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Optimization of Dairy Cold-Chain Distribution Routes Using an Ant Colony Algorithm: A Case Study of Ningbo Milk Group

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Abstract Demand for fresh dairy products places substantial pressure on distribution networks to deliver refrigerated goods efficiently while controlling operating costs, product deterioration, and transport-related emissions. Because dairy products are temperature-sensitive and have limited shelf lives, inappropriate routing decisions can increase vehicle mileage, refrigeration energy consumption, delivery time, and the risk of quality loss. This study develops a cost-oriented vehicle-routing model for a single dairy distribution center and applies an ant colony optimization algorithm to the route-planning problem. The proposed formulation considers fixed vehicle expenses, transport costs, refrigeration during travel and unloading, product damage, and carbon-emission costs. A case study of Ningbo Milk Group in Ningbo, China, considers a single distribution center serving ten specified customer delivery points. The algorithm is evaluated in MATLAB through ten simulation trials and is compared with genetic algorithm and tabu search approaches using the reported case parameters. The ninth of the ten simulation trials produces the lowest reported modeled distribution cost of RMB 2,160, with a total route length of 83 km and three refrigerated delivery vehicles. These numerical findings suggest that ant colony optimization can serve as a useful route-planning heuristic for the specified case-study delivery network and its assumed operating conditions. However, wider operational benefits, emissions reductions, and generalizability require additional field validation, sensitivity analysis, and comparison across multiple demand scenarios.

Index Terms dairy cold-chain logistics; ant colony optimization; vehicle routing; distribution cost; carbon emissions

I. Introduction

China's dairy sector faces a distribution challenge arising from the perishability of fresh milk and related dairy products. Although consumer demand and delivery channels have diversified, the time available for transporting these goods remains limited by refrigeration requirements, product quality considerations, and customer expectations. Refrigerated distribution therefore requires coordinated decisions about fleet deployment, delivery sequence, travel distance, and operating costs. The central problem is not simply to identify the shortest road itinerary but to construct feasible vehicle routes that satisfy delivery needs while reducing the combined costs of transportation, refrigeration, product deterioration, and environmental impacts [1], [2].

Cold-chain logistics differs from ordinary vehicle distribution because temperature control must be maintained during travel and at unloading points. Additional time spent on the road can increase refrigeration expenditure, while inefficient stopping sequences may expose products to handling losses and affect delivery reliability. Routing decisions may also influence fuel use and associated carbon emissions. Research on pollution-aware vehicle routing has demonstrated the importance of considering environmental costs alongside operating expenses rather than treating route distance as the only performance criterion [3]. For a dairy enterprise operating multiple local delivery points, such considerations are relevant to daily fleet planning as well as longer-term sustainability objectives.

The vehicle routing problem (VRP) provides an established mathematical framework for assigning customer requests to vehicles and determining delivery sequences under operational constraints [4], [5]. Nevertheless, including refrigeration, fixed fleet costs, product loss, and emissions produces a more demanding optimization problem. Ant colony optimization is an appropriate candidate heuristic because it constructs routes iteratively using edge-based pheromone information and a distance-related heuristic, while allowing the search to explore alternative feasible delivery sequences [6], [7]. Its usefulness in a practical setting must be assessed against the actual demand network, vehicle capacity, cost parameters, and alternative algorithms rather than assumed from general algorithmic principles.

This study examines the single-depot dairy distribution problem using the delivery network of Ningbo Milk Group

in Ningbo, China. A mathematical cost model is formulated and solved using an ant colony algorithm implemented in MATLAB. The analysis preserves the case-study demand values, vehicle characteristics, and simulation outcomes reported in the original dataset, including comparisons with genetic algorithm and tabu search methods. The study aims to identify a comparatively economical routing plan for the specified delivery points while considering refrigeration and carbon-related costs. The subsequent sections review the relevant literature, define the model and its assumptions, explain the optimization method, present the simulation findings, and discuss the practical limitations of the resulting route plan.

II. Review of Literature

The vehicle routing problem was introduced in an influential study by Dantzig and Ramser in 1959. Their truck-dispatching formulation demonstrated how the assignment of delivery locations and the selection of routes could be coordinated to reduce the total distance traveled by a vehicle fleet [4]. Later research extended this basic structure to accommodate stochastic requests, service-time restrictions, variable travel times, fleet characteristics, and environmental costs. Bent and Van Hentenryck investigated scenario-based planning for partly dynamic vehicle routing with stochastic customers, illustrating how anticipated demand can affect routing decisions [8]. A further class of problems incorporates vehicle or customer time windows and the operating constraints under which delivery plans must be executed [5].

The distribution of perishable products introduces additional objectives because travel and unloading decisions influence the marketable condition of goods. Osvald and Stirn developed a vehicle-routing approach for fresh vegetables and similar perishables that considers time-dependent travel and the economic implications of spoilage; the authors used a tabu-search-based heuristic to construct delivery schedules [9]. Kok and colleagues examined time-dependent vehicle routing with driving-hours rules and required breaks, demonstrating the importance of modeling operational restrictions rather than assuming unconstrained travel [10]. These studies establish that the apparent shortest route may not yield the most practical or least expensive distribution plan once service conditions and product characteristics are considered.

Environmental aspects have become increasingly important in vehicle-routing research. Bektaş and Laporte formulated the pollution-routing problem by incorporating travel times, fuel consumption, vehicle emissions, and associated costs into routing decisions [3]. Poonthalir and Nadarajan subsequently investigated a fuel-efficient green VRP with varying vehicle speeds using particle swarm optimization and a greedy mutation operator [11]. In a cold-chain setting, Liu and colleagues examined a joint distribution model with a carbon-trading mechanism, indicating how cooperation and environmental pricing may affect total distribution costs and emissions [12]. Research attributed to Pan and Gan also addresses cold-chain distribution under carbon-emission considerations; its bibliographic details are supported by a later scholarly review, although direct access to the original article was not available during this audit [13].

More recent work illustrates the breadth of cold-chain routing models. Zhao and colleagues presented an improved multi-objective ant colony method for cold-chain path optimization [14]. Pan and coauthors developed a mixed-vehicle cold-chain routing model that includes carbon-emission costs and examined its performance using case-based simulation [2]. Qi and Li's bibliometric review identifies multi-objective cost structures, temperature-control constraints, sustainability, and intelligent solution methods as continuing directions in this literature [1]. Together, these publications support the view that refrigerated vehicle routing should be considered as a combined operational and environmental optimization problem rather than as a shortest-distance exercise alone.

Ant colony optimization is relevant to these problems because artificial pheromone trails reinforce promising route segments while probabilistic construction mechanisms retain opportunities to explore competing routes. Dorigo and Gambardella described the underlying approach for the traveling salesman problem and established its role as a route-construction metaheuristic [6], [7]. Nevertheless, ant colony methods do not guarantee a global optimum for every instance, and their behavior depends on parameter settings, feasibility handling, stopping rules, and the quality of comparison methods. The present case study therefore tests whether an ant colony implementation offers useful routing outcomes for a specified dairy distribution network rather than claiming universal superiority.

Despite substantial progress, there remains a practical need for carefully documented case studies that combine fixed fleet costs, refrigeration, product deterioration, transport expenditure, and carbon-related charges within a single-depot distribution setting. The analysis presented here addresses that applied problem for ten demand points in Ningbo. Because the available data do not contain independently measured product freshness or post-implementation emissions, such outcomes are discussed as modeling objectives and potential implications rather than as experimentally established improvements.

III. Cost Model for Cold-Chain Logistics

A. Modeling Cold-Chain Logistics Route Planning

The dairy delivery problem is formulated as a refrigerated vehicle routing problem with one distribution center, a defined set of customer locations, and a fleet of delivery vehicles. Each vehicle departs from the depot, visits the customers assigned to its route, and returns to the same starting point. The routing design must account for customer demand, vehicle carrying capacity, transport time, continuous refrigeration requirements, and the total operating cost associated with serving every delivery location. The optimization objective combines fixed vehicle costs with distance-based transport expenses, refrigeration during movement and unloading, modeled product losses, and carbon-emission charges. The mathematical assumptions described below simplify this operational

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setting so that the relative performance of alternative routing sequences can be assessed consistently.

The mathematical formulation is based on the following operational assumptions:

(1) The aggregate demand allocated to each vehicle does not exceed its rated carrying capacity;

(2) Customer locations and their respective delivery quantities are known in advance;

(3) Unplanned disruptions caused by accidents, breakdowns, or emergency route closures are excluded;

(4) Vehicles are assumed to travel at a constant speed and stop only for the delivery operations included in the model;

(5) Internal vehicle temperature is assumed to remain stable, and the vehicle compartment remains sealed except during scheduled unloading;

(6) All delivery routes begin and end at the same single distribution center;

(7) Each customer is served by exactly one vehicle, and collection or pickup requests are not considered.

B. Parameter Definitions

The parameters used in the distribution-routing formulation are summarized in Table 1. They identify the depot and customer sets, vehicle-routing decisions, demand quantities, vehicle capacity, speed, and the coefficients associated with transport, refrigeration, damage, and carbon emissions. Defining these symbols explicitly is necessary to distinguish decision variables from observed input data, establish consistent terminology, and clarify the component-cost calculations used in the numerical experiment. Several symbols in the original formulation are reused for different quantities. Their meaning, dimensional units, and mathematical consistency must therefore be established before the numerical optimization model can be implemented independently.

C. Optimization Cost Analysis

Fixed costs represent expenditures associated with deploying a delivery vehicle, independently of the distance traveled on its assigned route. For the simplified fleet model, the total fixed component is proportional to the number of vehicles used, as expressed below:

$$C_1 = \varepsilon k. \tag{1}$$

Transportation costs reflect the distance covered by refrigerated delivery vehicles and the unit expense of moving the goods along each route. Vehicle speed is held constant in the case-study model, so the travel-time contribution can be derived directly from the route length. Although actual operating costs may also depend on congestion, road conditions, load, and changing fuel prices, these factors are not modeled dynamically in the present simulation. The simplified transportation-cost expression is given below, with the route-selection indicator determining whether a particular vehicle travels between two locations.

Table 1: Definitions of Model Parameters

Symbol	Definition
$u_0 = \{0, 1, \ldots, n\}$	All network nodes, with node 0 representing the depot and nodes 1 to n representing customers
$u_1 = \{1, 2, \ldots, n\}$	Set of customer demand locations
$u_2 = \{1, 2, \ldots, k\}$	Set of available delivery vehicles
x_{ijk}	Binary route indicator: 1 if vehicle k travels from node i to node j, and 0 otherwise
y_{ik}	Binary service indicator: 1 if vehicle k serves demand point i, and 0 otherwise
k	Vehicle index or number, depending on the expression
d_{ij}	Distance between nodes i and j
q_i	Delivery quantity requested at customer i
T	Rated carrying capacity of a vehicle
ε_0	Transport cost per unit distance
ε_1	Refrigeration cost per unit of travel time
ε_2	Refrigeration cost per unit of unloading time
ε_3	Product-damage cost coefficient per unit of travel time
ε_4	Product-damage cost coefficient per unit of unloading time
v	Assumed constant speed of delivery vehicles
t_s	Service or unloading duration at demand point i
r_i	Quantity remaining in the vehicle after leaving customer i
r	Carbon-price or tax coefficient
f	Carbon-emission conversion coefficient
q	Fuel consumption

$$C_2 = \sum_{k=1}^{k} \sum_{i=1}^{n} \sum_{j=1}^{n} \varepsilon_0 d_{ij} x_{ijk}. \tag{2}$$

Dairy products require refrigerated transportation to maintain the specified temperature range throughout delivery. Refrigeration imposes an energy and operating cost during both road travel and unloading, although the magnitude of these costs depends on the vehicle and the conditions of operation. The case-study formulation uses a homogeneous refrigerated fleet and separates the refrigeration component into travel-time and unloading-time contributions. Under the constant-speed assumption, travel time is proportional to distance, while service-time refrigeration depends on the duration of the delivery stop. The resulting cost expression is presented below:

$$C_3 = \sum_{k=1}^{k} \sum_{i=1}^{n} \sum_{j=1}^{n} \varepsilon_1 \frac{d_{ij}}{v} x_{ijk} + \varepsilon_2 t_s x_{ijk}, \tag{3}$$

Here, d_{ij}/v denotes the travel time between demand points i and j, whereas t_s denotes the unloading duration at demand point j. Both components are calculated under the assumed constant-speed operating condition and specified customer service times.

Dairy products may lose commercial value when they are exposed to prolonged transit, handling delays, or unsuitable storage conditions. The model represents this risk through two simplified cost components associated with travel duration and unloading duration. Although collisions, packaging damage, and fluctuations in internal temperature can influence losses in practice, the specific formulation assumes a constant refrigeration environment and excludes collision-related loss.

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Consequently, the product-damage term should be understood as a modeled time-related allowance rather than a direct measurement of spoilage in the case study. The expression used for this component is:

$$C_4 = \sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{n} \varepsilon_3 \frac{d_{ij}}{v} r_i x_{ijk} + \varepsilon_4 t_s r_i x_{ijk}. \tag{4}$$

Carbon-emission costs represent the monetary value assigned to greenhouse-gas emissions associated with the use of refrigerated delivery vehicles. In the simplified formulation, this cost depends on the assumed fuel consumption, an emissions conversion factor, and the carbon price or tax parameter. The corresponding expression is given below. The emissions assumptions should be interpreted as modeling inputs; independent verification would be required before treating the resulting cost as an observed environmental charge.

$$C_5 = \sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{n} qrfd_{ijk}x_{ijk}. \tag{5}$$

D. Establishment of the Optimization Model

The aggregate cost C_{total} is calculated as the sum of the five individual components, each of which represents a distinct category of modeled distribution expenditure, as follows:

$$\begin{aligned} C_{\text{total}} = {} & C_{\text{fixed}} + C_{\text{transportation}} \\ & + C_{\text{refrigeration}} + C_{\text{damage}} + C_{\text{carbonemission}}, \end{aligned} \tag{6}$$

Here, C_{fixed} represents the fleet-deployment cost assigned to the delivery operation. The transportation cost, $C_{\text{transportation}}$, depends on distance traveled, vehicle fuel consumption, and the assumed unit fuel price:

$$C_{\text{transportation}} = d \cdot c_{\text{fuel}} \cdot f_{\text{vehicle}}, \tag{7}$$

Here, d denotes traveled distance, c_{fuel} denotes fuel use per unit of distance, and f_{vehicle} denotes fuel cost per unit of fuel consumed.

The refrigeration cost, $C_{\text{refrigeration}}$, accounts for energy consumed while maintaining the required cargo temperature:

$$C_{\text{refrigeration}} = t \cdot e_{\text{refrig}} \cdot c_{\text{electricity}}, \tag{8}$$

Here, t represents refrigeration time, e_{refrig} represents refrigeration energy consumption per unit of time, and $c_{\text{electricity}}$ represents the relevant unit energy price. The product-damage component, C_{damage}, is estimated from cargo value and the assumed loss fraction:

$$C_{\text{damage}} = p_{\text{damage}} \cdot v_{\text{cargo}}, \tag{9}$$

In this expression, p_{damage} is the assumed probability of product damage and v_{cargo} denotes cargo value. The next term describes the modeled carbon-emission cost, estimated using a charge per unit of distance:

$$C_{\text{carbonemission}} = e_{\text{carbon}} \cdot d, \tag{10}$$

Here, e_{carbon} denotes the modeled emissions-related cost coefficient per unit distance and d denotes the total distance traveled. The original formula does not specify whether this coefficient incorporates the carbon price; the dimensional units therefore require confirmation.

The overall routing objective is therefore to minimize the combined cost while satisfying customer-service and vehicle-capacity constraints. The component formulas require consistent units and mutually exclusive cost definitions to avoid counting the same fuel or refrigeration expense more than once. In particular, the original description includes both a route-based transport term and a separate fuel-based illustration; their relationship should be clarified before the numerical model is reproduced.

IV. Solution Using the Ant Colony Algorithm

Ant colony optimization (ACO) is a population-based metaheuristic designed for combinatorial search problems in which many feasible route combinations must be evaluated. Its artificial agents construct candidate routes using pheromone information accumulated from earlier iterations and a heuristic preference for shorter or otherwise more promising links. After candidate solutions have been evaluated, pheromone values are updated to favor route components associated with relatively good solutions [6], [7]. The approach can balance exploration and exploitation, but it cannot by itself certify that a global mathematical optimum has been found.

For the dairy cold-chain application, the cost model incorporates fixed fleet costs, transport distance, refrigeration, modeled product damage, and carbon charges. Ant colony optimization is used to search the feasible routing space defined by the depot, ten customers, vehicle capacities, and service parameters. The reported MATLAB experiment specifies the number of ants, pheromone evaporation rate, search exponents, and maximum iteration count. These settings permit evaluation of solution quality across repeated simulation runs; comparison with genetic algorithm and tabu search provides an additional benchmark within the single case-study instance.

A. Initialization of the Ant Population

The ant colony procedure starts by establishing an initial set of candidate tours. Customer locations are encoded as nodes, and the distribution center serves as the common start and end point. For each artificial ant, an unvisited feasible customer is selected as the next destination according to the route-construction rule. The visited-customer record is then updated, and the process continues until a candidate solution covers all required demand points. Any route assignment must also respect the vehicle-capacity restriction and the requirement that each customer receive service once. After completing the candidate solution, the algorithm calculates its total cost and uses the result to inform subsequent pheromone updates.

The initialization and route-construction procedure is summarized in two steps. First, each ant begins at the depot and selects an eligible initial customer from the unvisited set.

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Second, it extends its current route in accordance with the transition rule, recording each selected customer and returning to the depot when the current vehicle's service sequence is complete. This process is repeated for the available vehicles until the proposed solution includes every demand point.

Ants select subsequent destinations by balancing a pheromone-guided preference for historically promising edges with a probabilistic selection mechanism. If the search relies too strongly on accumulated pheromone, candidate routes can become overly similar, increasing the risk of premature convergence to a local solution. The proposed implementation combines deterministic preference with roulette-wheel selection to retain a degree of exploration. The transition rule supplied in the original formulation is retained below for completeness; however, its branch notation, indexing, and probabilistic interpretation must be checked against the executable MATLAB algorithm before they can be reused reliably:

$$j_{ij}(k) = \begin{cases} \arg\max[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]\beta & (\text{If } q \leq q_0) \\ p_{ij}^{k}(t). \end{cases} \tag{11}$$

In the transition rule, q is a random value in $[0, 1]$ and q_0 is a selection threshold in the same interval. The function $\tau_{ij}(t)$ represents the pheromone level associated with travel from customer i to customer j at iteration t. The heuristic $\eta_{ij}(t)$ represents the attractiveness of selecting that edge and is typically based on the inverse of travel distance. The parameters α and β control the relative influence of pheromone information and heuristic desirability. The expression for the alternative probabilistic branch remains ambiguous in the source and requires technical verification.

When $q > q_0$, the method is described as using roulette-wheel selection. The following expression is, however, a pheromone-update equation rather than a complete probability-based destination-selection formula. Therefore, the distinction between stochastic customer selection and subsequent pheromone updating needs to be clarified against the implemented algorithm:

$$\tau(i) = (1 - \rho) \cdot \tau(i) + \Delta\tau(i). \tag{12}$$

Here, τ denotes a pheromone quantity, ρ is the evaporation coefficient, and $\Delta\tau$ is the pheromone increment applied during updating. These terms do not define a tabu list of unvisited demand locations, which must be maintained separately when candidate routes are constructed.

B. Pheromone Updating

After an ant has completed its proposed route, pheromone levels on the corresponding network edges are updated. The update combines evaporation of the previous trail with deposition associated with newly evaluated solutions:

$$\tau_{ij}(t + 1) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t), \tag{13}$$

Here, $\tau_{ij}(t)$ is the pheromone concentration on edge (i, j) at time t; ρ is the evaporation coefficient satisfying $0 < \rho < 1$; and $\Delta\tau_{ij}(t)$ represents the increment deposited in response to candidate solution quality.

The pheromone increment $\Delta\tau_{ij}(t)$ is expressed in the simplified model as:

$$\Delta\tau_{ij}(t) = \frac{Q}{L}, \tag{14}$$

The constant Q scales the deposition amount, whereas L represents the associated complete route length or cost, depending on the chosen implementation. This distinction needs to be fixed before applying the formula numerically.

Consequently, edges participating in favorable candidate routes can receive additional pheromone, while the evaporation term gradually reduces reinforcement associated with earlier choices. This mechanism is intended to prevent a single early route from dominating the search indefinitely, although its actual effectiveness depends on the evaporation coefficient, the deposit rule, and the stopping conditions. The mathematical notation should explicitly distinguish the total pheromone increment from an increment deposited by a single ant.

The ant-quantity model is represented in the manuscript by the following edge-based deposit rule:

$$\triangle\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{d_{ij}}, & \text{Ant } k \text{ passes through path } (i, j) \text{ at} \\ & \text{time } t \text{ and time t+1} \\ 0, & \text{Otherwise.} \end{cases} \tag{15}$$

In this expression, d_{ij} denotes the distance between nodes i and j, and a traversed edge receives a deposit that decreases as its distance increases. A zero deposit is intended for edges not used by the selected ant.

The alternative ant-density rule assigns a fixed deposit to an edge traversed by an ant, as follows:

$$\triangle\tau_{ij}^{k}(t) = \begin{cases} Q, & \text{Ant } k \text{ passes through path } (i, j) \text{ at time t} \\ & \text{and time t+1} \\ 0, & \text{Otherwise,} \end{cases} \tag{16}$$

The manuscript describes an ant-cycle updating approach for calculating $\triangle\tau_{ij}^{k}$, although the supplied description does not specify the complete implementation or which of the three deposit variants was ultimately used. That information should be reported to make the numerical results reproducible.

C. Selection of the Best Recorded Route

After the stipulated maximum number of iterations has been completed, the best recorded candidate is converted from its internal node encoding into a set of customer-service sequences. The resulting solution specifies the number of vehicles, the order in which each vehicle visits its assigned demand points, the corresponding travel distance, and the modeled distribution cost. The best recorded route should be described as the best solution found by the heuristic within the reported runs, not as a mathematically proven global optimum.

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D. Ant Colony Algorithm Workflow

Figure 1 summarizes the principal steps of the ant colony algorithm used for route construction and iterative improvement. The method was developed from research on pheromone-based cooperative search, and subsequent influential formulations for routing and traveling-salesman problems were described by Dorigo and Gambardella [6], [7]. The biological analogy begins with ants exploring several possible trails between a nest and a food source. Trails used more frequently tend to accumulate more pheromone and can attract subsequent ants, creating a positive-feedback mechanism. In artificial ant colony optimization, this process is abstracted as a route-construction rule in which earlier candidate solutions influence later ones through numerical pheromone weights. Shorter or otherwise more economical routes can be reinforced, but an explicit evaporation mechanism is needed to prevent indefinite accumulation of outdated information.

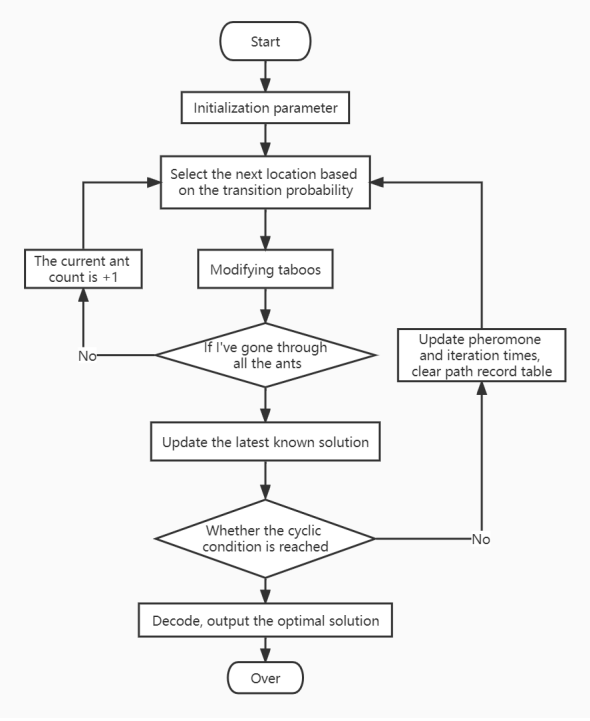


Figure 1: Flowchart of the Ant Colony Optimization Procedure

The effectiveness of the artificial system depends on maintaining a practical balance between reinforcement and diversity. Excessive reinforcement may lead to early convergence on a limited collection of routes, whereas excessive randomness may slow improvement by repeatedly exploring low-quality solutions. This trade-off provides the motivation for combining a deterministic preference with probabilistic selection and for specifying the relative influence of pheromone strength and distance-based heuristic information. The complete procedure is summarized in Figure 1.

V. Simulation Experiments

A. Case Study Background

Ningbo Milk Group Co., Ltd. is used as the case enterprise for examining urban refrigerated dairy distribution. According to the case description supplied with the manuscript, the enterprise operates an integrated chain involving dairy production, processing, distribution, and local retail channels. The routing problem concerns the delivery stage: refrigerated vehicles must depart from a distribution center, supply several city locations, and return to their depot while limiting mileage and cost. Because the company serves customers through a geographically dispersed network, route planning is operationally relevant to delivery reliability, energy use, and the control of refrigerated transport expenses.

The case narrative indicates that historical delivery routing has relied substantially on driver experience. Although experienced drivers can respond to local conditions, experience-based decisions alone may not consistently minimize the combined cost across an entire customer network. This research therefore uses recorded customer locations and delivery quantities to formulate a route-optimization instance. Some organization-specific background claims, including the company's founding history, earlier product portfolio, and geographical service coverage, are not independently documented in the available case-study materials. They are consequently distinguished from the numerical case inputs and are not treated here as independently verified empirical facts.

For the simulation, a single depot and ten distribution points within Ningbo are modeled. The numerical experiment uses the locations, demands, service times, refrigerated vehicle parameters, and cost coefficients shown in the following tables. The objective is to compare feasible route sequences under consistent modeling assumptions; actual realized costs and physical carbon emissions would require operational measurement beyond the available simulation report.

B. Case Study Description

The mapping system was used in this paper to determine the longitude and latitude positions of Ningbo Milk Group Co., Ltd. in Ningbo city. The table lists the depot as location 1 and the ten customers as locations 2 through 11. For the routing sequences reported later, the depot is instead coded as node 0 and customers as nodes 1 through 10. This one-position difference in node numbering must be considered when matching the recorded route sequences to the corresponding named delivery locations. Table 2 identifies the distribution center and ten delivery locations used in the routing analysis:

Table 2: Distribution Center and Customer Delivery Locations

No.	Requirement Point Name	Location
1	Distribution Center	No. 6 Hongsheng Road, Jiangbei, Ningbo
2	Ningbo Milk Group self-operated point 1	Southeast of Ningheng Road, Yinzhou, Ningbo
3	Ningbo Milk Group Jiangbei self-operated point	Southeast of Tonghui Road, Jiangbei, Ningbo
4	Ningbo Milk Group self-operated point 2	South of Sunshine South Road, Haishu, Ningbo
5	Ningbo Milk Group Canghai self-operated point	689 Canghai Road, Yinzhou, Ningbo
6	Ningbo Milk Group Changfeng self-operated point	Jinshui Bay, Huancheng South Road, Yinzhou, Ningbo
7	Ningbo Milk Group Panhuo self-operated point	267 Chunyuan Road, Yinzhou, Ningbo
8	Ningbo Milk Group self-operated point 3	Junya Garden, Airport Road, Haishu, Ningbo
9	Ningbo Milk Group self-operated point 4	South of Yongwang Road, Zhenhai, Ningbo
10	Ningbo Milk Group new road point	Qinsen Phase II, Qinghu Road, Jiangbei, Ningbo
11	Ningbo Milk Group Gaotang self-run point	South of Shuangdong Road, Jiangbei, Ningbo

Table 3 presents the geographical coordinates, demand quantities, and nominal service times of the depot and ten customer locations. The coordinate headings are specified as latitude followed by longitude, consistent with the numerical ranges recorded in the table. This ordering must also be retained when importing the locations into a geographical information system.

Table 3: Coordinates, Demands, and Service Times of Delivery Points

No.	Latitude (°N)	Longitude (°E)	Delivery quantity (t)	Service time (h)
1	29.93364	121.51751	0	0
2	29.84425	121.5867908	0.4	0.25
3	29.93996	121.502426	0.6	0.25
4	29.85743	121.558383	0.4	0.25
5	29.87362	121.60261	0.11	0.25
6	29.83926	121.54816	0.1	0.25
7	29.82722	121.581618	0.4	0.25
8	29.84219	121.503811	0.3	0.25
9	29.92375	121.651202	0.4	0.25
10	29.88998	121.555396	0.4	0.25
11	29.90424	121.534115	0.2	0.25

C. Analysis of Simulation Results

The simulation uses the Ningbo delivery network to assess the cost and route length generated by the selected ant colony configuration. It assumes that every customer must receive its allocated demand from the distribution center and that each vehicle travels at a constant nominal speed. Table 4 summarizes the rated capacity of the refrigerated vehicles and the input coefficients associated with fuel, fixed fleet costs, refrigeration, product damage, and carbon emissions. These coefficients are treated as assumptions specific to the reported case study rather than as independently verified, currently applicable fuel, refrigeration, or carbon-market prices:

Table 4: Refrigerated Vehicle Specifications and Cost Parameters

Project	Parameter	Project	Parameter
Speed	45 km/h	Carbon cost	2 RMB/kg
Rated load capacity	4 t	Fixed costs	120 RMB/vehicle
Refrigerated compartment temperature	0–3 °C	Transport refrigeration cost	7 RMB/h
Average fuel consumption	0.4 L/km	Unloading refrigeration cost	12 RMB/h
Carbon emissions	2.51 kg/L	Transportation damage cost	5 RMB/h
Carbon-price and emissions input parameters (verify definitions)	2 RMB/kg; 0.006	Unloading-related and other damage costs (clarify units)	10 RMB/h; 2 RMB/km
Diesel price	7.12 RMB/L		

The reported simulations were conducted on an HP Pavilion computer running Windows 10 Home, equipped with an Intel Core i5-8250U processor operating at 1.60 GHz. MATLAB R2021a was used for the calculations. Reporting the computational environment provides useful context for the recorded execution times, although the results also depend on algorithm implementation and random initialization.

The ant colony parameters were set to a pheromone exponent of $\alpha = 1.0$, heuristic exponent of $\beta = 5.0$, deposit constant $Q = 1.0$, colony size of $m = 15$ ants, maximum iteration count of $NC = 100$, and evaporation coefficient of $\rho = 0.1$. Table 5 presents the distances, modeled costs, and fleet sizes obtained across ten reported simulation runs. Because the individual random seeds, complete demand-distance matrix, and executable MATLAB source code were not supplied, the precise simulation outcomes cannot be reproduced independently from the manuscript alone:

As shown in Table 5, the ninth simulation trial records the lowest modeled cost among the ten runs. Its best recorded route totals 83 km, uses three vehicles, and costs RMB 2,160. Figure 2 illustrates the corresponding set of delivery routes as represented in the MATLAB simulation:

Table 5: Results of Ten Ant Colony Simulation Trials

Trial number	Total routedistance (km)	Reported distribution cost (RMB)	Number ofvehicles
1	83.35	2760	4
2	87.75	2970	3
3	85.59	2840	3
4	83.98	2270	3
5	85.15	2900	3
6	84.68	2290	3
7	84.02	2880	4
8	83.98	2230	3
9	83.00	2160	3
10	84.69	2300	3

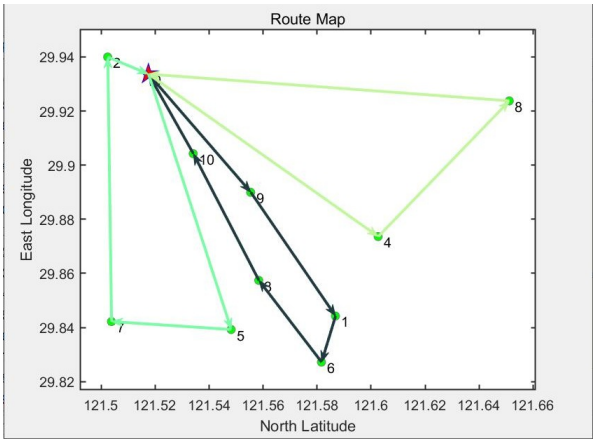


Figure 2: Best Recorded Distribution Routes

The route plan illustrated in Figure 2 allocates the ten customer delivery locations among three separate refrigerated vehicles, each returning to the common distribution center. Table 6 reports each vehicle's visit sequence, total travel distance, and assigned demand. The routes use a zero-based depot code, with customer identifiers from 1 to 10; this differs from the location numbers in Tables 2 and 3. The three tabulated vehicle distances sum to 83 km, and the assigned demand quantities total 3.31 tonnes; both totals can be checked arithmetically from the reported route entries.

Table 6: Selected Vehicle Routes, Travel Distances, and Delivery Quantities

Vehicle number	Recorded visit sequence	Total route distance (km)	Delivery quantity (t)
1	0→9→1→6→3→10→0	26	1.8
2	0→4→8→0	31	0.51
3	0→5→7→2→0	26	1

The iteration record suggests that the best recorded route stabilizes after approximately 20 iterations for the reported parameter settings, although repeated trials and convergence diagnostics are needed to assess robustness. Figure 3 depicts the reported convergence behavior over the course of the

algorithm iterations, while Figure 4 presents the associated distribution outcome for the case-study route network.

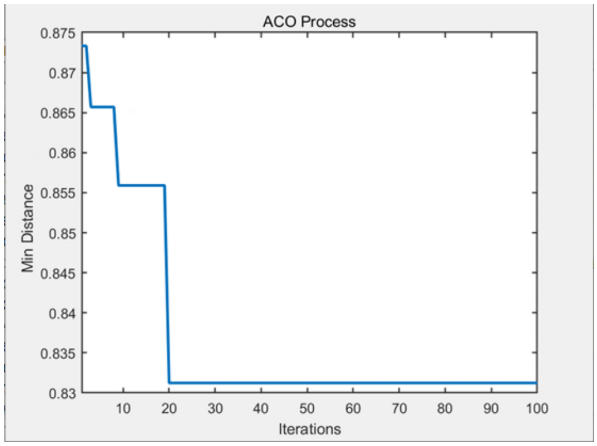


Figure 3: Ant Colony Convergence Across Iterations



Figure 4: Case-Study Distribution Route Results

D. Comparison of Optimization Algorithms

Table 7 compares the reported best routing distance, modeled distribution cost, and computation time for the ant colony, genetic algorithm, and tabu-search approaches under the same selected case-study network. Under the stated simulation conditions, the ant colony method achieves the lowest reported distance and cost, whereas tabu search has the shortest listed computation time. These comparisons are useful within the reported instance but do not establish that one method is uniformly superior across other networks, random seeds, or constraint configurations.

Table 7: Comparison of Routing Algorithms

Algorithm	Best recorded routelength (km)	Reported distribution cost(RMB)	Computation time (s)
Ant colony algorithm	83	2160	1.35
Genetic algorithm	91	2370	1.47
Tabu search algorithm	87	2260	1.25

VI. Conclusion

This study addresses the route-planning problem for a single-depot dairy cold-chain distribution network by applying an ant colony optimization algorithm to a cost formulation that includes fixed fleet expenses, transportation, refrigeration, modeled product losses, and carbon-emission charges. The proposed approach is evaluated using a case-study network associated with Ningbo Milk Group, consisting of one depot and ten delivery locations. The cost model is implemented in MATLAB and tested across ten reported simulation trials, with a genetic algorithm and a tabu-search algorithm serving as comparative heuristic approaches under the case-study conditions.

Among the ten ant colony simulation trials, the ninth produces the smallest recorded cost, RMB 2,160, with a route length of 83 km and a fleet of three refrigerated vehicles. In the reported algorithm comparison, the ant colony approach also yields a shorter route and a lower cost than the genetic algorithm and tabu search solutions for this particular instance. The tabu search method, however, records a slightly shorter computation time, illustrating the need to evaluate several performance criteria rather than route cost alone. These results support the practical relevance of cost-based route construction for the specified delivery network but do not demonstrate global optimality or field-level improvements in product freshness and customer satisfaction.

The findings should be interpreted in light of several limitations. The simulation assumes constant vehicle speed and stable refrigerated conditions, excludes unexpected operational disruptions, and relies on a single network and a restricted set of parameter values. Some original mathematical expressions also require normalization of symbols, summation indices, and cost units before independent reproduction. Furthermore, the supplied data do not provide measured baseline emissions, product-damage outcomes, or repeated out-of-sample delivery performance. Future research should test variable travel times and customer demand, provide reproducible code and complete input matrices, and evaluate additional scenarios using clearly defined operational and environmental indicators. Such validation would help determine whether the heuristic's modeled cost advantages translate into reliable benefits for commercial dairy cold-chain operations.

Conflicts of Interest

The author declares no conflicts of interest.

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Data Availability

The data used and analyzed to support the findings of this study are available from the corresponding author upon reasonable request.

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