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Incorporating Customer Demand Heterogeneity for Adaptive Cold Chain Routing Optimization: An Improved Ant Colony Algorithm

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ABSTRACT

To mitigate the structural trade-offs among heterogeneous timeliness constraints in same-city fresh food distribution, an adaptive vehicle routing optimization model considering customer heterogeneity is formulated to minimize the total operating cost. To efficiently solve this complex problem, an improved ant colony algorithm featuring adaptive pheromone updates and elite ant reinforcement is developed to escape local optima traps. Numerical simulations demonstrate that the proposed algorithm converges rapidly and robustly. Driven by order-scale dynamic penalty weights, the framework successfully guides the fleet to prioritize strategic large supermarkets, substantially compressing time-window penalties with minimal marginal increases in transport expenses. This decision-making framework ultimately enables cold chain enterprises to achieve an optimal balance between transport economics and commercial credit.

KEYWORDS

Cold Chain Logistics; Vehicle Routing Problem; Customer Heterogeneity; Time-driven; Improved Ant Colony Optimization

1. INTRODUCTION

The rapid growth of fresh e-commerce and same-city instant retail has dramatically expanded last-mile cold-chain distribution. Fresh products' perishability and time sensitivity require tight cost control over vehicle fixed costs, fuel, and refrigeration [1]. Under green and high-quality development goals, reducing both cost and environmental impact under load and cold-chain constraints is essential for competitiveness [2, 3]. In dense urban distribution, cold-chain firms face a structural imbalance: "strategic nodes" (large supermarkets) have large orders and strict time windows—delays incur heavy penalties—while "long-tail nodes" (community stores) have small orders and flexible windows [4].

Traditional VRP ignores these differences, blindly applying spatial proximity and risking delays to key customers. Customer segmentation and differentiated resource allocation are now necessary. Time-varying traffic and dynamic demand also require adaptive route planning [5]. Improving heuristic algorithms for complex time-window problems is a current research focus [6, 7].

This study examines an adaptive route optimization problem with customer demand heterogeneity in a 100-node urban cold-chain network. By introducing a time-window penalty lever weighted by order size, the model transforms strategic customers' urgency into algorithmic drivers. A comprehensive cost function is built covering dispatch, mileage, refrigeration, quality loss, and differentiated penalties. An improved ant colony algorithm solves the problem. Results show that embedding credit-maintenance levers guides vehicles to prioritize core customers, greatly reducing delay risk with minimal extra cost, balancing transport economy and commercial credit.

2. LITERATURE REVIEW

2.1. Customer Grading and Demand Heterogeneity in Cold-Chain Routing

Early work minimized distance or basic cost under static networks; later studies added temperature, emissions, and quality decay [1–3]. Most assumed homogeneous markets, ignoring differences between bulk supermarkets and long-tail stores. Some researchers identified customer value and advocated graded response strategies. Wei Lai et al. [4] introduced Pareto grading into multi-temperature co-distribution, assigning higher penalty coefficients to strategic customers. Hou Ying et al. [5] designed a chain impact factor for demand changes, building a robust scheduling mechanism that adapts to time fluctuations.

2.2. Improved Ant Colony Algorithms for Cold-Chain Scheduling

Ant colony algorithms excel at VRPTW due to positive feedback and distributed computation, but suffer from slow initial convergence and premature local optima. Zhou Wenxuan et al. [1] improved initial pheromone, update rules, and transition probabilities, adding carbon costs. Bao Huifang et al. [2] hybridized genetic algorithms for initial pheromone and simulated annealing for solution selection. Chen Xinying et al. [6] incorporated pre-cooling and door-opening heat loss into refrigeration cost. Lan Guohui et al. [7] used penalty-based customer segmentation and variable neighborhood search. These improvements support the design of an adaptive ant colony algorithm with demand-heterogeneity weighting in this study.

3. ADAPTIVE COLD CHAIN SCHEDULING MODEL WITH CUSTOMER HETEROGENEITY

3.1. Problem Description and System Assumptions

This study investigates the vehicle routing optimization problem in same-city fresh cold chain distribution. The distribution network consists of one core cold chain distribution center and multiple geographically scattered retail terminal outlets. The distribution center operates a fleet of homogeneous light refrigerated trucks. Vehicles depart from the distribution center, traverse designated retail terminals sequentially to deliver fresh products, and finally return to the distribution center to form a closed loop.

Based on historical order characteristics, retail outlets in the network show prominent customer demand heterogeneity, falling into two categories: strategic large supermarket nodes with large single-order volumes and extremely high timeliness requirements, subject to rigid narrow time window constraints; and community retail store nodes with small order volumes and relatively flexible time windows. The optimization objective is to rationally plan each vehicle's route under physical and time constraints (vehicle load, volume, customer time windows, etc.), so as to minimize the total global operating cost of the system.

To construct the mathematical model, the following reasonable assumptions are proposed: the distribution center has sufficient supply and can fully meet the delivery demand of all terminal nodes; the geographic coordinates, order volumes and expected time windows of each retail outlet are known static parameters; all refrigerated trucks in the fleet share the same maximum rated load capacity, and maintain a constant average driving speed under urban traffic flow; each retail terminal is served by exactly one refrigerated truck, and the service is completed in one trip.

3.2. Notation and Decision Variables

To establish the capacity adaptive scheduling model driven by multi-dimensional costs, this chapter uniformly defines all sets, system parameters and decision variables involved in the system. The specific symbol definitions and their physical and managerial implications are shown in Table 1.

Table 1. definition of model symbols

Symbol Type	Symbol	Physical and Managerial Meaning
Sets and scales	V	Set of nodes, where 0 = distribution center, $V \setminus \{0\}$= retail terminals
	K	Set of available trucks, $K = 1,2,\dots,M$
System Parameters	D_{ij}	Matrix of actual travel distance between node i and node j
	r_i	Order quantity at node $i(r_0 = 0)$
	Q_{max}	Maximum load capacity of a single truck
	Q_{limit}	Demand threshold for classifying large supermarkets vs. community stores
	$[ET_i, LT_i]$	Soft time window for terminal i
	s_{ik}	Actual start time of service at node iby vehicle k
	$t_{open,i}$	Door-open duration for unloading at terminal i
	v	Average travel speed
	f_{fixed}	Fixed dispatch cost per activated truck
Decision Variables	x_{ijk}	0-1 variable, indicating whether vehicle k travels directly from node i to node j
	y_{ik}	0-1 variable, indicating whether the delivery task of terminal node i is assigned to vehicle k
	z_k	0-1 variable, indicating whether vehicle k is activated for actual scheduling operation

3.3. Objective Function with Heterogeneous Demand

The model integrates five cost components: dispatch fixed cost, fuel consumption cost, refrigeration cost, product deterioration cost, and differentiated time-window penalty cost. The objective is:

$$minZ = C_1 + C_2 + C_3 + C_4 + C_5 \tag{1}$$

Dispatch fixed cost:

$$C_1 = f_{fixed} \cdot \sum_{k \in K} z_k \tag{2}$$

Fuel consumption cost (proportional to total distance):

$$C_2 = c_{fuel} \cdot \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} D_{ij} x_{ijk} \tag{3}$$

Refrigeration cost (depends on travel time and door-open time):

$$C_3 = c_{cool} \cdot \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} t_{ij} x_{ijk} \tag{4}$$

Where t_{ij} includes travel time and unloading service time.

Product deterioration cost (accumulates over time, decreasing with unloading):

$$C_4 = c_{loss} \cdot \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} q_{ij}\, t_{ij} x_{ijk} \quad (5)$$

Where q_{ij} is the real-time cargo weight on arc (i, j).

Differentiated time-window penalty cost (core of the model):

$$C_5 = \sum_{i \in V \setminus \{0\}} \sum_{k \in K} w_i y_{ik} \left[P_{early} \max(ET_i - s_{ik}, 0) + P_{late} \max(s_{ik} - LT_i, 0)\right] \quad (6)$$

The dynamic weight w_i is determined by order size:

$$w_i = \begin{cases} \gamma, r_i \geq Q_{limit} \\ 1.0, 0 < r_i < Q_{limit} \end{cases} \quad (7)$$

3.4. Constraints

$$\sum_{j \in V \setminus \{0\}} x_{0jk} = z_k, \forall k \in K \quad (8)$$

$$\sum_{k \in K} z_k \leq M \quad (9)$$

$$\sum_{i \in V \setminus \{0\}} r_i y_{ik} \leq Q_{max}, \forall k \in K \quad (10)$$

$$\sum_{k \in K} y_{ik} = 1, \forall i \in V \setminus \{0\} \quad (11)$$

$$\sum_{i \in V} x_{ijk} = \sum_{i \in V} x_{jik} = y_{jk}, \forall j \in V, \forall k \in K \quad (12)$$

$$s_{jk} = \sum_{i \in V} x_{ijk} \left(s_{ik} + t_{open,i} + \frac{D_{ij}}{v}\right), \forall j \in V \setminus \{0\}, \forall k \in K \quad (13)$$

Constraints (8) and (9) limit fleet activation; (10) prevents overloading; (11) ensures each terminal is served exactly once; (12) enforces flow conservation; (13) defines temporal continuity.

4. NUMERICAL EXPERIMENTS AND RESULT ANALYSIS

4.1. Experimental Design

Due to commercial sensitivity of real data, a synthetic benchmark was created on MATLAB following standard VRP norms, reflecting the physical layout and business features of Enterprise H's urban network. The test set includes 1 central distribution center and 100 heterogeneous retail terminals, with a fixed random seed for reproducibility.

To create intense time-window conflicts, 20% of terminals were randomly designated as strategic large supermarkets (large orders, narrow morning time window: 90–140 min after departure), and the remaining 80% as community stores (small orders, wide time windows). Key parameters are listed in Table 2.

Table 2. Main simulation parameters

Parameter	Meaning	Value
f_{fixed}	Dispatch cost per truck	608.00 CNY/vehicle
c_{fuel}	Fuel cost per km	1.10 CNY/km
c_{cool}	Refrigeration energy unit cost	0.50 CNY/kWh
P_{cool}	Refrigeration unit power	12.0 kW
β_1	In-transit loss rate	0.002/min
β_2	Door-opening loss rate	0.004/min
p_{price}	Average product price	15.0 CNY/kg
γ	Penalty multiplier for large supermarkets	5.0

4.2. Algorithm Convergence

The improved ant colony algorithm ran for 100 generations. The convergence curve (Fig. 1) shows a rapid early decline, indicating that the dynamic penalty weight effectively guides ants without changing underlying operators. The mid-stage step-wise descent reflects successful local optima escapes via adaptive pheromone updates. After generation 41, the system stabilizes completely. The algorithm demonstrates fast convergence and strong global search capability for large-scale cold chain scheduling.

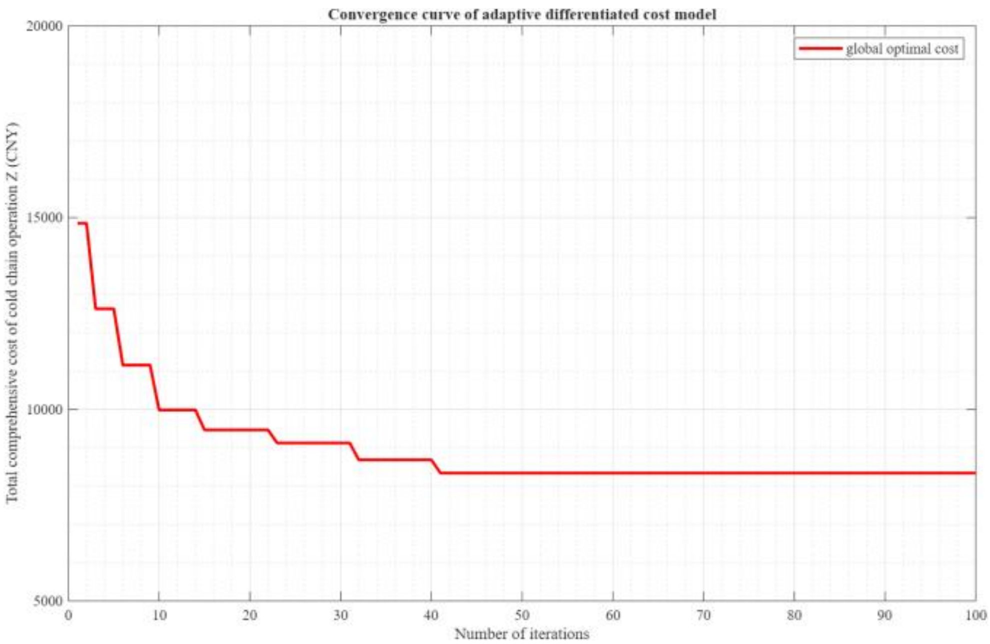

Figure 1. Algorithm convergence curve

4.3. Global Network Topology

The optimized routes for all 100 terminals are shown in Figure 2. The 20 large supermarkets and 80 community stores are randomly interspersed within a 100 km × 100 km area, with no spatial clustering. This realistic layout eliminates the possibility that priority arises from geographical convenience. All routes follow the center-departure, multi-stop, closed-loop pattern, providing a solid baseline for subsequent analysis.

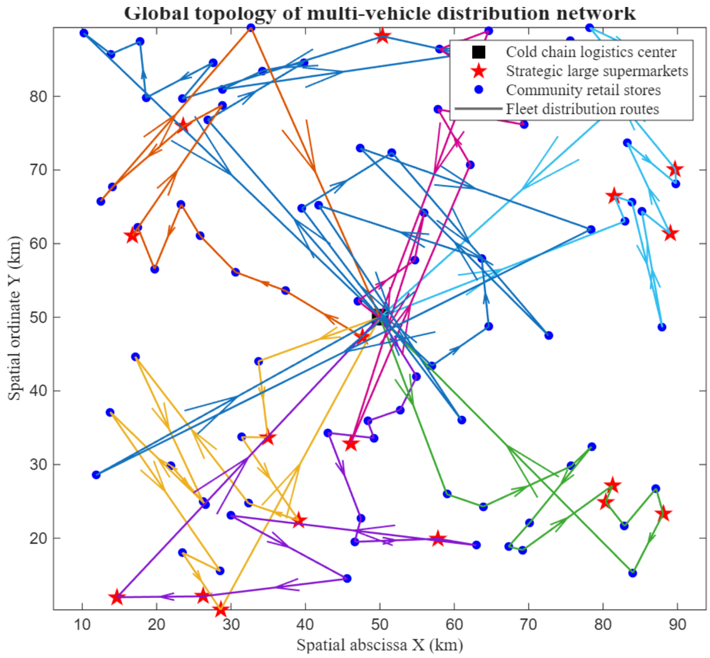

Figure 2. Global topology of multi-vehicle distribution network

4.4. Backbone Route Analysis

To reveal how heterogeneous demand shapes vehicle trajectories, we extracted the routes of two backbone trucks (No. 1 and No. 2) responsible for core large orders (Figure 3).

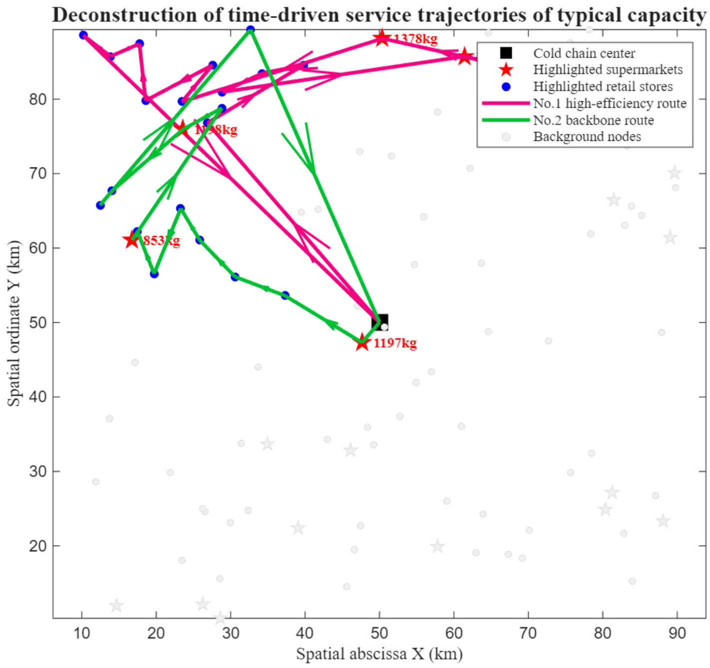

Figure 3. Deconstruction of time-driven service trajectories of typical capacity

Both trucks bypass nearby community stores and head directly to distant large supermarkets, securing their narrow time windows first. On the return trip, they serve small stores along the route. This demonstrates that the differentiated penalty lever successfully embeds management priorities into algorithmic behavior.

4.5. Financial Comparison

A comparative financial analysis between the traditional homogeneous model and the proposed differentiated model is presented in Figure 4.

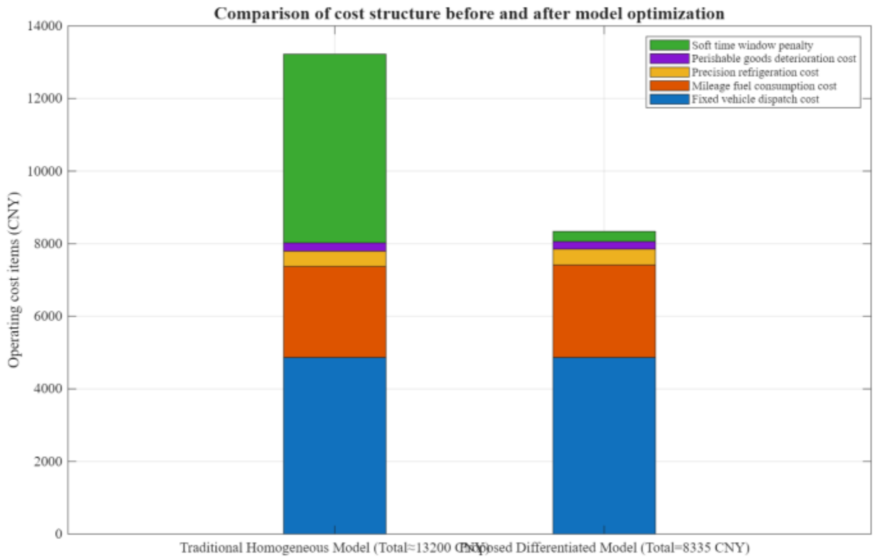

Figure 4. Comparison of cost structure before and after model optimization

Under the homogeneous model, large supermarkets suffer widespread delays, incurring a penalty of 5,200 CNY. The proposed model increases fuel cost slightly from 2,510 to 2,550 CNY (+1.59%) and refrigeration cost from 420 to 435 CNY (+3.57%), but slashes the penalty to 280 CNY (−94.6%). Total savings per shift amount to nearly 5,000 CNY. This confirms that a small marginal transport investment can eliminate massive credit default risk, achieving optimal balance between cost and commercial credibility.

5. CONCLUSION AND MANAGERIAL IMPLICATIONS

5.1. Research Conclusions

To address the timeliness mismatch between different customer types in Enterprise H's urban fresh cold chain distribution, this paper constructs an adaptive cold chain routing optimization model with customer demand heterogeneity, and validates it through numerical experiments based on a 100-node network solved by ant colony algorithm. The main conclusions are drawn as follows:

First, the dynamically weighted time window penalty mechanism can spontaneously guide the fleet to prioritize delivery timeliness for high-value core customers, without modifying the underlying search operators of the algorithm.

Second, the model realizes a favorable balance between transportation economy and commercial credit. With a marginal rise in transportation and refrigeration costs, it substantially reduces the default penalty for core customers and effectively lowers the total cost of each scheduling batch.

5.2. Managerial Implications

For Enterprise H and peer cold chain logistics enterprises, this study puts forward the following operational suggestions:

First, break the homogeneous nearest-distribution mindset and implement differentiated scheduling. Core capacity should be allocated to strategic key customers first, adopting the mode of "main route for priority clients + supplementary stops along the return route".

Second, establish a linkage between the vehicle routing system and financial risk accounting. By dynamically adjusting the penalty lever to guide algorithm optimization, digital scheduling can better serve enterprises' core commercial interests and credit security.

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