

Article

Optimization of Multimodal Transportation Routes for Refrigerated Goods Under Uncertain Demand

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Abstract

With rising customer demands for the timeliness and quality of refrigerated goods, the efficiency and fluidity of cold chain logistics remain inadequate, resulting in a notable imbalance between supply and demand in the cold chain market. To reduce the damage of fresh produce and lower logistics costs, this paper introduces multimodal transportation into the cold chain market and performs an analysis of optimizing multimodal transportation routes for refrigerated goods. This study constructs a mixed-integer programming model for cold chain multimodal transportation, aiming to minimize total costs while considering carbon emissions and uncertain demand. An improved adaptive large neighborhood search (ALNS) algorithm is developed to solve the mathematical model, featuring improved adaptive scoring and operator selection mechanisms. The algorithm's performance is validated through a real-world multimodal transportation network in China. Furthermore, a sensitivity analysis is performed on rail freight rates, confidence levels, and ambient temperature, from which we derive managerial insights with practical significance.

Keywords: multimodal transportation; refrigerated goods; route optimization; uncertain demand; adaptive large neighborhood search

1. Introduction

As living standards improve, public demand for diverse, fresh, and eco-friendly refrigerated goods continues to rise. Given their perishable nature, these goods require stringent temperature control throughout the logistics process, including pre-cooling, transportation, storage, and distribution in a low-temperature environment. To maintain optimal freshness upon delivery to consumers, cold chain logistics companies are investing heavily in the transportation phase. Nevertheless, the overall efficiency of cold chain logistics requires further improvement.

The development of cold chain logistics currently faces three major challenges. First, the high damage rate of refrigerated goods: Due to their short shelf life, long distance and prolonged transportation exacerbate damage. For instance, in China, the damage rate of agricultural products due to cold chain disruptions is one to two times higher than in developed countries, resulting in an annual waste of approximately 12 million tons of fruit and 130 million tons of vegetables, with economic losses exceeding RMB 100 billion.

Academic Editor: Giovanni Leonard

Received: 26 December 2025

Revised: 9 February 2026

Accepted: 23 February 2026

Published: 25 February 2026

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Second, the high transportation costs associated with cold chain logistics: The rapid expansion of the refrigerated goods market, driven by e-commerce and new retail models, necessitates the use of large transport vehicles, significantly increasing transportation costs. Third, the carbon emissions from cold chain logistics are higher than those of regular logistics [1]. Traditional cold chain logistics primarily relies on fuel-powered vehicles and uses refrigeration equipment during transit to maintain freshness, leading to substantial carbon emissions. Therefore, integrating energy conservation and emission reduction into cold chain logistics route optimization is essential for reducing fuel consumption and minimizing environmental carbon pollution.

Multimodal transportation offers a clear cost advantage and can reduce carbon emissions during transportation [2]. By leveraging the combined benefits of various transportation modes, it can effectively address the three major challenges. Although multimodal transportation has attracted significant academic interest as an innovative transportation model, the development of cold chain multimodal transportation remains in its early stages. The recent rise of refrigerated containers has addressed loading issues during mode transitions and established a solid foundation for the advancement of cold chain logistics. Therefore, this study explores the optimization of multimodal transportation routes for refrigerated containers to improve the overall efficiency of the cold chain logistics industry.

Our contributions are as follows: First, we construct a mixed-integer programming (MIP) model considering carbon emissions from transportation and demand uncertainty. The model fully accounts for the unique factors of refrigerated goods, such as refrigeration costs and cargo damage costs, to closely simulate the actual intermodal transport process. We utilize an improved adaptive large neighborhood search (ALNS) algorithm to solve this mathematical model, incorporating destroy and repair heuristic operators designed specifically for the model. The enhancements to the original ALNS algorithm improve its efficiency and accuracy, broadening its application in multimodal transportation route optimization. Finally, we validate the proposed mathematical model and algorithm through a case study based on a multimodal transportation network in China. This network includes 33 Chinese city nodes and 130 transportation arcs, integrating both road and rail modes. Sensitivity analysis of this case study provides valuable management insights for cold chain logistics companies.

In the remainder of this paper, Section 2 reviews multimodal transportation for refrigerated goods, related solution algorithms, and carbon emission considerations. Section 3 describes the problem and introduces the MIP model. Section 4 details the proposed solution algorithm. Section 5 presents a case study, followed by a discussion of the results in Section 6. Finally, Section 7 concludes this paper and outlines directions for future research.

2. Literature Review

Against the backdrop of global carbon reduction efforts, this study aims to improve transportation efficiency and customer satisfaction of cold chain logistics by applying multimodal transportation to refrigerated goods. This paper reviews three key areas: multimodal transportation for refrigerated goods, solution methods for multimodal transportation problems, and multimodal transportation with a focus on carbon emissions.

Perishable goods, unlike general cargo, require additional considerations for damage costs [3]. Liu et al. [4] analyzed the cold chain logistics of fresh products by incorporating both damage costs and refrigeration costs during transportation. Liu [5] proposed an optimization model which accounts for the impact of time-varying network on carbon emissions and employed the Arrhenius equation to estimate the damage costs. He found that a dynamic model based on a time-varying network more accurately captures the real-

world conditions of cold chain multimodal transportation. Bortolini et al. [6] developed a multi-objective model optimizing cost, carbon emissions, and time, accounting for the shelf life of produce. They represented the damage rate as a time-dependent linear function. SteadieSeifi et al. [7] examined the integration of perishable goods with reusable transport items (RTIs), constructing a model aimed at minimizing transportation and transshipment costs for both loaded and empty RTIs. They designed an adaptive large neighborhood search (ALNS) algorithm to solve this model. Subsequently, SteadieSeifi et al. [8] addressed demand uncertainty by proposing a rolling time horizon framework, converting the previous mixed-integer programming model into a scenario-based two-stage stochastic programming model, and optimizing the ALNS algorithm for periodic solutions. To further promote vaccine accessibility, Enayati et al. [9] introduced drone-based multimodal transportation into vaccine distribution networks. They developed two mathematical optimization models that jointly consider transportation time and cold chain time constraints, providing an effective framework for time-sensitive and temperature-controlled distribution. Zhang et al. [10] focused on the mode choice between reefer containers and bulk vessels in seaborne cold chains for time-sensitive products, integrating VBM with speed optimization, cargo depreciation, and greenhouse gas emission constraints. Their results showed that cargo perishability plays a more dominant role than environmental constraints, leading to adaptive mode selection and a size-differentiated deployment strategy, whereby smaller bulk and container ships are assigned to short-haul legs, while larger bulk vessels serve long-distance routes. Bilican et al. [11] investigated cargo transportation in containerized shipping and proposed a collaborative decision support framework that addresses cargo composition and stowage planning through a two-stage optimization approach. Their framework jointly determines the selection of containers to be transported and their allocation within the vessel while explicitly considering revenue maximization, ship stability, and crane utilization. However, although refrigerated containers are included as a cargo type, the analysis focuses primarily on stowage capacity constraints and does not account for temperature-dependent cargo deterioration characteristics, which are critical for refrigerated and perishable goods.

In addressing the multimodal transportation route optimization problem, several researchers have focused on the development of exact algorithms. For instance, Hao and Yue [12] developed an optimization model and corresponding dynamic programming algorithm. Wolfinger et al. [13] introduced a solution method based on a column generation framework combined with iterative local search. Although exact algorithms provide optimality guarantees, they suffer from exponential computational complexity, which limits their scalability to large, real-world networks. Consequently, heuristic and metaheuristic methods have gained prominence due to their flexibility and efficiency in handling multi-constraint problems. Among them, Chen and Schonfeld [14] utilized a hybrid heuristic technique combining sequential quadratic programming and genetic algorithms to solve the scheduling problem in intermodal transportation. Their problem considers loading and unloading, storage and cargo-processing operations, which can provide some flexibility in the management of general and perishable cargoes. Zhang et al. [15] integrated the Frank–Wolfe algorithm within a genetic algorithm framework to solve the model. Zhu and Zhu [16] developed a multi-level objective decision model for multimodal transportation and utilized the NSGA-II algorithm for its solution. Zhao et al. [17] proposed a hybrid heuristic algorithm combining Monte Carlo, neural network, and genetic algorithms. Abbassi et al. [18] merged the simulated annealing algorithm with exact algorithms, designing the PBSA–exact hybrid algorithm to solve the path planning problem, and validated its effectiveness through comparison with CPLEX, SA, and PBSA. From the perspective of carriers, Yang et al. [19] established a mathematical model to optimize multi-

modal transportation problems considering differences in cargo time sensitivity. They employed a bi-level genetic algorithm to solve the model, which demonstrated significantly better performance than the traditional single-level genetic algorithm. Zukhruf et al. [20] investigated the restoration problem of multimodal transportation networks and designed a novel particle swarm optimization algorithm for its solution. The proposed algorithm exhibits high stability in identifying a high-quality solution and achieves convergence within a shorter computation time. To address the multi-visits drone-vehicle routing problem with simultaneous pickup and delivery service, Zhang and Li [21] developed a three-stage solution framework that integrates an improved K-means++ algorithm with a tabu search strategy.

The transportation of goods generates large carbon emissions, contributing to global warming. Thus, exploring low carbon development strategies for multimodal transportation is important. Pizzol [22] demonstrated that multimodal transportation is more energy-efficient and emits fewer greenhouse gases than single-mode transportation, although there is still substantial room for further emission reductions. Most current research constructs multimodal transportation route optimization models from the perspective of carbon taxes to reduce both carbon costs and overall expenses through improved transport strategies. For example, Sun and Lang [23], Göçmen and Erol [24] each developed models with objective functions to minimize transportation costs and carbon emissions. In the context of low-carbon development, some researchers focus on optimizing models. Zhang et al. [25] proposed that multimodal transportation is influenced by external environmental factors, introducing the concepts of time delay and accident damage coefficients. Feng et al. [26] examined scenarios involving the loading and unloading of bulk cargo at specific transshipment ports, integrating containerization, load shedding and cargo damage costs into their optimization model. Since transportation time directly affects carrier profits, Zhang et al. [27] incorporated transportation time uncertainty into their modeling process. They introduced random variables following a positively skewed distribution to characterize this uncertainty and developed a bi-objective optimization model to capture the trade-off between transportation efficiency and cost. As research into low carbon transport deepens, the uncertainty of carbon trading prices has also been investigated. Li and Sun [28] addressed demand uncertainty and the stochastic nature of carbon-trading prices, employing scenario analysis to describe demand uncertainty and intervals to represent carbon trading prices. Considering transportation time, transportation cost and carbon emission minimization, Gao [29] proposed a mathematical model to synthesize and optimize multimodal transportation issues such as flow distribution, node selection and mode selection. The model can generate multiple routes by splitting and transporting shippers' containers, helping management make multimodal transportation route decisions. Furthermore, Zhang et al. [30] considered the combined effects of mandatory carbon emissions, carbon tax, carbon trading, and carbon offset policies in the context of multimodal transportation. To evaluate the impacts of different low-carbon policies on multimodal route planning, they transformed their model under various policy scenarios, providing valuable insights into the policy-driven optimization of sustainable logistics networks.

Although previous studies on cold chain and multimodal transportation have incorporated cargo damage costs, carbon emissions, and demand uncertainty, these factors are typically modeled as independent parameters, with limited attention paid to their intrinsic interrelationships. In particular, existing studies often focus on either operational-level decisions (e.g., speed or mode selection) or economic and environmental objectives, rather than their underlying physical-economic interactions in refrigerated transportation systems.

To address this gap, the primary methodological contribution of this study is the development of an integrated physical–economic coupling framework for cold chain multimodal transportation under demand uncertainty. Specifically, a three-parameter Weibull model is introduced to characterize the nonlinear physical deterioration process of refrigerated goods, and under a fuzzy demand context, this deterioration process is simultaneously integrated with refrigeration energy consumption and carbon emission costs. As a result, cargo damage, refrigeration energy consumption, and carbon emissions are no longer treated as isolated cost components, but as interdependent outcomes jointly determined by transport mode selection and transit time. This integrated modeling approach reveals the inherent trade-off between low-carbon, longer-duration transport options and high-speed, higher-emission preservation strategies, which cannot be captured by models that treat these elements separately. In addition, an improved ALNS algorithm is specifically developed to solve the proposed cold chain multimodal routing problem, with customized destroy and repair operators that explicitly account for cargo deterioration and emission-related costs.

3. Problem Description and Model Formulation

3.1. Problem Description

The optimization of multimodal transportation routes for refrigerated goods can be described as follows: In a directed transport network, M represents the set of nodes, with at least one mode of transportation connecting adjacent nodes. A is the set of transportation arcs, where road and rail arcs have different distances and speeds. N is the set of n transportation tasks, indicating that n goods need to be transported from their respective origins to their respective destinations. K represents the set of transportation modes between nodes, with different mode choices forming multiple routes from the origin to the destination.

There are currently n refrigerated goods orders that need to be transported from their respective origins to their destinations within specified time windows, passing through multiple intermediate nodes. Each node has a different ambient temperature, and between each pair of connected nodes, there is at least one mode of transportation, either road or rail. The transportation cost, transit time, carbon emissions, and ambient temperature vary for each mode of transport.

Figure 1 presents a simple example to help readers in understanding the cold chain multimodal transportation route optimization problem. This example includes one origin, five intermediate nodes, and two destinations.

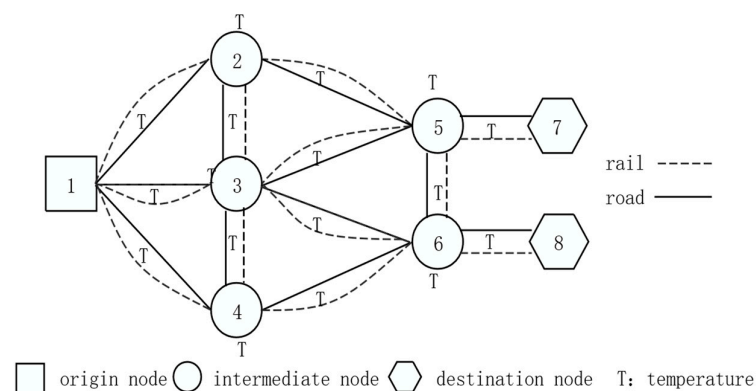


Figure 1. A simple example of cold chain multimodal transportation.

To ensure an appropriate storage environment throughout the transportation process, this study focuses on refrigerated goods transported via refrigerated containers. The objective of this paper is to identify a high-quality transportation path and mode that accounts for refrigeration, cargo damage, in-transit transport, transfer, time window penalty, and carbon emission costs under conditions of demand and carbon emission uncertainty.

3.2. Model Formulation

Compared with existing cold chain transportation models, this model explicitly integrates fuzzy uncertain demand and carbon emission costs, while the deterioration of refrigerated goods is characterized using a three-parameter Weibull function, enabling a more realistic representation of cold chain transportation dynamics.

3.2.1. Model Assumptions

For the cold chain multimodal transportation problem, we have developed an MIP model. To facilitate modeling and computation, the following assumptions are made based on real-world conditions: (1) both road and rail transport modes operate at constant given speeds; (2) refrigerated containers and goods are pre-cooled before loading; (3) goods in the same shipment cannot be split during transport; (4) transfer vehicles are sufficiently available, allowing for immediate transfer upon arrival at a node, with transfer time dependent only on the number of refrigerated containers; (5) transfer and in-transit transport use 20 ft refrigerated containers as carriers; and (6) the temperatures of transport arcs and nodes are considered as average temperatures.

3.2.2. Notation Definition

The notation for the cold chain multimodal transportation route optimization problem is described in Table 1.

Table 1. Cold chain multimodal transportation model parameter and variable definition.

Notation	Meaning
Sets:	
K	set of transportation modes.
O	set of origin nodes.
D	set of destination nodes.
H	set of intermediate nodes.
M	set of nodes.
N	set of transportation tasks n .
A	set of transportation arcs, $(i, j) \in A$.
Parameters:	
m_n	weight of a refrigerated container for transportation task n .
d_{ij}^k	distance from node i to node j using transportation mode k .
v^k	average speed of transportation mode k .
$(T^{n,early}, T^{n,end})$	earliest and latest time windows for transportation task n .
p^1	storage cost that arrives earlier than the time window.
p^2	penalty cost that arrives later than the time window.
tt_i^{kl}	transfer time from transportation mode k to l at node i .
c^k	in-transit transport cost for transportation mode k .
cc_i^{kl}	transfer cost from transportation mode k to l at node i .
zz_i^{kl}	transfer carbon emission factor at node i .
o^k	fuel consumption per distance and weight.
ω	unit cost of carbon emissions.

r^k	emission factor of fuel consumption.
ET_i	average external ambient temperature at node i .
ET_{ij}	average external ambient temperature on arc (i, j) .
ET_n	optimal storage temperature for transportation task n .
θ^n	maximum allowable damage for transportation task n .
f	unit cost of energy.
B_n	indicator of whether the goods undergo respiration (1 if yes, 0 otherwise).
F^n	price of goods in transportation task n .
η_n	respiratory heat generated by goods in transportation task n .
β	cooling capacity generated per unit of energy.
δ	heat transfer coefficient.
S	heat transfer area of the container.
u_{ij}^k	maximum capacity of mode k from node i to node j .

Decision variables:

t_{ij}^k	travel time between nodes i and j using mode k .
$\bar{Q}_n$	uncertain number of containers for transportation task n .
T^n	arrival time of transportation task n at the destination node.
t_{in}^{kl}	transfer time at node i .
C_{ij}^{kn}	total in-transit transport costs for task n between nodes i and j using transportation mode k .
C_{in}^{kl}	total transfer costs for task n when switching from transportation mode k to l at node i .
Z_{in}^{kl}	total carbon emissions for task n when switching from transportation mode k to l at node i .
e_{ij}^{kn}	total carbon emissions for task n between nodes i and j using transportation mode k .
L_i^{kn}	departure time of task n from node i using mode k .
T_i^{kn}	arrival time of task n at node i using mode k .
x_{ij}^{kn}	= 1 if task n transport from node i to node j using mode k , and 0 otherwise.
y_{in}^{kl}	= 1 if task n switches from mode k to l at node i , and 0 otherwise.

3.2.3. Mathematical Model

To systematically coordinate multiple transportation tasks within the cold chain network, the optimization model is formulated within the framework of a Capacitated Multicommodity Flow (CMCF) problem. Under this formulation, each task n is treated as an individual commodity defined by a unique origin–destination pair. The structural integrity of the model rests on two fundamental principles: flow conservation for each task and shared capacity constraints across network arcs. Together, these components establish the underlying network flow backbone, whose definitions are provided in the following subsections.

Extending this classical CMCF structure, the proposed model further incorporates cold-chain-specific economic mechanisms into the objective function. Unlike conventional freight systems, refrigerated transportation is governed by an interplay among time-dependent cargo damage, refrigeration energy consumption, and carbon emission costs. These elements form a physical–economic coupling that reflects the unique operational characteristics of perishable goods logistics. Specifically, because refrigerated containers require continuous cooling to mitigate product deterioration, it is essential to rigorously define the refrigeration and cargo damage cost functions before presenting the complete mathematical formulation.

Refrigeration costs for refrigerated goods:

In cold chain multimodal transportation, the refrigeration energy consumption of refrigerated containers primarily consists of two components: (i) the energy required to remove heat generated by the respiratory activity of the goods, and (ii) energy losses due to heat transfer through the container walls and air leakage. Specifically, perishable goods produce heat through respiration during storage, which raises the internal temperature of the container. To maintain the desired temperature and prevent quality deterioration, additional cooling is required. The corresponding refrigeration costs incurred to offset the respiratory heat, referred to as the respiratory refrigeration costs, are calculated using Equation (1).

$$C_1 = \sum_{n \in N} f \frac{0.0036 m_n \widetilde{Q}_n \eta_n T^n B_n}{\beta} \quad (1)$$

For respiring products, the respiration time equals the total transportation time; for non-respiring products, the respiration time is zero.

Heat transfer in the container occurs through conduction between the container and the external environment. Heat leakage results from poor sealing or aging insulation, allowing external heat to penetrate the container. Both heat transfer and leakage raise the container's temperature, impacting the preservation of refrigerated goods. To counteract this, refrigeration equipment is necessary, incurring container heat transfer and leakage costs, calculated by Equation (2).

$$C_2 = f \cdot \frac{E}{\beta} \cdot t = f \widetilde{Q}_n \left[\sum_{n \in N} \sum_{i \in M} \sum_{k, l \in K} \frac{3.6 \delta S (ET_i - ET_n)}{\beta} t_{in}^{kl} y_{in}^{kl} + \sum_{n \in N} \sum_{(i,j) \in A} \sum_{k \in K} \frac{3.6 \delta S (ET_{ij} - ET_n)}{\beta} t_{ij}^k x_{ij}^{kn} \right] \quad (2)$$

E represents the refrigeration energy consumption, t denotes the transportation time, and S is the average heat transfer area of the container, with $S = \sqrt{S_1 S_2}$, where S_1 and S_2 are the internal and external surface areas of the container, respectively.

Damage costs for refrigerated goods:

In the transportation phase of refrigerated goods, damage is often unavoidable due to the perishable nature of the goods. This study employs a three-parameter Weibull distribution function to compute damage costs, as given by Equation (3). This model uses the total transportation time as the independent variable and determines the three parameters based on the characteristics of different goods, considering the impact of transportation time on damage. This approach provides a more realistic cost estimation and decision support for optimizing cold chain multimodal transportation routes. To maintain mathematical rigor and ensure the term $(T^n - \gamma)$ in the Weibull function remains non-negative, we define the damage cost as zero when the transportation time T^n is less than γ . This assumption ensures the model's physical consistency and provides a more realistic cost estimation for optimizing cold chain routes.

$$C_{damage} = \sum_{n \in N} \widetilde{Q}_n m_n F^n \begin{cases} 1 - e^{-\alpha(T^n - \gamma)^\beta}, & T^n \geq \gamma \\ 0, & T^n < \gamma \end{cases} \quad (3)$$

The parameters α , β , and γ represent the scale, shape, and location factors of the Weibull function, respectively.

Based on the above analysis, we construct the following optimization model for cold chain multimodal transportation.

$$\begin{aligned}
\min C &= C_{ij}^k + C_i^{kl} + C_1 + C_2 + C(T) + C_{damage} + C_{emission} \\
&= \sum_{n \in N} \sum_{(i,j) \in A} \sum_{k \in K} \bar{Q}_n d_{ij}^k c^k x_{ij}^{kn} + \sum_{n \in N} \sum_{i \in H} \sum_{k,l \in K} \bar{Q}_n c c_i^{kl} y_{in}^{kl} \\
&\quad + f \bar{Q}_n \left[\sum_{n \in N} \frac{0.0036 m_n \eta_n T_n}{\beta} \right. \\
&\quad + \sum_{n \in N} \sum_{i \in M} \sum_{k,l \in K} \frac{3.6 \delta S (ET_i - ET_n)}{\beta} t_{in}^{kl} y_{in}^{kl} \\
&\quad + \sum_{n \in N} \sum_{(i,j) \in A} \sum_{k \in K} \frac{3.6 \delta S (ET_{ij} - ET_n)}{\beta} t_{ij}^k x_{ij}^{kn} \left. \right] \\
&\quad + \sum_{n \in N} P^1 \bar{Q}_n \max[(T^{n,early} - T^n), 0] \\
&\quad + \sum_{n \in N} \sum_{n \in N} P^2 \bar{Q}_n \max[(T^n - T^{n,end}), 0] + \sum_{n \in N} \bar{Q}_n m_n F^n (1 \\
&\quad - e^{-\alpha(T^n - \gamma)^\beta}) + \omega \left(\sum_{n \in N} \sum_{(i,j) \in A} \sum_{k \in K} \bar{Q}_n m_n o^{k,r^k} d_{ij}^k x_{ij}^{kn} \right. \\
&\quad \left. + \sum_{n \in N} \sum_{i \in H} \sum_{k,l \in K} z z_i^{kl} \bar{Q}_n m_n y_{in}^{kl} \right)
\end{aligned} \tag{4}$$

$$t_{ij}^k = \frac{d_{ij}^k}{v^k}, \quad \forall (i,j) \in A; \forall k \in K \tag{5}$$

$$T_i^{kn} = L_i^{kn} + t_{i-i}^k \quad \forall i^-, i \in M; \forall k \in K; \forall n \in N \tag{6}$$

$$L_i^{ln} = T_i^{kn} + t_{in}^{kl} y_{in}^{kl}, \quad \forall i \in M; \forall k, l \in K; \forall n \in N \tag{7}$$

$$T^n = \sum_{(i,j) \in A} \sum_{k \in K} t_{ij}^k x_{ij}^{kn} + \sum_{i \in M} \sum_{k,l \in K} t_{in}^{kl} y_{in}^{kl} \quad \forall n \in N \tag{8}$$

$$\sum_{i^+ \in M} \sum_{k \in K} x_{ii^+}^{kn} - \sum_{i^- \in M} \sum_{k \in K} x_{i-i}^{kn} = \begin{cases} 1 & i = O \\ -1 & i = D \\ 0 & i = H \end{cases}, \quad \forall i \in M; \forall n \in N \tag{9}$$

$$\sum_{i \in O} \sum_{j \in M} \sum_{k \in K} x_{ij}^{kn} \leq 1 \quad \forall n \in N \tag{10}$$

$$\sum_{i \in M} \sum_{j \in D} \sum_{k \in K} x_{ij}^{kn} \leq 1 \quad \forall n \in N \tag{11}$$

$$\sum_{k \in K} x_{ij}^{kn} \leq 1 \quad \forall i, j \in M; \forall n \in N \tag{12}$$

$$\sum_{k,l \in K} y_{in}^{kl} \leq 1 \quad \forall i \in M; \forall n \in N \tag{13}$$

$$(1 - e^{-\alpha(T^n - \gamma)^\beta}) \leq \theta^n \tag{14}$$

$$\sum_{i^- \in M} \sum_{k \in K} x_{i-i}^{kn} + \sum_{i^+ \in M} \sum_{k \in K} x_{ii^+}^{ln} \geq \sum_{k,l \in K} y_{in}^{kl} \quad \forall i \in H; \forall n \in N \tag{15}$$

$$\sum_{n \in N} \bar{Q}_n m_n x_{ij}^{kn} \leq u_{ij}^k \quad \forall i, j \in M; \forall k \in K \tag{16}$$

$$x_{ij}^{kn} = \begin{cases} 0 \\ 1 \end{cases} \quad \forall i, j \in M; \forall k \in K; \forall n \in N \quad (17)$$

$$y_{in}^{kl} = \begin{cases} 0 \\ 1 \end{cases} \quad \forall i \in M; \forall k, l \in K; \forall n \in N \quad (18)$$

The objective function (4) aims to minimize the total costs of cold chain multimodal transportation. The total costs comprise six components: in-transit transport costs C_{ij}^k , transfer costs C_i^{kl} , refrigeration costs C_1 and C_2 , time window penalty costs $C(T)$, damage costs C_{damage} , and carbon emission costs $C_{emission}$. Constraint (5) represents the transit time of goods on each transportation arc. Constraint (6) specifies the arrival time at node i . Constraint (7) specifies the departure time from node i . Constraint (8) denotes the total time for a transportation task to reach its destination. Constraint (9) ensures flow conservation: a net flow of 1 at the origin, -1 at the destination, and balanced flow at intermediate nodes. Constraints (10) and (11) ensure the uniqueness of the origin and destination of the goods. Constraint (12) ensures that goods are transported between nodes i and j using at most one mode of transport. Constraint (13) ensures that goods are transferred at most once at any node. Constraint (14) represents cargo damage. Constraint (15) ensures transfer balance at intermediate nodes. Constraint (16) indicates the transportation capacity of the arcs. Constraints (17) and (18) define the transportation mode variable x_{ij}^{kn} on the arcs and the mode conversion variable y_{in}^{kl} at intermediate nodes, both represented as binary decision variables.

To make the multi-task coordination mechanism mathematically explicit, the model instantiates the CMCF structure through specific network flow constraints. While Constraint (9) ensures the individual flow continuity (node balance) for each specific task n , the coupling and resource competition among multiple tasks are explicitly governed by Constraint (16). By aggregating the volumes of all commodities sharing the same arc (i, j) and mode k , the model accounts for the shared nature of network capacity. This ensures that the routing decision of one task potentially restricts the feasible space for others, effectively representing the systemic optimization of the cold chain network.

To handle such uncertainty, many researchers have employed triangular fuzzy numbers [31]. Following this line of research, we use triangular fuzzy numbers to represent demand uncertainty. The triangular fuzzy demand for transportation order n is $\tilde{Q}^n = (Q_l^n, Q_m^n, Q_u^n)$, where $0 \leq Q_l^n \leq Q_m^n \leq Q_u^n$. $\tilde{Q}^n$ is the uncertain demand, Q_l^n is the most conservative estimate, Q_m^n is the most likely estimate, and Q_u^n is the most optimistic estimate. To handle the model with fuzzy demand clearly, we adopt the fuzzy chance constrained programming model proposed by Liu and Iwamura [32]. For a minimization problem, the goal is to find the minimum value of the objective function achievable with a probability of no less than the confidence level. The fuzzy chance constrained programming model is as follows:

$$\min \bar{f} \quad (19)$$

$$s. t. Pr\{f(\mathbf{x}, \boldsymbol{\varepsilon}) \leq \bar{f}\} \geq \alpha \quad (20)$$

$$Pr\{g_i(\mathbf{x}, \boldsymbol{\varepsilon}) \leq 0, i = 1, 2, \dots, p\} \geq \beta_i \quad (21)$$

$\mathbf{x}$ is the fuzzy decision vector, $\boldsymbol{\varepsilon}$ is the fuzzy vector, α is the confidence level of the objective function, β_i is the confidence level of the constraints, $f(\mathbf{x}, \boldsymbol{\varepsilon})$ is the objective function, and $g_i(\mathbf{x}, \boldsymbol{\varepsilon})$ is the constraint of the fuzzy programming.

Therefore, the chance-constrained programming model with fuzzy variables in this paper is given by Equations (22)–(25).

$$\min \bar{C} \quad (22)$$

$$Pr\{C(\mathbf{x}, \mathbf{y}) \leq \bar{C}\} \geq \alpha \quad (23)$$

$$Pr\{\sum_{n \in N} \bar{Q}^n m_n x_{ij}^{kn} \leq u_{ij}^k\} \geq \beta \quad \forall i, j \in M; \forall k \in K \quad (24)$$

$$\alpha, \beta \in [0, 1] \quad (25)$$

$\mathbf{x}$ and $\mathbf{y}$ are the fuzzy decision vectors, α is the confidence level of the objective function, β is the confidence level of the constraints, and $C(\mathbf{x}, \mathbf{y})$ is the objective function.

According to the theorem for handling fuzzy demand, for any confidence level θ ($0 < \theta < 1$), $Pr\{\bar{Q}^n \leq b\} \geq \theta$ if and only if $(1 - \theta)Q_l^n + \theta Q_m^n \leq b$. Thus, the final model expression in this paper is as follows:

$$\min \bar{C} \quad (26)$$

$$\begin{aligned} \bar{C} \geq & [(1 - \alpha)Q_l^n + \alpha Q_m^n] \left(\sum_{n \in N} \sum_{(i,j) \in A} \sum_{k \in K} d_{ij}^k c c_{ij}^k x_{ij}^{kn} + \sum_{n \in N} \sum_{i \in H} \sum_{k,l \in K} c c_i^{kl} y_{in}^{kl} \right) \\ & + f[(1 - \alpha)Q_l^n + \alpha Q_m^n] \left[\sum_{n \in N} \frac{0.0036 m_n \eta_n T_n}{\beta} \right. \\ & + \sum_{n \in N} \sum_{i \in M} \sum_{k,l \in K} \frac{3.6 \delta S(ET_i - ET_n)}{\beta} t_{in}^{kl} y_{in}^{kl} \\ & + \sum_{n \in N} \sum_{(i,j) \in A} \sum_{k \in K} \frac{3.6 \delta S(ET_{ij} - ET_n)}{\beta} t_{ij}^k x_{ij}^{kn} \left. \right] + [(1 - \alpha)Q_l^n \\ & + \alpha Q_m^n] \left[\sum_{n \in N} P^1 \max[(T^{n,early} - T^n), 0] \right. \\ & + \sum_{n \in N} \sum_{n \in N} P^2 \max[(T^n - T^{n,end}), 0] \left. \right] + [(1 - \alpha)Q_l^n \\ & + \alpha Q_m^n] \left[\sum_{n \in N} m_n F^n (1 - e^{-\alpha(T^n - \gamma)^\beta}) \right] + \omega[(1 - \alpha)Q_l^n \\ & + \alpha Q_m^n] \left(\sum_{n \in N} \sum_{(i,j) \in A} \sum_{k \in K} m_n o^k r^k d_{ij}^k x_{ij}^{kn} \right. \\ & + \sum_{n \in N} \sum_{i \in H} \sum_{k,l \in K} m_n z z_i^{kl} y_{in}^{kl} \left. \right) \end{aligned} \quad (27)$$

$$[(1 - \beta)Q_l^n + \beta Q_m^n] \sum_{n \in N} m_n x_{ij}^{kn} \leq u_{ij}^k \quad (28)$$

Additionally, Equations (5)–(15), (17), (18) and (25) all hold.

4. An Improved ALNS Algorithm

Ropke and Pisinger [33] enhanced the large neighborhood search (LNS) algorithm and introduced the ALNS algorithm. Unlike LNS, ALNS dynamically adjusts the weights of the destruction and repair operators during the search process. This adaptability enables ALNS to more effectively explore the solution space and identify superior solutions, leading to its widespread application in vehicle routing problems. In this paper, we apply an improved ALNS to the multimodal transportation problem and refine the operators based on the specific model characteristics. To ensure mathematical consistency with the fuzzy model assumptions, the algorithm incorporates a pre-processing stage for demand uncertainty. Specifically, before the iterative search begins, the fuzzy demand $\bar{Q}^n$ is transformed into a deterministic equivalent value $Q^n(\alpha)$ based on the predefined confidence level α , following the chance-constrained programming derivation in Equation (26). This defuzzification-then-optimization framework guarantees that the ALNS operates in a deterministic search space while preserving equivalence with the original credibility-based

fuzzy chance constraints. Furthermore, the scoring mechanism and operator selection strategy of the ALNS algorithm are improved in this study, thereby improving the algorithm's performance and broadening the scope of applications. Figure 2 illustrates the flowchart of the improved ALNS algorithm.

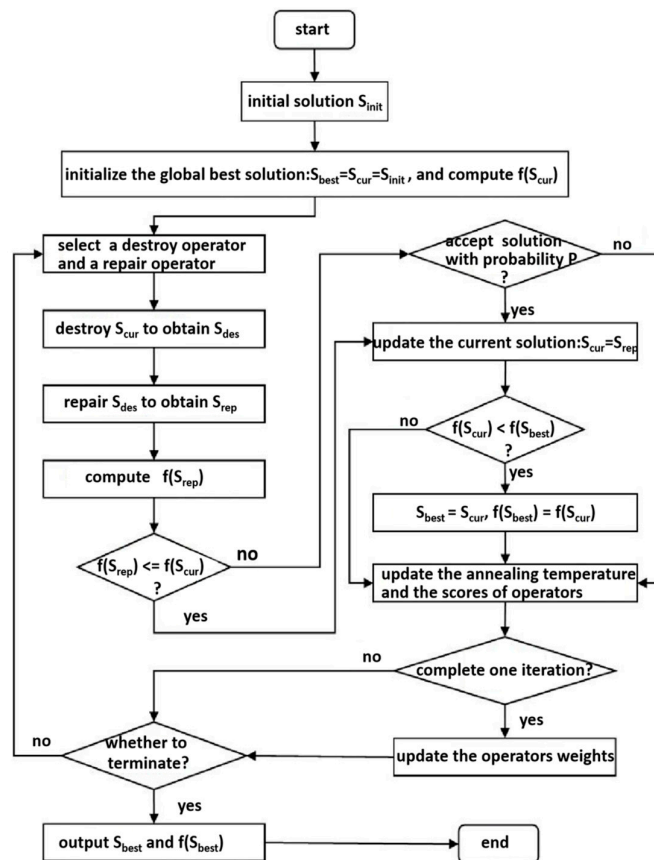


Figure 2. The flowchart of the improved ALNS algorithm.

4.1. Initial Feasible Solution

Step 1: starting from the origin node O , select a directly connected and unvisited node i as the next node to visit.

Step 2: Add node i to the current path and remove it from the set of unvisited nodes. Then, use node i as the new starting point to find the next directly connected and unvisited node j .

Step 3: Repeat step 2 until the designated destination is reached. Upon reaching the destination, connect all remaining unvisited nodes sequentially to the end of the current path. Finally, generate a random transportation mode sequence and append it to the generated transport path, completing the initial feasible solution.

4.2. Destroy Operators

Random removal: randomly select two nodes and remove all routes between these nodes.

Worst removal: Remove the path segment between the nodes with the highest and second highest costs. The costs of node m are defined as the sum of the in-transit transport costs, carbon emission costs between node $m - 1$ and node m , and the transfer costs and carbon emission costs at node $m - 1$.

Shaw removal: if a path contains more than the specified number of consecutive road segments, these segments are deemed highly correlated, and the path is removed.

4.3. Repair Operators

Random insertion: randomly select a node directly connected to the previous node that has not been visited and insert it as a new intermediate node into the previously removed path.

Greedy insertion: In each iteration, the next node connected to the current node is selected together with the corresponding transportation mode, such that the total costs are minimized. The total costs consider in-transit transportation costs, transfer costs, carbon emission costs, respiratory refrigeration costs, and container heat transfer and leakage costs. This process continues until a complete path is formed.

Worst insertion: When repairing the path between two nodes, choose the next node connected to the previous node that results in the highest total costs and its corresponding transportation mode. The cost calculation is the same as in greedy insertion.

Suboptimal insertion: select the next node connected to the current node that results in the second lowest total costs and determine the best transportation mode for this connection.

4.4. Adaptive Mechanism

The adaptive mechanism dynamically adjusts the selection probability of operators, gradually focusing the search on better performing ones to find high-quality solutions more quickly. After completing a search cycle, the weight of each operator is updated based on its score in that cycle. The weight update formula is $\omega_{i,j+1} = (1 - \rho)\omega_{i,j} + \rho \frac{s_{i,j}}{u_{i,j}}$, where $\omega_{i,j}$ represents the weight of operator i in cycle j , ρ is the weight update coefficient, s_i is the score of operator i , and $u_{i,j}$ indicates the usage frequency of operator i . The specific scoring strategy is as follows: If the new solution is better than the best-found solution, it scores Score1; if the new solution is better than the current solution but worse than the best-found solution, it scores Score2; if the new solution is worse than the current solution but accepted, it scores Score3; if the new solution is worse than the current solution and not accepted, it scores Score4.

4.5. Acceptance Criterion

When the new solution is better than the current solution, it is accepted and replaces the current one. When the new solution is worse, it is accepted with a probability P . This algorithm uses the concept of simulated annealing to determine the acceptance criterion, and P is expressed as $P = e^{-\frac{f(S_{repair}) - f(S_{curr})}{T_n}}$, where $f(S_{repair})$ denotes the objective function value of the candidate solution after destruction and repair, $f(S_{curr})$ represents the objective function value of the current solution. T_n is the temperature at the current iteration in the simulated annealing algorithm. As the iterations progress, the temperature T decreases gradually at a cooling rate c . With S_0 as the initial feasible solution, the initial temperature T_1 is set as $T_1 = -\frac{0.05}{\ln 0.5} f(S_0)$. The pseudocode for the improved ALNS is provided in Algorithm 1.

Algorithm 1. Pseudocode for the improved ALNS.

Input: initial solution S_o , destroy operator set D , repair operator set R , cooling rate c , initial temperature $T_{initial}$

Output: the best-found solution S_b

1: Step 1: initialize

2: $S_b \leftarrow S_o$ //the best-found solution

```

3:   $S_c \leftarrow S_o$  //current solution
4:   $T \leftarrow T\_initial$ //initial simulated annealing temperature
5: Step 2: iterative search
6:  while the iteration termination condition is not met then
7:    //choose an operator using roulette wheel mechanism
8:     $j \leftarrow$  use roulette wheel mechanism to choose a destroy operator from  $D$ 
9:     $i \leftarrow$  use roulette wheel mechanism to choose a repair operator from  $R$ 
10:   //operate on the current solution to generate a new solution
11:    $S_n \leftarrow$  apply the destroy operator  $j$  and the repair operator  $i$  to  $S_c$ 
12:   //assess the new solution
13:   if  $f(S_n) < f(S_b)$  then
14:      $S_b \leftarrow S_n$  //update the best-found solution
15:      $S_c \leftarrow S_n$  //update current solution
16:   else if the simulated annealing acceptance criterion is met then
17:      $S_c \leftarrow S_n$  //accept the new solution as the current solution according to
the simulated annealing criterion
18:   end if
19:   //update simulated annealing temperature
20:    $T \leftarrow T * c$ 
21:   if algorithm reaches the specified number of iterations, then
22:     update operator weights based on previous performance data
23:   end if
24: end while
25: Step 3: Output results:
26:   Output the best-found solution  $S_b$ 

```

4.6. Methodological Enhancements of the Improved ALNS Algorithm

To strengthen the methodological contribution, this study introduces two targeted enhancements to the standard ALNS algorithm, focusing on the adaptive scoring mechanism and the operator selection strategy.

1. Improved adaptive scoring mechanism: Most existing ALNS implementations adopt fixed scores to evaluate operator performance, which limits the algorithm's adaptability and may hinder its ability to escape local optima. To address this issue, a randomized adaptive scoring mechanism is proposed. Instead of using fixed values, each score level is defined as a random variable within a predefined interval: Score1 $\in [28, 33]$, Score2 $\in [18, 23]$, Score3 $\in [8, 13]$, and Score4 $\in [3, 8]$. By dynamically varying the scores within reasonable bounds, the algorithm enhances search diversity and improves its global exploration capability without sacrificing solution stability.
2. Alternating a dual-weight operator selection strategy: In the conventional ALNS framework, operator selection probabilities are fully driven by accumulated weights. Although effective in exploitation, this mechanism may lead to excessive reliance on operators that perform well in early iterations, thereby reducing search diversity in later stages. To mitigate this imbalance, an alternating dual-weight strategy is proposed. Two weighting schemes are employed: dynamically updated weights following the standard ALNS mechanism, and fixed uniform weights that assign equal selection probabilities to all operators. The algorithm alternates between these two schemes across iterations, using dynamic weights in odd-numbered iterations and uniform weights in even-numbered iterations. This strategy balances exploitation and exploration, prevents operator overuse, and improves overall search robustness.

These enhancements constitute methodological refinements to the ALNS framework, leading to improved performance in complex multimodal transportation optimization problems.

5. Case Study

In this section, we employ the improved ALNS algorithm to address the multimodal transportation route optimization for refrigerated goods in China. Considering the geographical imbalances in the distribution of refrigerated goods resources across the country, we design a comprehensive multimodal transportation path covering the entire nation. This design aims to validate the model's effectiveness and the feasibility of the improved ALNS solution strategy in practical applications.

5.1. Background of Case

Based on several major cities in China, we construct a multimodal transportation network comprising 33 city nodes and 130 transportation arcs utilizing both road and rail transportation modes, as depicted in Figure 3. The numerical labels (1–33) in the figure represent the indices of the city nodes. Solid lines represent connections between cities that support both road and rail transportation, while dashed lines indicate connections that are limited to road transportation only.

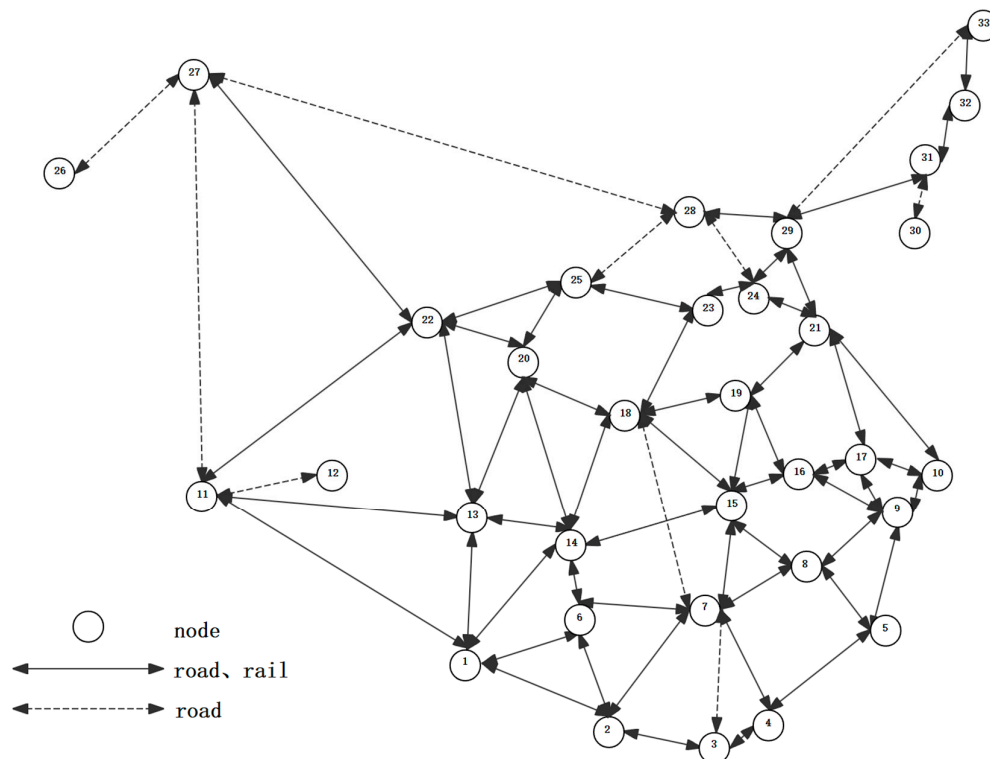


Figure 3. The network structure for multimodal transportation.

Since refrigeration costs are influenced by ambient temperature, each city node in this study is assigned a reasonable ambient temperature. The average temperature for each transportation arc is calculated as the mean of the temperatures at its two endpoints.

In selecting refrigerated goods, we consider the specialty products of the source locations and the actual demand in the destination areas. We choose the strawberry for transport from Dandong to Guangzhou, the apple transport from Aksu to Hangzhou, the

bean transport from Maoming to Beijing, and the yak meat transport from Leiwuqi to Shanghai.

Considering real-world conditions, we set the parameters for the model. The average speed for road transport is 80 km/h, with a transport cost of 6.45 RMB/km · TEU and a carbon emission coefficient of 3.1 kg CO₂/kg. According to the China Railway Network, the average speed of rail transport is 60 km/h, with a transport cost of 4.14 RMB/km · TEU and the same carbon emission coefficient of 3.1 kg CO₂/kg. The transfer cost between road and rail is 150 RMB/TEU, with a transfer time of 0.267 h/TEU and a transfer carbon emission coefficient of 0.128 kg/t. The thermal conductivity of refrigerated containers is 2.5 W/(m² · °C), with a heat transfer area of 31.91 m². Based on the actual specifications of the 20 ft refrigerated container, the refrigeration output per unit of energy is 3000 W/kg, and the unit energy cost is 8.82 RMB/kg. The unit storage cost is assumed to be 200 RMB/TEU · h, the unit penalty cost 400 RMB/TEU · h, and the unit carbon emission cost 0.2 RMB/kg. The parameters of the three-parameter Weibull distribution used to estimate cargo deterioration in this study are based on the work of Sun [34]. To better reflect the damage characteristics of refrigerated goods under the specific conditions considered here, these parameters were slightly adjusted. Tables 2 and 3 summarize the parameters for the selected refrigerated goods and the three-parameter Weibull model, respectively. The temperature settings for different perishable goods follow the Technical Requirements for Temperature-Controlled Transportation of Perishable Food (GB/T 22918-2008) [35]. Since yak meat is transported in a frozen state, it does not generate respiratory heat and therefore does not require additional refrigeration to offset respiration. As a result, quality deterioration during transportation is considered negligible. In this study, the damage of yak meat is assumed to be zero.

Table 2. Parameters related to refrigerated goods.

Refrigerated Goods	Origin-Destination	Weight	Volume	Time Windows	Temperature	Respiratory Heat	Value
strawberry	30–4	8	(16, 20, 22)	24–48	2	41	20,000
apple	26–9	16	(17, 25, 28)	70–80	0	31	12,000
bean	3–29	10	(5, 18, 23)	48–60	8	24	13,200
yak meat	12–10	20	(20, 28, 34)	60–70	−18	—	60,000

Table 3. The three-parameter Weibull model for refrigerated goods.

Refrigerated Goods	Three-Parameter			Maximum Allowable Damage θ^n
	α	β	γ	
strawberry	0.00002	2	−20	20%
apple	0.005	0.45	−30	5%
bean	0.00006	1.6	10	10%
yak meat	0	0	0	0

5.2. Result of Case

Based on the above case analysis and related parameters, we implemented the improved ALNS algorithm using MATLAB R2021a on a laptop with an Intel Core i7-12700H 2.3 GHz CPU and 16 GB RAM (ASUSTeK Computer Inc., Taipei, China). The algorithm parameters were set as follows: a maximum of 500 iterations, an initial simulated annealing temperature of 500, a cooling rate of 0.9, and 20 iterations per stage. The results of the improved ALNS algorithm, including the routes and total cost for the refrigerated goods, are shown in Figure 4.

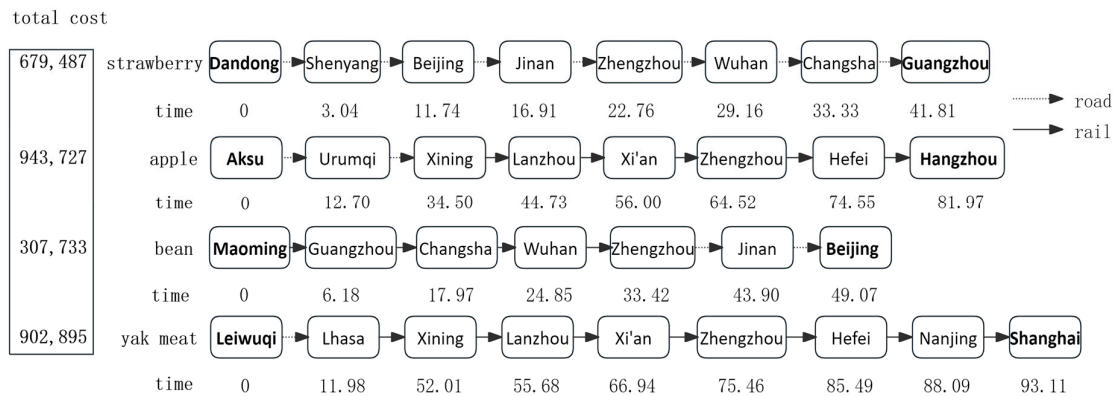


Figure 4. Transportation routes and total cost for each commodity.

The route selection results indicate that the multimodal transportation paths for the refrigerated goods align with actual conditions, avoiding unreasonable phenomena such as circuitous or repetitive routes. This demonstrates that our designed improved ALNS algorithm exhibits high feasibility in real-world scenarios.

The total cost shown in Figure 4 encompasses in-transit transport, transfer, refrigeration, time penalty, cargo damage, and carbon emission costs. The proportion of each cost component to the total cost varies across different types of refrigerated goods.

Figures 5–8 reveal that in-transit transport costs consistently dominate the total expenses across all scenarios. For strawberry, the short shelf life necessitates the use of road transport for the entire journey, as any extension in transportation time significantly increases damage costs. In the case of yak meat transportation, the section from Leiwuqi to Lhasa is only accessible by road, making road transport the only viable option. In the central and western regions, the rail distance is greater than the road distance. To minimize time and refrigeration costs, the initial part of the route still utilizes road transport. The transportation of apple and bean uses a combination of road and rail. These commodities maintain quality over longer periods in refrigerated conditions, and the damage costs incurred over time are lower than the additional costs of exclusive road transport.

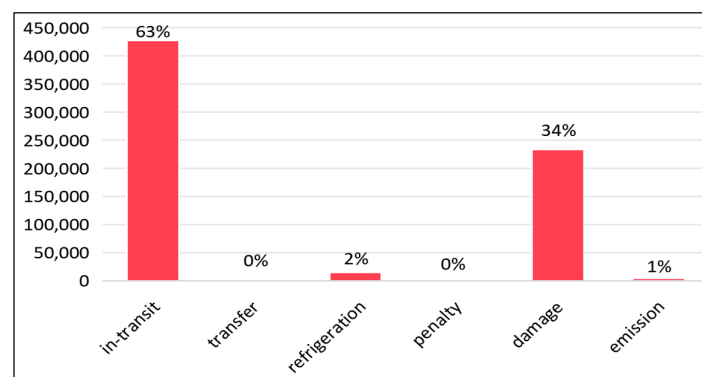


Figure 5. Cost composition for transporting strawberry from Dandong.

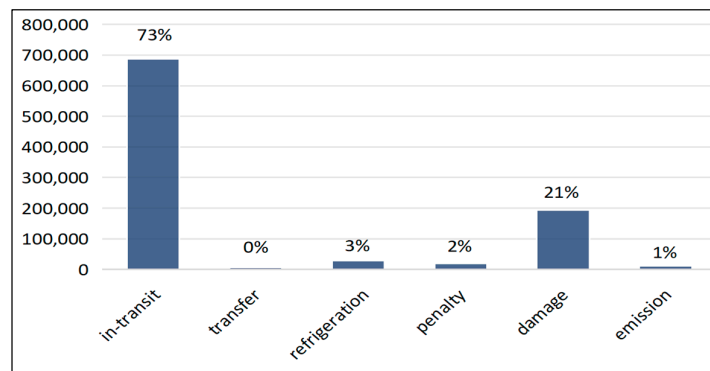


Figure 6. Cost composition for transporting apple from Aksu.

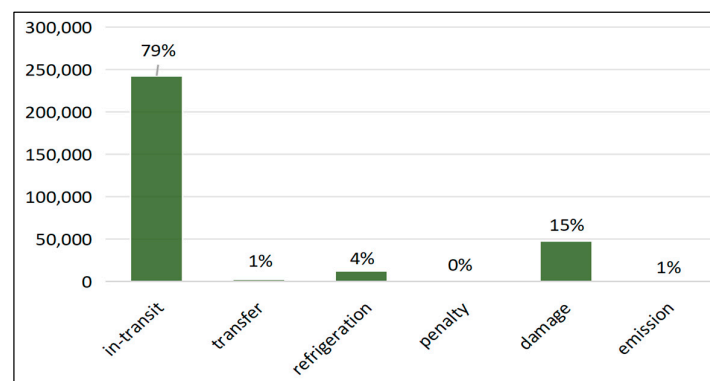


Figure 7. Cost composition for transporting bean from Maoming.

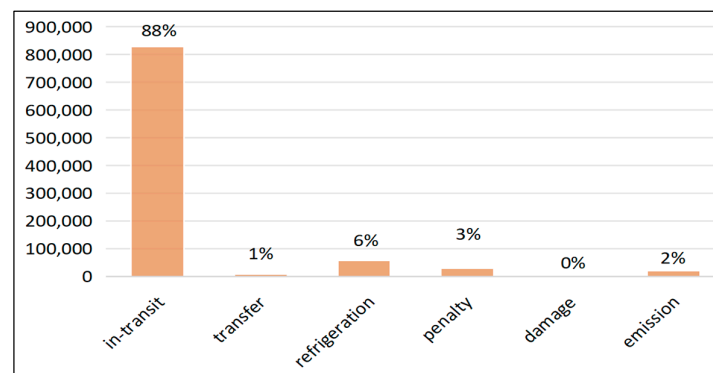


Figure 8. Cost composition for transporting yak meat from Leiwuqi.

5.3. Comparative Analysis of Results

To verify the effectiveness of the improved ALNS, this study conducts two sets of comparative experiments: (1) a test comparing ALNS with Gurobi, and (2) a comparison between ALNS and the Genetic Algorithm (GA).

5.3.1. Comparison with Gurobi

In this study, given the metaheuristic nature of the improved ALNS, the solutions obtained are local optimal solutions, rather than the exact global optimal solutions. While it cannot provide a mathematical guarantee of global optimality, the effectiveness of our proposed improved ALNS algorithm is shown by comparing with the solutions obtained

by Gurobi, thereby providing some insights for cold chain decision-making. Table 4 presents the comparative results of the total cost and computational efficiency for the four types of refrigerated goods considered under study.

Table 4. Comparison of improved ALNS with Gurobi.

Cargo	ALNS		Gurobi		Comparison Result	
	Total Cost	Time	Total Cost	Time	Gap1	Gap2
Strawberry	679,487	0.23	679,487	127.11	0.00%	−99.82%
Apple	943,727	0.24	943,727	1.4	0.00%	−82.86%
Bean	307,733	0.25	296,927	0.67	3.64%	−62.69%
Yak Meat	939,855	0.19	939,855	10.07	0.00%	−98.11%

It is noteworthy that, for the small-to-medium-scale instances considered, the solutions obtained by the Gurobi solver represent global optima of the model. Therefore, the corresponding objective values can be regarded as strong lower bounds for evaluating the performance of the proposed heuristic. From this perspective, the comparison in Table 4 does not merely reflect a heuristic–exact contrast, but provides a lower-bound benchmark against which the solution quality of ALNS can be quantitatively assessed.

Specifically, for the strawberry, apple, and yak meat instances, the solutions obtained by ALNS reach the same objective values as those reported by Gurobi under the experimental settings considered. In contrast, in the bean transportation case, due to the stochastic nature and local optimality of the heuristic search, ALNS converges to a near-optimal local solution. In this case, the relative optimality gap with respect to the Gurobi lower bound is 3.64%, which remains within an acceptable range for metaheuristic approaches.

Although Gurobi guarantees mathematical optimality, the ALNS demonstrates a clear computational advantage. As shown in Table 4, the runtime of ALNS is lower than that of Gurobi in all test instances. The time savings are particularly significant in the strawberry and yak meat cases, where the computational time is reduced by over 98% compared with the exact solver. This evidence indicates that the proposed ALNS can obtain high-quality solutions with higher time efficiency, highlighting its practical suitability for cold chain multimodal routing problems.

5.3.2. Comparison with GA

Genetic algorithms are extensively used in the existing literature to solve multimodal transportation problems. To validate the effectiveness of the improved ALNS algorithm, we applied both the improved GA algorithm and the improved ALNS algorithm to the case study of transporting bean from Maoming to Beijing. The parameters of the GA algorithm are set as follows: the maximum number of iterations is 400, the population size is 50, the crossover probability is 0.8, the mutation probability is 0.2, and the elite ratio is 0.1. The solution results obtained by the two algorithms are presented in Figure 9 and Figure 10.

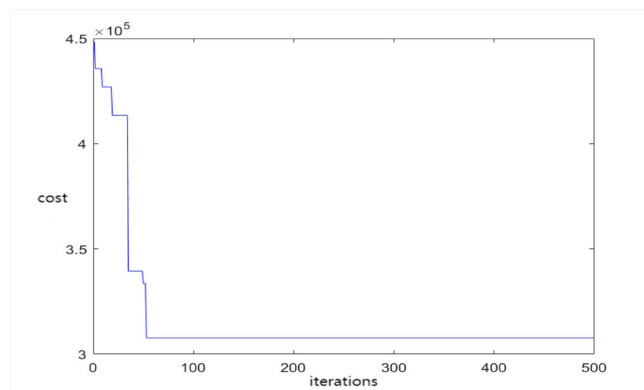


Figure 9. The improved ALNS algorithm.

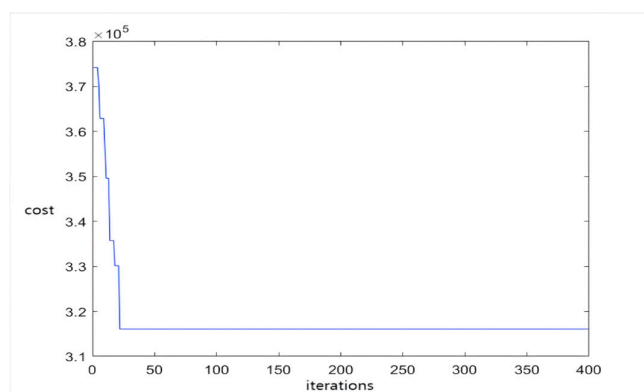


Figure 10. The improved GA algorithm.

As shown in Figure 9, the improved ALNS algorithm yields a minimum total cost of RMB 307,733, with the optimized transportation route being $3 \rightarrow [\text{Rail}] \rightarrow 4 \rightarrow [\text{Rail}] \rightarrow 7 \rightarrow [\text{Rail}] \rightarrow 15 \rightarrow [\text{Rail}] \rightarrow 19 \rightarrow [\text{Road}] \rightarrow 21 \rightarrow [\text{Road}] \rightarrow 29$. In contrast, as illustrated in Figure 10, the improved GA algorithm produces a total cost of RMB 316,082, and the corresponding transportation route is $3 \rightarrow [\text{Rail}] \rightarrow 4 \rightarrow [\text{Rail}] \rightarrow 7 \rightarrow [\text{Rail}] \rightarrow 15 \rightarrow [\text{Rail}] \rightarrow 16 \rightarrow [\text{Rail}] \rightarrow 17 \rightarrow [\text{Rail}] \rightarrow 21 \rightarrow [\text{Road}] \rightarrow 29$.

By comparing these results, the improved ALNS algorithm clearly exhibits superior optimization capabilities over the improved GA algorithm. To further validate the performance of the improved ALNS algorithm, we conducted 20 iterations for each algorithm, recording the results in detail. The specific data are presented in Figure 11.

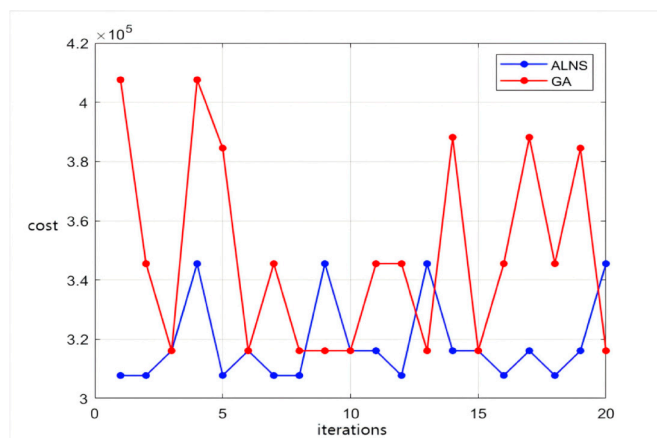


Figure 11. Results of 20 runs.

As shown in Figure 11, although neither heuristic algorithm completely avoids local optima, the improved ALNS algorithm generally produces better solutions than the improved GA algorithm. Thus, the improved ALNS algorithm exhibits a higher global search capability, thereby achieving superior performance.

The improved performance of the proposed ALNS compared with the standard ALNS and GA algorithm can be attributed to its problem-specific methodological enhancements. The destroy and repair operators—designed for cold chain multimodal transportation, including random, worst, and Shaw removal, as well as random, greedy, worst, and suboptimal insertion—enable flexible yet guided modifications in solution paths. In particular, greedy and suboptimal insertions focus the search on cost-intensive segments considering transport, carbon, and refrigeration costs, while random insertion preserves solution diversity, allowing the algorithm to exploit the problem structure effectively and explore alternative paths more efficiently than GA.

In addition, the randomized adaptive scoring mechanism and alternating dual-weight operator selection strategy further enhance search robustness. Dynamic variation in operator scores promotes global exploration and reduces the risk of getting trapped in local optima, while alternating between accumulated and uniform weights maintains operator diversity throughout iterations. Together, these enhancements improve solution quality, explaining the observed advantages of ALNS for cold chain multimodal transportation optimization.

5.4. Sensitivity Analysis

In this section, we perform a sensitivity analysis on rail freight rates, confidence levels, and ambient temperature to offer valuable management insights for cold chain logistics companies. First, we analyze the impact of rail freight rates on the selection of multimodal transportation routes. With other parameters held constant, we gradually reduce the rail freight rate in 10% increments, ensuring the total reduction ranges from 0% to 50%. Figure 12 shows the effects of these rail freight rate changes on the rail proportion.

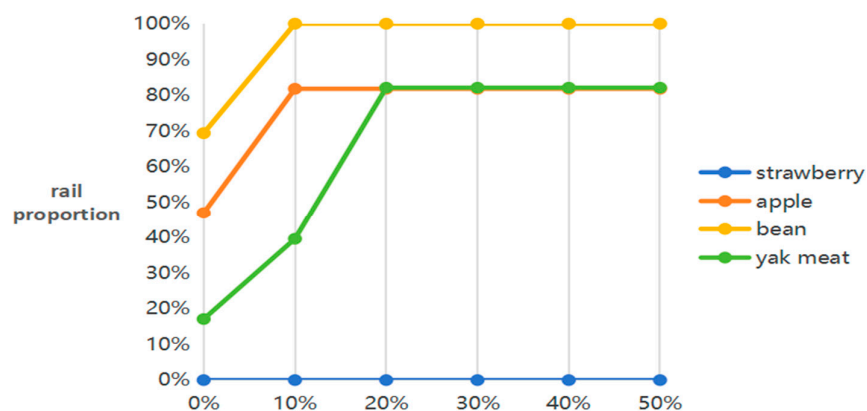


Figure 12. Impact of rail freight rates changes on rail proportion.

Figure 12 reveals that regardless of changes in rail transport rates, highly perishable goods like strawberry tend to favor faster road transport to minimize damage, resulting in zero rail proportion for strawberry. Conversely, for less perishable goods such as apple, bean and yak meat, decreasing rail rates lead to a preference for rail transport on all segments where it is available, with road transport only used for segments lacking rail access.

As rail transport rates decrease, the total transportation cost for refrigerated goods shows a significant downward trend, as illustrated in Figure 13. Once rail rates reach a certain level, the transport routes stabilize, and the decline in total cost closely matches

the reduction in rail rates. During this phase, the primary driver of cost reduction is the decrease in transportation expenses, while other cost factors remain constant.

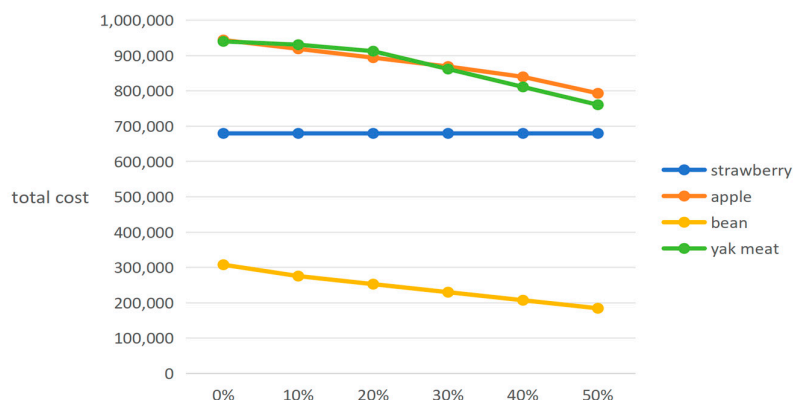


Figure 13. Impact of rail freight rates changes on total cost.

It can be observed that reducing rail transport rates not only effectively lowers transportation costs but also encourages companies to adopt more energy-efficient and environmentally friendly rail transport methods. When rail rates decrease by 10% to 20%, the proportion of rail transport in multimodal transportation increases substantially. However, excessive reductions in rail rates might adversely affect the economic viability of road transport and place additional operational pressure on railways. Therefore, the railway authorities must set rail rates judiciously to maximize overall benefits.

In the previous case study, we assumed that the capacity of rail transport arcs could accommodate the required transport volume. However, in practical applications, rail transport capacity can occasionally be insufficient. To analyze the sensitivity of confidence levels, we impose capacity constraints on certain rail transport arcs, with specific maximum flows detailed in Table 5.

Table 5. Maximum flow limits for rail transportation arcs.

Arc	Maximum Flow	Arc	Maximum Flow
Urumqi (27)–Xining (22)	23	Zhengzhou (19)–Jinan (21)	17
Hefei (16)–Hangzhou (9)	24	Nanjing (17)–Shanghai (10)	27
Guangzhou (4)–Changsha (7)	16	Wuhan (15)–Hefei (16)	26

Parameter α represents service reliability, ensuring that the optimized multimodal transportation plan satisfies uncertain customer demand with a specified probability. Parameter β denotes the confidence level of cost stability, reflecting the tolerance for cost fluctuations caused by environmental variability, such as changes in ambient temperature that affect refrigeration expenses. Given the high reliability requirements of cold chain logistics, relatively high confidence levels are essential to prevent stockouts and the resulting losses of perishable goods. Therefore, following relevant research [36,37], this study varies the confidence level within the range of 75–95% in increments of 5%. From the rail transport pricing sensitivity analysis, it is observed that strawberry, due to perishability, is transported entirely by road. Therefore, rail transport capacity constraints do not affect it. Consequently, this section focuses on the three types of refrigerated goods: apple, bean, and yak meat. Tables 6–8 present the impact of confidence level changes on the route choices and total cost for each type of perishable goods, where “—” represents road transport and “-” represents rail transport.

Table 6. Changes in transportation routes for apple.

Confidence Level	Route	Total Cost
95%	Aksu–Urumqi–Hohhot–Shijiazhuang–Jinan–Nanjing–Hangzhou	993,151
90%	Aksu–Urumqi–Hohhot–Shijiazhuang–Jinan–Nanjing–Hangzhou	976,920
85%	Aksu–Urumqi–Xining–Lanzhou–Xi’an–Zhengzhou–Hefei–Hangzhou	910,846
80%	Aksu–Urumqi–Xining–Lanzhou–Xi’an–Zhengzhou–Hefei–Hangzhou	894,461
75%	Aksu–Urumqi–Xining–Lanzhou–Xi’an–Zhengzhou–Hefei–Hangzhou	878,112

Table 7. Changes in transportation routes for bean.

Confidence Level	Route	Total Cost
95%	Maoming–Changsha–Wuhan–Hefei–Nanjing–Jinan–Beijing	324,355
90%	Maoming–Changsha–Wuhan–Zhengzhou–Jinan–Beijing	310,354
85%	Maoming–Changsha–Wuhan–Zhengzhou–Jinan–Beijing	297,955
80%	Maoming–Guangzhou–Changsha–Wuhan–Zhengzhou–Jinan–Beijing	275,996
75%	Maoming–Guangzhou–Changsha–Wuhan–Zhengzhou–Jinan–Beijing	264,819

Table 8. Changes in transportation routes for yak meat.

Confidence Level	Route	Total Cost
95%	Leiwuqi–Lhasa–Chengdu–Chongqing–Wuhan–Hefei–Nanjing–Shanghai	963,625
90%	Leiwuqi–Lhasa–Chengdu–Chongqing–Wuhan–Hefei–Nanjing–Shanghai	949,659
85%	Leiwuqi–Lhasa–Chengdu–Chongqing–Wuhan–Hefei–Nanjing–Shanghai	921,124
80%	Leiwuqi–Lhasa–Chengdu–Chongqing–Wuhan–Hefei–Nanjing–Shanghai	906,248
75%	Leiwuqi–Lhasa–Chengdu–Chongqing–Wuhan–Hefei–Nanjing–Shanghai	880,928

Further analysis of Tables 6–8 indicates that the impact of the confidence level is reflected not only in cost levels but also in structural changes in modal choice. First, for all three categories of goods, the total cost decreases monotonically as the confidence level declines. This finding is consistent with theoretical expectations: lower service reliability requirements reduce the need for capacity redundancy and expensive high-speed transport options.

Second, regarding modal selection, a higher confidence level leads to a larger deterministic equivalent demand, which may exceed railway capacity on certain arcs and consequently force some route segments to be served by road transport. For example, in the apple transportation case, increasing the confidence level from 85% to 90% results in the inclusion of one additional road segment in the solution. This observation is consistent with findings in a conventional multimodal transportation study [38], which indicate that as the required feasibility degree for satisfying capacity constraints increases, cost-efficient rail services with insufficient capacity are often excluded from feasible routing options.

However, the underlying mechanism driving this modal shift in the proposed cold chain model differs from that in traditional freight transportation. In conventional multi-modal studies, the objective function typically emphasizes direct transportation and transshipment costs, often represented as linear functions of distance and unit cost. Under such a cost-first structure, routing decisions tend to favor slower and less expensive modes, and rail transport is generally abandoned only when rigid capacity constraints are violated.

In contrast, the proposed cold chain model explicitly incorporates nonlinear Weibull-based cargo damage costs and continuous refrigeration energy consumption. Because product deterioration accelerates nonlinearly with transit time, routing decisions for perishable goods must balance cost efficiency against timeliness and reliability, often prioritizing high-efficiency modes such as road transport to mitigate irreversible quality loss. Consequently, although lowering the confidence level alleviates capacity pressure and allows for greater utilization of rail services, the extent of this modal shift remains structurally constrained by cargo perishability. Unlike traditional freight transportation—where rail usage is primarily limited by network capacity—rail utilization in cold chain logistics is jointly constrained by both capacity availability and the physical “freshness window” of the cargo.

Although the total cost and modal shares vary with the confidence level, several findings remain structurally robust: (1) rail transport remains the preferred mode whenever capacity constraints permit; and (2) commodities with extremely strict temperature requirements (e.g., yak meat) exhibit smaller modal shifts, indicating that temperature sensitivity limits the impact of relaxing uncertainty constraints. Overall, uncertainty assumptions primarily affect the magnitude of cost savings. Therefore, when designing multi-modal transportation strategies, decision-makers should carefully determine the confidence level to balance uncertain demand satisfaction against cost efficiency, thereby achieving overall cost optimization.

To investigate the impact of external environmental changes on the total cost of multimodal transportation, a sensitivity analysis was conducted with respect to ambient temperature fluctuations. Considering the seasonal characteristics of temperature variation in cold chain logistics, the ambient temperature was adjusted in increments of 5 °C, with a deviation range from −10 °C to +10 °C relative to the baseline temperature. Figures 14 and 15 illustrate the effects of temperature fluctuations on the total cost and refrigeration costs, respectively.

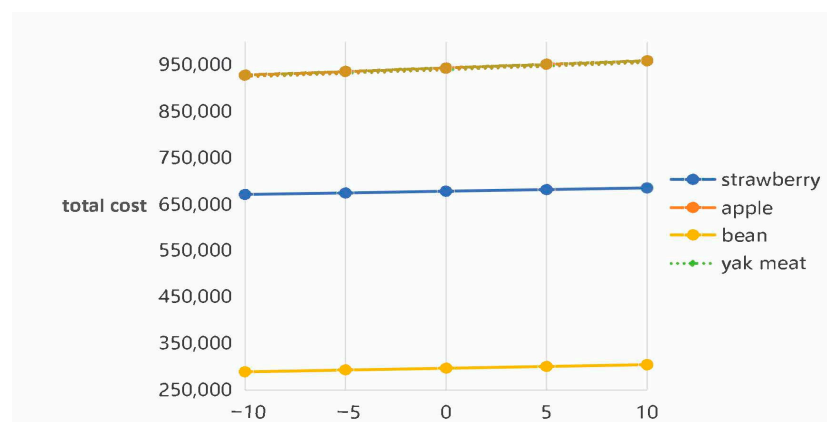


Figure 14. Impact of ambient temperature changes on total cost.

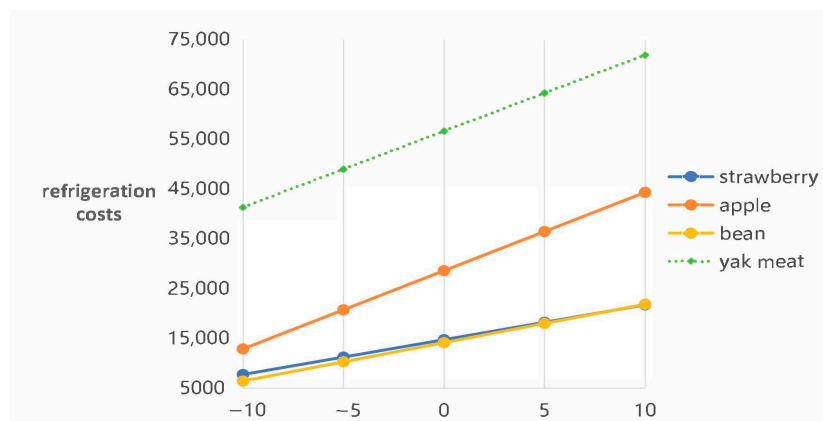


Figure 15. Impact of ambient temperature changes on refrigeration costs.

As shown in Figure 14, the total cost for all types of refrigerated goods exhibits an increasing trend as the ambient temperature rises. This trend is primarily driven by the growth in refrigeration costs. Higher ambient temperatures intensify the heat exchange between the refrigerated container and the external environment, leading to increased energy consumption to maintain the required internal temperature. Consequently, refrigeration costs increase significantly, which, in turn, raises the overall transportation cost.

Figure 15 further shows that refrigeration costs increase for all types of goods under higher ambient temperatures. Among them, yak meat experiences the most pronounced cost increase due to its required storage and transportation temperature of -18°C , which demands the highest level of cooling and energy consumption. In contrast, bean, with an optimal temperature of 8°C , requires less cooling energy and therefore exhibits the smallest increase in refrigeration costs.

These findings indicate that ambient temperature is a critical external factor affecting the operational cost of cold chain multimodal transportation. Therefore, logistics enterprises should account for seasonal and regional temperature differences when planning transportation routes and selecting transport modes to achieve an effective balance between transportation efficiency and operating costs.

6. Discussion

The sensitivity analyses of rail freight rates, confidence levels, and ambient temperature provide several important insights for decision-making in cold chain logistics. Regarding rail freight rates, the results indicate that moderate rate reductions can substantially increase the share of rail transport in multimodal operations, leading to both cost savings and reductions in carbon emissions. This finding suggests that policymakers should adopt differentiated pricing strategies that enhance the competitiveness of rail transport while maintaining overall system efficiency. At the operational level, logistics enterprises should dynamically adjust routing strategies in response to freight rate fluctuations, prioritizing rail transport for less perishable goods and reserving faster road transport for highly time-sensitive commodities.

With respect to demand uncertainty, lower confidence levels may reduce total cost but at the expense of a higher risk of unmet demand. This trade-off highlights the need to align the selected confidence level with a firm's risk tolerance and service commitments. Enterprises serving key customers or handling high-value perishable goods may prefer higher confidence levels to ensure service reliability, whereas firms operating in more price-sensitive markets may adopt lower confidence levels to improve cost efficiency.

Ambient temperature represents another critical factor that should not be overlooked in transportation planning. The results demonstrate that higher external temperatures significantly increase refrigeration energy consumption, thereby raising overall logistics costs. Cold chain enterprises are therefore encouraged to implement seasonal routing strategies. During hot summer periods or when routes traverse high-temperature regions, priority should be given to transport modes and routes with shorter transit times or superior thermal insulation performance. In addition, greater investment in advanced cold chain technologies is recommended. Since refrigeration costs are highly sensitive to external temperature conditions, improving the insulation performance of refrigerated containers—such as through the adoption of high-efficiency insulating materials—can effectively reduce the total cost.

These managerial implications should, however, be interpreted in light of the modeling assumptions adopted in this study. The model assumes constant travel speeds and average ambient temperature along routes, whereas real-world operations may be affected by traffic congestion or extreme weather events. The additional sensitivity analysis indicates that although the total cost is responsive to temperature peaks, the optimized route structure remains stable within a ± 5 °C range. This suggests that the proposed model exhibits reasonable robustness to moderate environmental fluctuations.

Finally, the generalizability of the findings merits careful consideration. The improved ALNS algorithm demonstrates superior solution quality compared with the GA algorithm and therefore has the potential to be applied to similar multimodal transportation and cold chain routing problems. In contrast, the specific quantitative outcomes—such as the exact percentage of cost savings—are case-dependent. These results are influenced by the particular network structure of the Chinese cold chain as well as the high perishability characteristics of the products examined in this study (e.g., strawberries).

7. Conclusions

This study presents an MIP model that incorporates carbon emissions and uncertain demand to optimize multimodal transportation routes for refrigerated goods. The model integrates key characteristics of refrigerated goods, such as refrigeration and damage costs, filling a gap in the existing literature. As the problem is NP-hard, we develop an improved ALNS algorithm, making enhancements to the adaptive mechanism. The case study in China demonstrates that the improved ALNS algorithm outperforms the improved GA algorithm, delivering high-quality route selection solutions in a shorter time.

Additionally, sensitivity analysis of the case study provides the following insights: reducing rail rates for refrigerated multimodal transportation can attract more cargo; scientifically selecting the confidence level helps satisfy customer demand while reducing costs; and effective temperature management can limit refrigeration energy consumption, thereby lowering overall logistics costs. Overall, these findings offer valuable managerial insights for cold chain logistics companies and have significant practical implications.

Future research could further enhance the applicability and robustness of the proposed model by relaxing some of its simplifying assumptions. First, the current model assumes constant travel speeds across transportation modes. However, in practical operations, travel speeds are often affected by factors such as traffic congestion, weather conditions, and infrastructure limitations. Future studies could incorporate uncertain or stochastic variables to better capture this variability.

Second, this study assumes that shipments cannot be split, whereas in real-world multimodal transportation, less-than-container-load and partial shipments are common. Future research could extend the model and algorithm to handle multiple demand orders and partial load assignments, thereby improving operational flexibility.

Finally, the model presumes ideal transfer conditions and neglects rail schedule constraints. In reality, train timetables and synchronization issues can significantly influence routing and scheduling decisions. Future work could therefore investigate the multi-modal transportation of refrigerated cargo with multiple origins and destinations under explicit rail schedule and transfer time constraints, providing a more realistic and operationally viable framework.

Author Contributions: Conceptualization, G.H. and S.Z.; methodology, G.H.; software, G.H.; validation, G.H., F.D. and Y.-C.C.; formal analysis, G.H.; writing—original draft preparation, G.H.; writing—review and editing, S.Z., F.D. and Y.-C.C.; supervision, S.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The source code of the improved ALNS algorithm and a demonstration dataset supporting the findings of this study are openly available on GitHub at [https://github.com/willTerner/ColdChain-Multimodal-ALNS], accessed on 11 February 2026. Detailed experimental data are available from the corresponding author upon reasonable request.

Acknowledgments: During the preparation of this manuscript, the authors used ChatGPT (version GPT-4o, OpenAI) for language polishing. The authors reviewed and edited the content and took full responsibility for the final manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviation

The following abbreviation is used in this manuscript:

ALNS	Adaptive large neighborhood search
MIP	Mixed-integer programming

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