Optimization of Cold Chain Logistics Distribution Pathways Considering Carbon Emission Costs

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Abstract. Based on the "dual carbon" strategic goal, this paper takes the optimization problem of cold chain logistics vehicle paths as the research object, considers carbon emission costs into the path optimization problem, and establishes a cold chain logistics distribution model with the goal of minimizing the total cost. At the same time, an improved ant colony algorithm was designed from two aspects: fitness function and local search strategy, in response to the disadvantage of traditional genetic algorithms easily falling into local optima. Finally, the effectiveness of the model and algorithm was verified through simulation experiments and algorithm comparisons, providing reference for enterprises to improve the economic benefits and energy conservation and emission reduction of cold chain logistics.

Keywords: Cold Chain Logistics; Route Optimization; Genetic Algorithm; Carbon Emissions

1 INTRODUCTION

According to the "Climate Change 2022: Impacts, Adaptation, and Vulnerability" report by the Intergovernmental Panel on Climate Change (IPCC), the negative impacts of global warming are more severe than expected, including the death of animal and plant populations and irreversible ecological issues. Therefore, it is imperative to consider carbon emissions comprehensively and plan reasonable vehicle routes.

In 1959, Ramser and Dantzig et al[1]. first proposed the vehicle routing problem, and since then, more and more scholars have focused on this important research field. Solomon and Desrosiers et al[2]. were the first to apply constraints with time windows to vehicle routing, providing useful guidance for the future route planning of fresh logistics vehicles. Lian[3] established a multi-objective optimization model for the transshipment scheduling of cold chain logistics vehicle routes with fuzzy time windows. Cui et al[4]. incorporated traffic congestion indices into the cold chain distribution route optimization model to address actual traffic congestion during transportation. Liao et al[5]. converted carbon emissions into economic costs in the form of carbon trading prices and incorporated them into the cold chain logistics distribution route optimiza-

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tion model. Deng et al[6]. considered the impact of the convection of hot and cold air when the doors of refrigerated trucks are opened on the spoilage rate of products, as well as the carbon emission costs generated during refrigerated transportation.

Based on this, this paper fully considers fuel consumption and carbon emissions in distribution, constructs a green route optimization model for cold chain logistics distribution with the goal of minimizing total comprehensive costs, and designs an improved ant colony algorithm to solve the model.

2 PROBLEM DESCRIPTION AND MODEL ESTABLISHMENT

2.1 Problem Description

The research problem is described as follows: Within a specified region, a cold chain logistics distribution center of a fresh produce e-commerce company serves multiple randomly distributed customer demand points. With the goal of minimizing the total cost, the appropriate number of vehicles and routes are selected to complete the delivery task of fresh products. To ensure the feasibility of the constructed model, the following assumptions are made: (1) There is only one distribution center and there are enough vehicles; (2) The distribution center is well-stocked, and the locations, unloading volumes, demand volumes, and time window requirements of all customer points are predetermined; (3) Road conditions and congestion are not considered, and all vehicles perform delivery tasks at a uniform speed; (4) The fuel in the vehicle's tank is sufficient to complete the assigned delivery tasks; (5) The starting and ending points of the delivery tasks for transport vehicles are always the distribution center; (6) Each customer point is served by a single vehicle, each vehicle can serve multiple customer points, and each customer point is delivered to only once.

2.2 Parameter and Variable Definitions

To better describe the model, the parameters and variables are defined in Table 1.

Table 1. Parameter and Variable Symbol Descriptions

Symbols	Meanings	Symbols	Meanings
O	Distribution Center	c_d	Unit cost of cargo damage
I	Set of Customer Points, $i \in I$	a_{fuel}	Base fuel consumption
J	Set of Vehicles, $j \in J$	b_{fuel}	Load-dependent fuel consumption coefficient
d_i	Demand at Customer Point i	r	Loss rate constant
$[e_i, l_i]$	Time window at Customer Point i, where e_i is the earliest arrival time and l_i is the latest arrival time	M	A large constant used for logical constraints in the model

t_{ij}	Travel time from Customer Point i to Customer Point j	x_{ijk}	1 if Vehicle j travels directly from Customer Point i to Customer Point k, 0 otherwise.
c_{ij}	Transportation cost from Customer Point i to Customer Point j	p_a, p_b, p_c	Penalty cost coefficient for the soft time window
f_j	Fixed cost of Vehicle j	e_i', l_i'	Start and end times of the soft time window
C	Capacity of each vehicle	w_{ij}	Time Vehicle j arrives at Customer Point i
β	Unit cost of carbon emissions	v_j	1 if Vehicle j is used, 0 otherwise
v	Speed of the vehicle	q_j	Load weight of Vehicle j
α	Carbon emission coefficient corresponding to fuel consumption	s_{ij}	Remaining freshness ratio of the product after arriving at Customer Point i
D_j	Total distance traveled by Vehicle j on the route	$fuel_j$	Total amount of gasoline consumed by Vehicle j on its delivery route

2.3 Model Construction

Establish the objective function to minimize the total distribution costs, which include transportation costs, fixed costs, time window penalty costs, costs due to loss of freshness, refrigeration costs, and carbon emission costs:

$$\text{Minimize } Z = \sum_{j\in J}\left(f_j v_j + \sum_{i\in I}\sum_{k\in I} c_{ik}x_{ijk}\right) + \sum_{i\in I}\left(p_a \cdot \max(0, e_i' - w_{ij}) + p_b \cdot \max(0, w_{ij} - l_i')\right) + \sum_{j\in J} \beta \cdot \alpha \cdot \left(a_{fuel} \cdot D_j + b_{fuel} \cdot q_j \cdot D_j\right) + \sum_{i\in I}\sum_{j\in J} d_i \cdot (1 - e^{-r\cdot w_{ij}}) \cdot c_d \tag{1}$$

$$CO_j = \sum_{j\in J} \beta \cdot \alpha \cdot fuel_j,\ \forall j \in J \tag{2}$$

$$fuel_j = a_{fuel} \cdot D_j + b_{fuel} \cdot q_j \cdot D_j,\ \forall j \in J \tag{3}$$

$$\sum_{j\in J}\sum_{k\in I} x_{ijk} = 1,\ \forall i \in I \tag{4}$$

$$\sum_{i\in I} x_{ijk} = \sum_{k\in I} x_{ikj} = v_j,\ \forall j \in J, k \in I \tag{5}$$

$$q_j = \sum_{i\in I} d_i \cdot x_{ijk} \le C,\ \forall j \in J \tag{6}$$

$$e_i \le w_{ij} \le l_i,\ \forall i \in I, j \in J \tag{7}$$

$$e_i' \leq w_{ij} \leq l_i', \ \forall i \in I, j \in J \tag{8}$$

$$\begin{aligned} w_{ij} &\geq e_i' - M \cdot (1 - x_{ijk}), \quad \forall i \in I, j \in J \\ w_{ij} &\leq l_i' + M \cdot (1 - x_{ijk}), \quad \forall i \in I, j \in J \end{aligned} \tag{9}$$

$$s_{ij} = e^{-r \cdot w_{ij}}, \ \forall i \in I, j \in J \tag{10}$$

$$\mathrm{w_{ij}} + \mathrm{t_{ik}} \leq \mathrm{w_{kj}} + M \cdot (1 - \mathrm{x_{ijk}}), \ \forall \mathrm{i}, \mathrm{k} \in \mathrm{I}, \mathrm{j} \in \mathrm{J} \tag{11}$$

In the model: Eq. (1) represents the objective function for minimizing total costs Eq; (2) represents the carbon emissions cost associated with the delivery route; Eq. Eq. (3) is used to calculate the vehicle fuel consumption; (4) ensures that every customer point is served exactly once; Eq. (5) ensures flow balance, with equal numbers of vehicles entering and exiting each customer point; Eq. (6) ensures that no vehicle exceeds its capacity, calculated based on the cumulative demands of the customer points it serves; Eq. (7) addresses time window and service time constraints at each customer point; Eq. (8) involves the soft time window constraints; Eq. (9) relates to penalty costs associated with deviations from time windows; Eq. (10) is used for calculating the degradation of product freshness due to transportation time; Eq. (11) is used to represent time continuity constraints, where M is a large constant to ensure that when $\mathrm{x_{ijk}} = 0$, it does not affect $\mathrm{w_{ij}}$.

3 IMPROVED GENETIC ALGORITHM DESIGN

Genetic Algorithm (GA) is a heuristic search algorithm inspired by Darwin's theory of natural selection. When applying genetic algorithms to solve the Vehicle Routing Problem (VRP), the algorithm first generates a random population, each individual representing a possible vehicle routing configuration. The fitness of each individual is assessed by a carefully designed function. Through the selection process, individuals with higher fitness are retained and new generations are created through crossover and mutation. This process is iterated until a preset termination condition is reached, such as reaching the maximum number of iterations or when the quality of the solution no longer significantly improves. The main advantages of genetic algorithms in VRP include their robust global search capabilities and good flexibility. However, genetic algorithms may also fall into local optima due to premature convergence. Therefore, the following improvements are proposed:

In this study, the fitness function is defined as the reciprocal of the route cost, expressed as follows:

$$\mathrm{f(x)} = \frac{1}{\text{Minimize Z}} \tag{12}$$

Introduce 2-opt local search. The 2-opt algorithm is a local optimization algorithm widely used in combinatorial optimization problems such as the Traveling Salesman Problem (TSP). Its fundamental idea is to reduce the total path length by exchanging two edges in the path and reversing the sequence of nodes between them. In each generation of the genetic algorithm, the 2-opt algorithm is applied to optimize each solution through local search, reducing the route length by local reversal operations. This enhances the efficiency and effectiveness of the genetic algorithm in solving VRP problems.

4 SIMULATION ANALYSIS

4.1 Case Description

This case study focuses on a cold chain logistics distribution center of a fresh produce e-commerce company. The distribution center provides delivery services to 20 customer points within its service area. Deliveries start at 4:00 AM daily to avoid peak travel times and enhance distribution efficiency. Early morning deliveries also benefit customer points by allowing timely shelving and secondary processing of products. The distribution center is labeled as 0, and the customer points are randomly labeled from 1 to 20. Information about their locations, demand volumes, and time windows is provided, as shown in Table 2.

Table 2. Information on the Distribution Center and Customer Points

Number	Coordinates	Demand/t	Optimal service time window	Acceptable time window	residence time/min
0	(15.00，15.00)				
1	(32.50，22.20)	0.25	[05:00—05:20]	[04:30—05:50]	11
2	(19.70，8.60)	0.67	[06:00—06:40]	[05:30—07:20]	36
3	(26.80，10.90)	0.35	[04:20—04:50]	[04:00—05:00]	16
4	(18.10，11.30)	1.20	[05:45—07:45]	[05:20—08:00]	54
5	(31.70，5.40)	0.20	[04:30—05:00]	[04:00—05:30]	10
6	(27.50，30.10)	0.37	[05:20—05:50]	[05:00—07:00]	17
7	(20.00，25.00)	0.47	[06:00—06:50]	[05:30—07:20]	24
8	(12.00，37.20)	0.68	[06:00—06:30]	[05:00—07:00]	31
9	(20.70，17.10)	0.55	[04:20—04:50]	[04:00—05:20]	26
10	(7.30，6.00)	0.45	[04:30—05:00]	[04:00—05:30]	21
11	(19.30，3.90)	0.14	[05:30—06:00]	[05:00—06:30]	7
12	(2.80，16.80)	0.23	[06:20—06:50]	[05:50—07:20]	15
13	(30.70，7.50)	0.48	[05:35—06:05]	[05:05—06:35]	22
14	(22.50，32.80)	0.32	[06:00—06:20]	[05:30—06:50]	15
15	(25.40，26.80)	1.10	[06:00—07:00]	[05:30—07:30]	50
16	(16.70，21.00)	0.44	[07:00—07:50]	[06:00—08:20]	21
17	(10.00，18.90)	0.05	[06:00—06:20]	[05:50—06:30]	3
18	(32.50，10.00)	0.48	[05:30—06:00]	[05:10—06:20]	11
19	(29.30，22.70)	0.86	[06:00—07:00]	[05:00—07:30]	43
20	(37.90，18.90)	0.75	[04:30—06:00]	[04:00—06:30]	34

The distribution center has 3 refrigerated trucks available, each with a fixed dispatch cost of 200 RMB. During delivery tasks, the average speed is 50 km/h, the maximum load capacity is 5 tons, and the average travel cost is 2 RMB/km. The fuel price used by these refrigerated trucks is 7.5 RMB/L, with a base fuel consumption of 0.2 L/km when unladen, and a fuel consumption coefficient of 0.4 L/km when loaded. The vehicle carbon emission factor is α=0.05, and the product loss rate coefficient during transport is r=0.1; the penalty coefficient for vehicle early arrival per unit time is p_a=0.2 RMB/min, and the penalty coefficient for late arrival per unit time is p_b=0.8 RMB/min, with a daily carbon emission cost of 60 RMB/t.

Using Matlab R2023a software, the model was simulated with the aforementioned data, setting the maximum number of iterations to 100. The computer operating system is Windows 11, with a running memory of 16GB and a CPU of Intel (R) Core (TM) i7-12700H (2300 MHz).

4.2 Model Solution and Result Analysis

Using an improved genetic algorithm and taking carbon emissions costs into account, the algorithm converges to a stable solution after approximately 46 iterations. The optimal solution route after 100 iterations is shown in Figure 1. To verify the effectiveness of the algorithm proposed in this paper for solving VRP problems, the Matlab Genetic Algorithm Toolbox (GA) will be used to solve the distribution route, shortest distribution mileage, minimum total cost, and carbon emission cost, respectively. The results will be compared with those obtained by the algorithm proposed in this paper, and the statistical results are shown in Table 3.

Table 3. Algorithm calculation results

	Improved Genetic Algorithm	**Traditional Genetic Algorithm**
Delivery Route	Vehicle 1: 0→4→2→11→3→13→5→18→0 Vehicle 2: 0→9→16→7→15→6→14 →8→0 Vehicle 3: 0→17→12→10→19→1→20→0	Vehicle 1: 0→17→12→10→11→2→3→4→0 Vehicle 2: 0→13→5→18→1→19→9 →0 Vehicle 3: 0→20→15→6→14→18→7→16→0
Shortest Delivery Mileage/km	242.47	293.78
Minimum Total Cost/RMB	1786.73	1964.85
Carbon Emission Cost/RMB	5.82	7.56

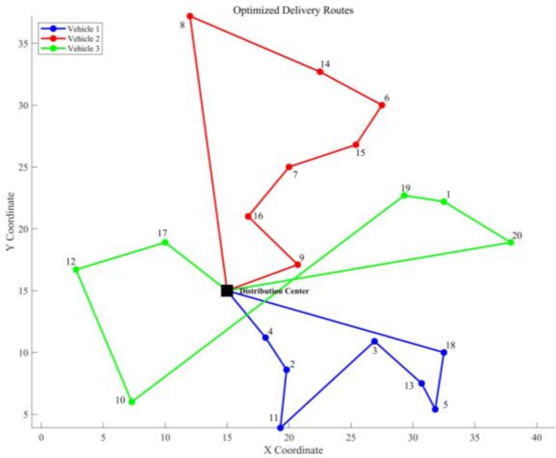

Fig. 1. Optimal Delivery Route of Improved Genetic Algorithm

Comparing the two scenarios, it is evident that using the improved genetic algorithm, the total mileage of vehicle travel paths is 242.47 km and 293.78 km respectively, with the former being 51.31 km less than the latter, a reduction of 17.5%. The total costs incurred are 1786.73 RMB and 1964.85 RMB, and the carbon emission costs are 5.82 RMB and 7.56 RMB, respectively, showing reductions of 9.1% and 23.0%. This demonstrates that the improved genetic algorithm has more advantages in the optimization process. The cost of using fixed speed and time-varying speed during vehicle operation is different, and the analysis results are shown in Table 4.

Table 4. Cost Comparison at Different Speeds

State	Total cost/RMB	Carbon emission cost/RMB
Fixed speed	1786.73	5.82
Time-varying speed	1723.24	4.76
Percentage Reduction Compared to Base/%	3.6	18.2

According to Table 4, while ensuring the on-time delivery rate of goods, the total cost of distribution using time-varying speed in refrigerated truck transportation is reduced by 3.6% compared to fixed speed, and the carbon emission cost is reduced by 18.2%. From this, it can be seen that using time-varying speed to reduce carbon emission costs and total delivery costs is more in line with the operating conditions of vehicles in reality and has more practical significance.

5 CONCLUSION

This paper primarily explores the optimization of cold chain logistics delivery routes for fresh products. Based on a comprehensive consideration of traditional economic costs such as vehicle fixed costs, transportation refrigeration costs, penalty costs, and cargo damage costs, a cold chain logistics distribution model incorporating carbon emissions is established. Subject to constraints such as customer locations, time windows, and demand volumes, an optimized genetic algorithm was employed to solve the model. Comparative analysis of the examples demonstrates that the optimized genetic algorithm can optimize calculation results to a certain extent, reduce total costs and carbon emission costs, enhance corporate benefits while reducing the carbon footprint of logistics activities. The improved algorithm is effective and feasible, providing a reference for enhancing the economic benefits of cold chain logistics enterprises.

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