-carbon logistics route optimization model that integrates traditional logistics with the concept of a low-carbon economy and considers the high demands of customers for delivery timeliness by incorporating time window constraints. Consequently, an optimized model is proposed to minimize total costs, including vehicle fixed costs, transportation costs, carbon emission costs, and time window penalty costs. To address the issues of slow convergence and susceptibility to local optima inherent in the basic ant colony algorithm, this paper improves the heuristic function and state transition probability, adjusts the pheromone update mechanism, and introduces a chaos perturbation mechanism to enhance the algorithm's search efficiency and convergence. The performance of the revised algorithm is validated through case analysis using MATLAB software. By applying specific case data to the optimized algorithm, an optimized delivery solution that minimizes total costs is analyzed, demonstrating the effectiveness of the improved ant colony algorithm and furthering the achievement of low-carbon economic goals. Additionally, the introduction of a carbon tax system for quantitative analysis of carbon emission costs allows for better measurement of corporate carbon costs and analysis of how delivery costs and carbon emissions vary with carbon tax rates.

REFERENCES

1. XIANG X, QIU J, XIAO J. Demand coverage diversity based ant colony optimization for dynamic vehicle routing problems. Engineering Applications of Artificial Intelligence, 2020, 91: 103582-.
2. LI Y, SOLEIMANI H, ZOHAL M. An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives. Journal of cleaner production, 2019, 227(Aug.1): 1161-1172.Author, F., Author, S., Author, T.: Book title. 2nd edn. Publisher, Location (1999).
3. NG K K H, LEE C K M, ZHANG S Z. A multiple colonies artificial bee colony algorithm for a capacitated vehicle routing problem and re-routing strategies under time-dependent traffic congestion. Computers & Industrial Engineering, 2017, 109: 151-168.LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
4. CHIABWOOT R. Modified Ant Colony Optimization with Route Elimination and Pheromone Reset for Multiple Pickup and Multiple Delivery Vehicle Routing Problem with Time Window. jaciii, 2022, 26: 959-964.
5. OZGUR K, S E M. A green vehicle routing problem with multi-depot, multi-tour, heterogeneous fleet and split deliveries: a mathematical model and heuristic approach. Journal of Combinatorial Optimization, 2023, 45 [7] .