

Article

A Scenario-Based Multi-Objective Multimodal Route Optimization Model Considering Demand Uncertainty and Traffic Congestion

Lin Qi, Chunjian Shang * and Liang Ma

Business School, University of Shanghai for Science and Technology, No. 516 Jungong Road, Shanghai 200093, China

* Correspondence: scancan1216@163.com

Abstract

Multimodal transport plays an irreplaceable role in international trade due to its cost and efficiency advantages. However, optimizing multimodal transport paths that simultaneously consider economic costs, carbon emissions, demand uncertainty, and traffic congestion remains a critical challenge. This paper establishes a scenario-based multi-objective optimization model to minimize total transportation costs and carbon emissions under uncertain demand and road congestion. To address this complex combinatorial problem, we propose LMSSA, an improved multi-objective salp swarm algorithm that integrates Bernoulli chaotic mapping, adaptive parameter adjustment, and a co-directional leader–follower update strategy. These enhancements significantly improve the balance between global exploration and local exploitation, overcoming premature convergence common in traditional salp swarm algorithms. The algorithm’s effectiveness is validated through extensive experiments on 50 instances of varying scales (8 to 100 nodes) and a real-world case study of multimodal transport in northern China. Results demonstrate that LMSSA outperforms the standard multi-objective salp swarm algorithm in convergence speed, solution quality, and robustness, providing enterprises with more economical, low-carbon, and resilient transportation decisions under uncertain and congested conditions.

Keywords: low-carbon multimodal transport; multi-objective route optimization; salp swarm algorithm; traffic congestion; uncertain demand

MSC: 90B50; 90B06



Academic Editor: Anna Sciomachen

Received: 24 May 2026

Revised: 21 June 2026

Accepted: 24 June 2026

Published: 30 June 2026

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1. Introduction

According to the latest report from the United Nations Conference on Trade and Development, global trade is projected to grow by 7% in 2025, exceeding \$35 trillion, which places greater demands on logistics and transportation systems [1]. The implementation of policies encouraging the shift of freight transport from road to rail and from road to waterways has further impacted trade transportation [2]. Multimodal transport refers to the transportation of goods through two or more modes. As a crucial aspect of modern logistics, it leverages the advantages of different modes, including road, rail, and waterway, to provide flexible and reliable cargo routing [3]. On average, multimodal transport systems can save transport costs compared to single-mode systems [4]. It offers faster speeds and shorter transfer times compared to single-waterway transport, while providing “door-to-door” services absent in single-rail transport. Furthermore, it is more environmentally

sustainable than single-road transport. Overall, multimodal transport plays a pivotal role in mitigating traffic congestion, reducing costs and carbon emissions [5], and enhancing efficiency, thus garnering increasing global attention.

However, selecting optimal multimodal routes involves numerous challenges. A 2023 report by the International Energy Agency (IEA) noted that carbon emissions from the transportation sector surged by nearly 240 million tons, accounting for 58.5% of the total increase in global carbon emissions that year; therefore, reducing carbon emissions from transportation is of critical importance [6]. Moreover, global energy efficiency strategies compel companies to lower carbon emissions while ensuring economic viability. Unreasonable routing can cause delivery delays and subsequent economic losses.

Consequently, investigating the multi-objective multimodal route planning problem, which balances economic costs and carbon emissions, has become particularly urgent. While the existing literature extensively covers single-objective optimization (focusing solely on minimizing time, cost, or emissions), very few studies address the multi-objective nature of real-world logistics [7]. Single-objective solutions lack the flexibility to adjust transportation plans according to diverse, often conflicting, decision-making requirements. Thus, it is imperative to comprehensively consider both economic and environmental factors in multimodal route optimization.

Most multimodal transport models assume all parameters are deterministic. However, real-world scenarios are fraught with uncertainty. For instance, seasonal variations and sudden replenishments can cause unpredictable shifts in transport demand [8]. Therefore, incorporating uncertain demand is essential for practical route optimization. Furthermore, ground transportation frequently suffers from traffic congestion during peak hours or special events. This congestion drastically alters not only the travel time but also the carbon emissions generated [9]. Most existing studies assume vehicles travel at a constant speed, neglecting congestion impacts, which fails to reflect real-world delivery efficiency and emissions accurately.

To address these challenges, robust and stochastic optimization methods are commonly utilized. To clarify the distinction as required by rigorous modeling formulation: robust optimization (RO) seeks to immunize decisions against the worst-case realization within a predefined uncertainty set without requiring probability distributions. Stochastic optimization (SO), in contrast, assumes that uncertain parameters follow known probability distributions to optimize expected performance. The scenario-based approach adopted herein discretizes the uncertainty into a finite set of possible outcomes with associated probabilities, serving as a practical approximation of SO. Additionally, to generate stable decision-making schemes under uncertainty, integrating regret constraints—a concept derived from RO—can effectively control the maximum deviation from the optimal scenario.

To solve this complex NP-hard problem, heuristic algorithms are highly preferred over exact methods. Among various swarm intelligence algorithms, the salp swarm algorithm (SSA) stands out due to its simple structure, robust global search capabilities, and fewer control parameters, making it highly adaptable to discrete routing problems. However, standard multi-objective algorithms still struggle with local optima in multimodal transport.

Therefore, this study constructs a multi-objective route optimization model aiming to minimize transport costs and carbon emissions, strictly incorporating demand uncertainty and traffic congestion constraints. We employ a scenario-based stochastic optimization approach with regret constraints. Demand uncertainty is characterized by discrete scenarios with historical occurrence probabilities. Finally, an improved multi-objective salp swarm algorithm (LMSSA) is developed to obtain optimal, Pareto-efficient transport solutions within a reasonable computation time.

Finally, the main contributions of this paper are presented as follows:

1. A multi-objective route optimization model is established to simultaneously satisfy economic and environmental requirements in multimodal transport.
2. To expand the application of the salp swarm algorithm (SSA), an improved multi-objective variant (LMSSA) with chaotic mapping and parameter adaptive adjustment is proposed, significantly enhancing its performance in discrete routing problems.
3. A scenario-based stochastic optimization method with regret constraints is formulated to handle demand uncertainty, thereby enhancing the robustness of transport solutions and improving enterprise risk resilience without violating probabilistic assumptions.
4. The dynamic impacts of traffic congestion on both transport time and carbon emissions are fully integrated into the cost calculations, making the model more realistic.
5. The proposed model and LMSSA are rigorously validated using a real-world multimodal transport case in northern China.

The remainder of the paper is organized as follows: Section 2 reviews the related works and identifies research gaps in the literature. Section 3 presents a detailed description and mathematical modeling of the problem addressed in this study. Section 4 details the proposed algorithm. Section 5 reports the results of the numerical experiments and analyzes the real case. Finally, Section 6 shows the general overview and describes possible directions for future research.

2. Literature Review

In recent years, scholars have conducted extensive research on the multimodal transport route optimization problem. Previous studies have primarily focused on optimization from the perspectives of minimizing comprehensive transportation costs, transportation risk, and transportation time, while maximizing customer satisfaction [10–15]. For instance, Zhang et al. [16] established a multi-objective optimization model for minimizing costs and carbon emissions. Guo et al. [17] proposed a procurement and routing strategy for multiperiod multimodal transport. While the majority of the literature typically focuses on a single objective, considering multiple objectives provides a more comprehensive representation of real-world challenges. Therefore, this article formulates a multi-objective model that concurrently optimizes carbon emissions and total costs.

The multimodal transport route planning problem becomes increasingly complex when carbon emissions are factored into the objectives or constraints of the model. Martínez-Moya et al. [18] examined modeling under carbon emissions trading and carbon tax policies. Lin [19] integrated carbon emissions into multimodal transport route optimization studies and established a low-carbon model. Mohammadi et al. [20] established a multi-objective model of costs and GHG carbon emission rates. Guo et al. [21] analyzed the effect of traffic congestion on transport time and carbon emissions in a time-varying vehicle routing problem considering emission pollution, finding that reasonable idling reduces vehicle carbon emissions. Hence, this paper considers the impact of traffic congestion on carbon emissions in the multimodal transport route planning problem.

In road transport systems, the fuel consumption of vehicles can be calculated by methods such as load assessment models, the methodology for calculating transportation emissions and energy consumption (MEET), and the comprehensive modal emission model (CMEM) [22–24]. It has been shown that vehicle speed may be significantly affected by factors such as traffic congestion and vehicle density. This implies that there are limitations in representing vehicle fuel consumption solely with the CMEM. Simultaneously, the load assessment model does not accurately reflect the actual fuel consumption of the vehicle. Therefore, to get closer to real-world scenarios, the MEET model, which takes into account a comprehensive range of factors, was adopted in this study to calculate the carbon emissions of trucks.

The multimodal transport process involves numerous transport links and faces many uncertainties, such as variations in transport time, prices, capacity, and transport demand [16]. Therefore, overcoming the adverse effects of uncertainty and developing reliable routing schemes are critical. The majority of related studies have been conducted in deterministic scenarios, with few addressing uncertain environments [25]. To deal with parameter uncertainty, fuzzy theory, stochastic approaches, and robust optimization are commonly employed [20,26–29]. For instance, Wang et al. [30] considered both transport time and demand uncertainty, while Wang and Meng [31] additionally addressed transport capacity uncertainty. Jiang et al. [32] used interval planning theory to handle demand uncertainty. Demir et al. [33] used a stochastic approach for transport time uncertainty, and Assavapokee et al. [34] proposed a finite scenario-based stochastic optimization approach. Recognizing the challenge of obtaining exact continuous probability distributions for demand-related parameters, this paper establishes a multimodal scenario-based stochastic optimization model incorporated with regret constraints. This approach classifies the demand into a finite number of discrete scenarios with estimated probabilities, while utilizing regret limits to ensure decision stability across all scenarios.

It should be acknowledged that an alternative approach to characterizing demand uncertainty is distributionally robust optimization (DRO), which constructs an ambiguity set of plausible probability distributions around historical or empirical data and optimizes against the worst case within this set, thereby avoiding reliance on a single fixed probability distribution. Recent work has applied Wasserstein-based DRO to chance-constrained problems under demand uncertainty, offering a principled framework when historical probability estimates are themselves subject to limited data and estimation error [35]. Compared with this paradigm, the scenario-based approach adopted in this paper assigns fixed probabilities to a finite set of discrete demand scenarios based on seasonal historical patterns. While DRO offers stronger theoretical guarantees against distributional ambiguity, it typically requires solving an additional inner optimization problem over the ambiguity set for each candidate solution, which would substantially increase computational cost when combined with the discrete, combinatorial routing decisions and multi-objective, regret-constrained structure considered here. The scenario-based formulation, by contrast, preserves computational tractability within the proposed metaheuristic framework while still incorporating a robustness mechanism through the regret constraints in Equations (19) and (20). Extending the proposed LMSSA framework to a Wasserstein-DRO setting, in which the ambiguity set replaces the fixed scenario probabilities, represents a promising direction for future research.

Furthermore, scholars have considered different constraints in multimodal transport route planning problems to make the models more realistic. The service time window is a critical factor to consider. Fazayeli et al. [12], Miranda and Conceição [36], and Taş et al. [37] are among the few studies that have taken the service time window into account. Therefore, in this study, we also considered service time windows. Scholars have continually sought effective ways to solve multi-objective route planning problems. Recently, various heuristic algorithms have been developed, such as multi-objective genetic algorithms and multi-objective simulated annealing algorithms [38–41]. Menares et al. [42] solved a bi-objective time-dependent vehicle routing problem using a multi-objective genetic algorithm. Al Theeb et al. [43] proposed a heuristic approach utilizing the greedy random search method to solve the two-echelon vehicle routing problem. Zaretaab et al. [44] adopted a multi-objective simulated annealing algorithm to optimize a series-parallel system. Lu et al. [45] proposed a sparrow search algorithm to solve the collaborative optimization of environmental protection and economic efficiency in isolated microgrids. While these algorithms provide new insights, their practical performance often requires further improvement. The multi-objective salp swarm algorithm (MSSA) is a widely recognized optimization algorithm, yet it is seldom applied in the field of

multimodal transport [46]. Therefore, this paper aims to fill this gap by proposing an improved multi-objective salp swarm algorithm tailored for multimodal transport applications.

Finally, in order to illustrate the distinctions between our problem and the multimodal transport path planning problems considered in the literature, we analyzed the relevant studies and summarized our research results in Table 1. According to Table 1, we observe the details listed below.

Table 1. Literature summary.

References	Multi-Objective	Time Window	Uncertainty	Carbon Emission	Traffic Congestion	Case Study	Solution Approach	Uncertainty Paradigm
[47]				✓				
[48]		✓		✓	✓			
[37]		✓				✓	Heuristic	
[49]				✓				
[33]	✓	✓	✓	✓	✓		Heuristic	Stochastic
[36]		✓				✓	Heuristic	
[31]			✓		✓	✓	Heuristic	Stochastic
[50]				✓		✓	Heuristic	
[30]		✓	✓			✓	Heuristic	Stochastic
[12]		✓	✓			✓	Heuristic	Fuzzy
[19]				✓		✓		
[51]	✓	✓		✓		✓		
[10]	✓	✓		✓		✓	Heuristic	
[20]	✓	✓		✓			Heuristic	Stochastic
[26]			✓	✓			Exact	Robust
[27]			✓	✓				Robust
[28]			✓	✓				Robust
[16]	✓			✓		✓	Heuristic	
[29]	✓						Heuristic	
[52]	✓					✓	Heuristic	
This Paper	✓	✓	✓	✓	✓	✓	Heuristic	Stochastic

1. Most of the literature adopts the idea of transforming multi-objective problems into single-objective ones, but these methods cannot handle the complex trade-offs between multiple conflicting objectives effectively. While swarm intelligence algorithms can overcome this limitation to a certain extent, their application in multimodal transport remains limited. In this study, we propose an improved multi-objective salp swarm algorithm (LMSSA) directly tailored for solving the multi-objective multimodal transport route planning problem.
2. Regarding uncertainty modeling, existing research predominantly relies on traditional stochastic approaches and fuzzy theory, whereas studies integrating robust optimization concepts to hedge against severe demand fluctuations remain remarkably scarce. To bridge this gap and address the practical challenge of estimating exact continuous probability distributions, this paper adopts a scenario-based stochastic optimization approach augmented with regret constraints. This methodology enhances the robustness of the model's decisions without completely abandoning the probabilistic nature of demand forecasting.
3. Although individual studies have considered the impact of road congestion on transport time in multimodal routing problems, there is a relative lack of research that further investigates the cascading impact of traffic congestion on carbon emissions during the multimodal transport process. In this paper, we comprehensively incorporate the dynamic impacts of traffic congestion into the calculation of both transport time costs and carbon emissions.

3. Problem Description and Mathematical Formulation

3.1. Problem Statement

In a containerized multimodal transport network, logistics enterprises must determine the optimal transportation path from origin to destination, selecting among road, rail, and waterway modes while passing through multiple trans-shipment nodes. This decision-

making process is complicated by three major real-world complexities: (1) the conflicting objectives of minimizing total transportation cost and carbon emissions, (2) demand uncertainty caused by seasonal fluctuations and market volatility, and (3) time-dependent traffic congestion on road links that significantly increases both travel time and carbon emissions. While rail and waterway modes generally produce lower emissions, they are less flexible in responding to sudden demand changes and may suffer from limited capacity and fixed schedules. These factors collectively make the multimodal route optimization problem highly challenging. The structure of the considered multimodal transport network is illustrated in Figure 1.

To effectively handle demand uncertainty while maintaining solution robustness, this paper develops a scenario-based stochastic optimization model augmented with regret constraints. The model aims to generate transportation plans that perform well across multiple demand scenarios without assuming perfect foresight.

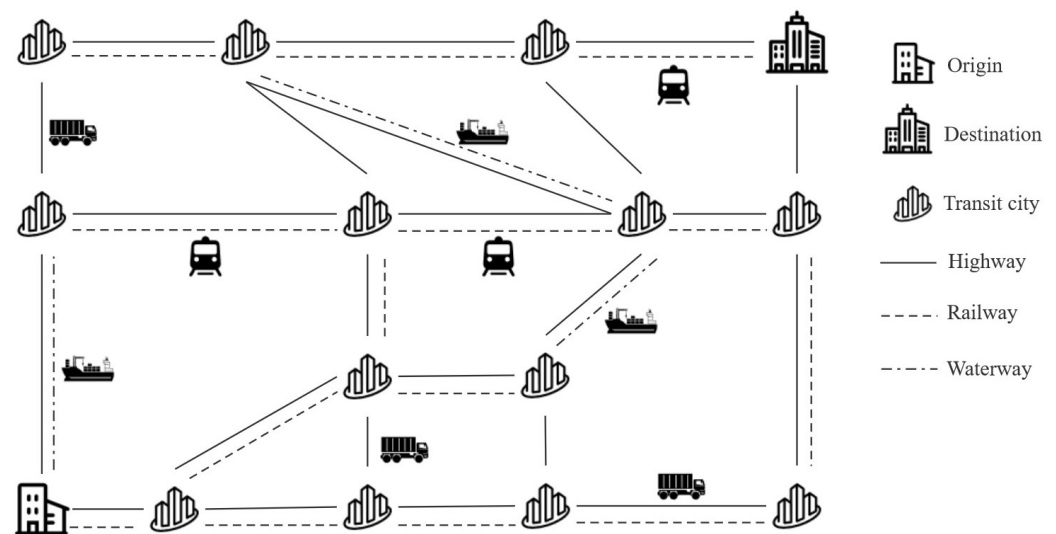


Figure 1. Multimodal transport network.

3.2. Model Assumptions

To facilitate the model development, the following assumptions are taken into account:

Assumption 1. *The goods to be transported are indivisible, and there exists only one directed link between any pair of adjacent nodes for each transportation mode.*

Assumption 2. *Mode transfers can only occur at intermediate nodes and are allowed at most once along any path.*

Assumption 3. *Railway and waterway transportation are not affected by traffic congestion due to dedicated channels, whereas road transportation is subject to congestion effects.*

Assumption 4. *Waiting time and associated costs at trans-shipment nodes are negligible compared to transportation time and cost.*

Assumption 5. *Transport demand and travel time are independent of each other.*

Assumption 6. *Factors such as severe weather conditions, cargo damage, and vehicle breakdowns are not considered in this study. These simplifications allow the model to focus on the core interactions among transportation cost, carbon emissions, demand uncertainty, and traffic congestion.*

It should be noted that Assumption 4 primarily concerns crossmodal transfers, which are explicitly modeled through the transfer time and transfer cost terms and are limited to at most one occurrence per route. An additional source of delay specific to railway operations, namely the waiting time incurred when switching between different railway lines at an intermediate node due to fixed train timetables, is not separately modeled and is implicitly absorbed into this simplification. Incorporating such schedule-dependent waiting times represents a refinement for future work. These assumptions are reasonable in the context of strategic–tactical multimodal route planning and are commonly adopted in the related literature.

3.3. Notations

Let $G = (M, K)$ denote a multimodal transport network. The definitions and descriptions of the sets, parameters, and decision variables used in the proposed model are given below.

3.3.1. Sets

I is the set of previous transport nodes, $I \in \{1, 2, \dots, M\}$. J is the set of next transport nodes, $J \in \{1, 2, \dots, M\}$. O is the set of transit nodes, $O \in \{1, 2, \dots, M\}$. k and l are the set of transportation modes, $k, l \in \{1, 2, 3\}$.

3.3.2. Parameters

C is the total cost. C_g is the total transport cost. C_t is the total time cost. C_{ij}^k is the unit transport cost incurred when using transport mode k between node i and j . C_i^{kl} is the unit fixed cost of transforming from k to l at node i . P_e is the unit storage cost of transported goods due to early arrival at the destination. P_l is the unit penalty cost of transported goods due to delayed arrival at the destination. d_{ij}^k is the transport distance when using transport mode k between nodes i and j . q_{ijs} is the uncertain demand in scenario s between nodes i and j . $T_{\max}$ is the upper limit of the time window for delivery goods. $T_{\min}$ is the lower limit of the time window for delivery goods. T is the actual transport time. t_{ij}^k is the transport time when using transport mode k between nodes i and j . t_i^{kl} is the unit time of when transforming from k to l at node i . t_{ij}^{k0} is the transport time on an uncongested road. q_{ij} is the deterministic transport demand between nodes i and j . E is the total carbon emission. E_{ij}^k is the carbon emission when using transport mode k between nodes i and j . E_i^{kl} is the carbon emission when transforming from k to l at node i . e_i^{kl} is the carbon emissions per unit when transforming from k to l at node i . e_{ij}^k is the fuel consumption when using transport mode k between nodes i and j . θ^k is the carbon emission factor for transport mode k . α and β are the parameters of the Bureau of Public Roads (BPR)'s congestion function. f is the actual traffic flow on the road link. c is the design capacity of road. m^r is the road transport mode. m^o is the rail transport mode. m^w is the waterway transport mode. F_r is the fuel consumption rate of a truck per unit distance. v^{k0} is the normal speed for transport mode k . e^k is the unit fuel consumption for railway transport. v_0 is the design speed of ship. p_α is the power of the ship's main engine; p_β is the power of auxiliary equipment. C_S^* is the expected cost corresponding to the optimal solution in the transportation scenario. E_S^* is the expected carbon emissions corresponding to the optimal solution in the transportation scenario. γ is the regret factor. $\rho_0, \rho_1, \dots, \rho_6$ are the regression coefficients of the truck fuel consumption model [23]. The values are $\rho_0 = 1576$, $\rho_1 = -17.6$, $\rho_2 = 0$, $\rho_3 = 0.0017$, $\rho_4 = 0$, $\rho_5 = 36,067$, and $\rho_6 = 0$, respectively.

3.3.3. Decision Variables

x_{ij}^k is a binary variable indicating the transportation between nodes i and j is performed using transport mode k (1 if selected, 0 otherwise).

y_i^{kl} is a binary variable indicating the transport mode is switched from k to l at node i (1 if selected, 0 otherwise).

3.4. Mathematical Model

Based on the stated assumptions and definitions, a deterministic bi-objective multi-modal transportation model is formulated as a baseline. The comprehensive objectives and constraints are constructed as follows:

$$\min C = C_g + C_t = \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} C_{ij}^k \cdot q_{ij} \cdot d_{ij}^k \cdot x_{ij}^k + \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} C_i^{kl} \cdot q_{ij} \cdot y_i^{kl} + P_e \cdot q_{ij} \cdot \max\{T_{min} - T, 0\} + P_l \cdot q_{ij} \cdot \max\{T - T_{max}, 0\} \quad (1)$$

$$\min E = \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} E_{ij}^k x_{ij}^k + \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} E_i^{kl} y_i^{kl} \quad (2)$$

$$T = \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} t_{ij}^k \cdot x_{ij}^k + \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} t_i^{kl} \cdot q_{ij} \cdot y_i^{kl} \quad (3)$$

$$E_i^{kl} = e_i^{kl} \cdot q_{ij} \quad (4)$$

$$E_{ij}^k = \theta^k \cdot e_{ij}^k \quad (5)$$

$$t_{ij}^k = \begin{cases} t_{ij}^{k0} \cdot \left[1 + \alpha \cdot \frac{f \cdot \beta}{c}\right] \cdot x_{ij}^k, k \in m^r \\ \frac{d_{ij}^k}{v_k} \cdot x_{ij}^k, k \in m^o \end{cases} \quad (6)$$

$$v_{ij}^k = \frac{d_{ij}^k}{t_{ij}^{k0} \left[1 + \alpha \cdot \frac{f \cdot \beta}{c}\right]} = v^{k0} \cdot \frac{1}{\left[1 + \alpha \cdot \frac{f \cdot \beta}{c}\right]} \quad (7)$$

$$e_{ij}^k = e^k \cdot d_{ij} \cdot q, k \in m^o \quad (8)$$

$$e_{ij}^k = F_r \cdot d_{ij} \cdot \left\lceil \frac{q}{2} \right\rceil, k \in m^r \quad (9)$$

$$F_r = \rho_0 + \rho_1 v + \rho_2 v^2 + \rho_3 v^3 + \frac{\rho_4}{v} + \frac{\rho_5}{v^2} + \frac{\rho_6}{v^3} \quad (10)$$

$$e_{ij}^k = \left(p_\alpha \left(\frac{v_{ij}}{v_0} \right)^3 + p_\beta \right) \frac{d_{ij}}{24v_0}, k \in m^w \quad (11)$$

$$\sum_{k \in K} x_{ij}^k \leq 1, \forall i, j \in M \quad (12)$$

$$\sum_{k \in K} \sum_{l \in K} y_i^{kl} \leq 1, \forall i \in M \quad (13)$$

$$x_{ij}^k + x_{jo}^l \geq 2y_j^{kl}, \forall i, j, o \in M, k, l \in K \quad (14)$$

$$x_{ij}^k = \begin{cases} 0 & \forall i, j \in M, k \in K \end{cases} \quad (15)$$

$$y_i^{kl} = \begin{cases} 0 & \forall i \in M, k, l \in K \end{cases} \quad (16)$$

The logical connections and physical meanings of the aforementioned formulations are elaborated as follows:

Objective Functions: Equations (1) and (2) constitute the core optimization objectives of this model. Objective (1) minimizes the comprehensive total cost, which integrates three distinct components: the direct transportation cost, the fixed operational cost incurred during mode transfers at transit nodes, and the penalty costs associated with failing to

meet the specified delivery time window (including both early storage and late penalties). Objective (2) minimizes the total carbon emissions generated throughout the multimodal routing process, encompassing both the en-route transportation phase and the nodal transfer operations.

Time and Emission Calculations: Equation (3) calculates the cumulative transport time, adding the actual travel times on the links and the transfer times at the nodes. Equations (4) and (5) quantify the carbon emissions. Specifically, Equation (4) computes emissions generated during mode transfers, while Equation (5) calculates the transportation emissions by multiplying the fuel consumption by the specific emission factor of the chosen mode.

Traffic Congestion and Fuel Consumption: To reflect real-world dynamics, road transport times are adjusted for traffic congestion. Equation (6) utilizes the widely recognized Bureau of Public Roads (BPR) function to determine the actual travel time t_{ij}^k based on the traffic volume-to-capacity ratio (f/c), where the parameters α and β are empirically set to 0.15 and 4, respectively. Equation (7) correspondingly derives the actual road transport speed under congested conditions. Furthermore, fuel consumption models vary significantly across transport modes. Equation (8) computes the fuel consumption for rail transport based on the distance-driven method from the IPCC guidelines [53]. Equation (9) calculates road transport fuel consumption, where q denotes the cargo volume (TEU) on the corresponding link, i.e., $q = q_{ij}$ in the deterministic model and $q = q_{ijs}$ in the scenario model. The term $\lceil q/2 \rceil$ accurately reflects the equivalent number of truck trips required, given a standard truck capacity of 2 TEU (see Table A2). Equation (10) formulates the fuel consumption per unit mile for trucks, incorporating vehicle-specific regression coefficients (ρ_0 to ρ_6) provided by [23]. Equation (11) estimates the fuel consumption for waterway transport, integrating the ship's main and auxiliary engine powers, the actual travel speed, and the design speed.

Logical and Network Constraints: Equations (12) through (16) enforce the operational feasibility of the network. Constraint (12) ensures that transport between any two adjacent nodes is executed by at most one transport mode. Constraint (13) dictates that a mode transfer at any given transit node can occur at most once. Constraint (14) guarantees network connectivity and flow conservation, ensuring the continuous movement of cargo from origin to destination. Finally, Constraints (15) and (16) define the binary domains for the routing and mode transfer decision variables, respectively.

3.5. Scenario-Based Stochastic Optimization with Regret Constraints

To address demand uncertainty, a scenario-based stochastic programming model with regret constraints is established. Unlike conventional set-based robust optimization that relies on predefined uncertainty sets, this paper characterizes demand uncertainty via a finite set of discrete scenarios. Each scenario s corresponds to a specific demand realization q_{ijs} , and its probability p_s is derived from historical observations or expert estimation.

Building upon the deterministic Formulations (1)–(16), the scenario-based extension introduces a scenario index $s \in \{1, \dots, S\}$. The deterministic demand q_{ij} is replaced by the scenario-dependent parameter q_{ijs} . Notably, the routing and mode-choice decision variables x_{ij}^k and y_i^{kl} remain scenario-independent, representing a here-and-now decision made before demand uncertainty resolves. Objective functions (17) and (18) minimize the expected total cost and expected carbon emissions weighted by scenario probabilities p_s . Constraints (19) and (20) are newly added regret constraints, where C_s^* and E_s^* denote the optimal cost and emissions of scenario s when solved as an independent deterministic problem. These constraints ensure that the proposed solution in any scenario does not deviate

by more than a fraction γ from the scenario-specific optimum. The mathematical formulation is given as follows:

$$\min C = \sum_{s=1}^S p_s \cdot C_s = \sum_{s=1}^S p_s \cdot (C_g + C_t) = \sum_{s=1}^S p_s \cdot \left(\sum_{i \in M} \sum_{j \in M} \sum_{k \in K} C_{ij}^k \cdot q_{ijs} \cdot d_{ij}^k \cdot x_{ij}^k \right. \\ \left. + \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} C_i^{kl} \cdot q_{ijs} \cdot y_i^{kl} + P_e \cdot q_{ijs} \cdot \max\{T_{min} - T, 0\} + P_l \cdot q_{ijs} \cdot \max\{T - T_{max}, 0\} \right) \quad (17)$$

$$\min E = \sum_{s=1}^S p_s \cdot E_s = \sum_{s=1}^S p_s \cdot \left(\sum_{i \in M} \sum_{j \in M} \sum_{k \in K} E_{ij}^k x_{ij}^k + \sum_{i \in M} \sum_{j \in M} \sum_{k \in K} E_i^{kl} y_i^{kl} \right) \quad (18)$$

$$C_s \leq (1 + \gamma) C_s^* \quad (19)$$

$$E_s \leq (1 + \gamma) E_s^* \quad (20)$$

$$\sum_{s=1}^S p_s = 1 \quad (21)$$

It is subject to constraints (12)–(16), (19)–(21).

Before proceeding, it is necessary to clarify how the reference values used in the regret constraints, Equations (19) and (20), are obtained, as this involves a two-stage procedure that is implicit but not formally described above. In the first stage, for each scenario, the deterministic model formulated in Equations (1)–(16) is solved independently, treating that scenario's demand realization as the sole input. Because this deterministic model is itself bi-objective, the scenario-specific reference values, denoted as the optimal cost and the optimal emissions for scenario s , are defined as the components of the ideal point for that scenario: the optimal cost is obtained by solving the deterministic model with total cost (Equation (1)) as the sole objective, while the optimal emissions value is obtained by solving it with carbon emissions (Equation (2)) as the sole objective. These two single-objective solutions may correspond to different routing and mode configurations, and the resulting values therefore serve as reference benchmarks representing the best achievable performance on each objective individually under scenario s , rather than the cost and emissions of a single feasible solution. In the second stage, these reference values are treated as fixed parameters and substituted into the scenario-based stochastic model, shown in Equations (17)–(21), which is then solved to obtain the final regret-constrained transportation plan. Within the proposed LMSSA framework, this two-stage procedure is implemented by first applying the algorithm independently to each scenario under each single-objective formulation to obtain the reference values, and subsequently applying it to the full scenario-based regret-constrained model to obtain the final solution.

Equation (17) represents the cost function for all demand scenarios. Equation (18) represents the carbon emission function for all demand scenarios. Constraints (19) and (20) indicate the proximity of each feasible solution to the optimal value of the scenario s . Constraint (21) indicates that the sum of the probabilities of occurrence of each scenario s is 1. The resulting mathematical formulation integrates the expected-value framework of stochastic programming with the relative regret control of robust optimization. The objective functions (17) and (18) minimize the expected total cost and carbon emissions weighted by scenario probabilities p_s . Constraints (19) and (20) ensure that, for each scenario s , the cost and emissions do not exceed $(1 + \gamma)$ times the scenario-specific optimal values C_s^* and E_s^* , thereby controlling the relative regret. It should be emphasized that assigning probabilities to scenarios is a hallmark of stochastic programming, whereas the regret constraints are inspired by robust optimization to hedge against scenario-wise suboptimality.

3.6. Model Complexity Analysis

The complexity of the proposed model arises from the need to make simultaneous decisions regarding routing and transportation modes. In a multimodal transportation network, nodes act as both starting and ending points for multiple modes. To simplify the network structure and improve its computational clarity, we construct an expanded “virtual” transportation network using a node-splitting technique. Specifically, we separate the origin and destination of each transportation mode at each physical node, treating them as separate virtual nodes. Subsequently, these virtual nodes are interconnected based on the connectivity of the initial network, resulting in a transformed multimodal transportation network. A schematic diagram of this network complexity analysis is shown in Figure 2.

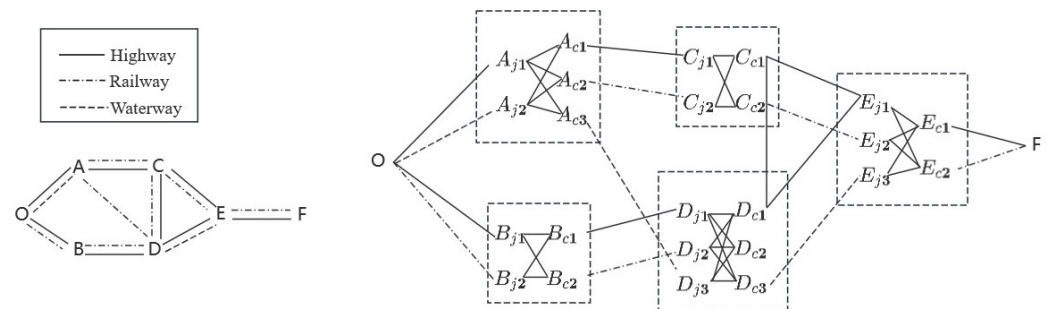


Figure 2. Multimodal transportation network complexity analysis.

To formalize the network expansion, let n denote the total number of physical nodes, m denote the number of physical directed edges, and H denote the maximum number of available transportation modes. For each directed physical edge, at most H different transportation options are theoretically possible. Therefore, the network transformation derives at most Hm new directed edges. Simultaneously, considering the possible transfers between transportation modes within individual nodes, at most nH^2 directed transfer edges may be formed between the inbound and outbound virtual nodes. Consequently, the expanded “virtual” network contains up to $Hm + nH^2$ directed edges. If the computational time to process a single initial assignment is denoted as T , the total computational complexity of evaluating the entire transformed network is bounded by:

$$O(T) = O(T(Hn + (Hm + nH^2))) \quad (22)$$

It should be noted that the complexity bound in Equation (22) characterizes the network expansion dimension of a single deterministic evaluation and does not yet account for the scenario dimension introduced in Section 3.5. In the scenario-based stochastic model, evaluating the fitness functions F_1 and F_2 for a single candidate solution requires computing the cost and emission, C_s and E_s , for each of the S demand scenarios, as well as checking the corresponding regret constraints against the scenario-specific reference values C_s^* and E_s^* for every scenario. Consequently, the computational cost of evaluating a single individual scales linearly with S , and the overall complexity becomes:

$$O(T_{\text{scenario}}) = O(S \cdot T(Hn + (Hm + nH^2))) \quad (23)$$

In addition, obtaining the scenario-specific reference values C_s^* and E_s^* requires an initial preprocessing stage in which the deterministic model is solved independently for each of the S scenarios under each single objective, incurring a one-time cost on the order of $O(S \cdot T(Hn + (Hm + nH^2)))$ prior to the main optimization. While this introduces an additional linear factor of S , the number of scenarios considered in this study is small,

$S = 5$, so this factor does not alter the qualitative NP-hard nature of the problem discussed below, but is explicitly acknowledged here for completeness.

Although this network expansion technique simplifies the mode selection process, it significantly increases the dimensionality of the decision space. Furthermore, the multimodal route optimization problem—particularly when incorporating multiple conflicting objectives (costs and carbon emissions), strict time windows, and regret-based stochastic constraints for demand uncertainty—is inherently NP-hard. As the problem scale increases, the computational time required by exact algorithms (e.g., branch-and-bound and dynamic programming) grows prohibitively, making it infeasible to obtain exact solutions within polynomial time.

To address this computational intractability, metaheuristic algorithms are highly preferred in practice. While exact algorithms struggle with the computational burden and rigidity of large-scale multimodal environments, metaheuristics offer flexible and highly efficient alternatives. They utilize intelligent search mechanisms to escape local optima and find high-quality, near-optimal solutions within a reasonable computational timeframe. Given the NP-hard nature of the proposed multi-objective, scenario-based stochastic model, deploying an advanced metaheuristic algorithm is a scientifically justified and practically necessary approach to ensure a rapid response and robust decision-making for multimodal transport enterprises.

4. The Proposed Algorithm

The salp swarm algorithm (SSA), originally proposed by Mirjalili et al. [54], is an advanced swarm intelligence optimizer. It has been successfully applied to various path planning and scheduling problems owing to its simple structure and favorable exploration capabilities. In this study, its multi-objective variant (MSSA) is deliberately selected over other widely used metaheuristics (such as genetic algorithms or Particle Swarm Optimization) as the baseline solver for three compelling reasons. First, MSSA handles conflicting multi-objective problems using a rigorous Pareto archive mechanism rather than artificially aggregating objectives via weighted sums. Second, it requires significantly fewer control hyperparameters, which facilitates seamless adaptation to the highly constrained, discrete multimodal routing problem. Third, its inherent structural simplicity provides high computational efficiency, making it particularly suitable for processing the multiple demand scenarios required by our scenario-based stochastic optimization model.

The standard SSA mimics the swarming behavior of salps navigating oceans as a chain, comprising a single leader and multiple followers. The leader explores the search space toward a food source, while followers update their positions strictly based on the preceding individual [54]. Despite its advantages in implementation, the standard MSSA suffers from two critical limitations when applied to complex discrete multimodal networks. On the one hand, the fixed ratio of leaders to followers leads to insufficient global exploration during early iterations and inadequate local exploitation in later stages. On the other hand, the strictly one-way information propagation between adjacent salps severely slows down convergence and increases the risk of premature stagnation in local optima. While various improved variants have been proposed for continuous machine scheduling and network training [55–57], their direct application to discrete multimodal transport routing under uncertainty remains underexplored.

To explicitly overcome these algorithmic drawbacks and enhance optimization performance for multimodal routing, this paper proposes an improved multi-objective salp swarm algorithm (LMSSA). The claimed improvements are meticulously designed around three core mechanisms: (1) A parameter adaptive adjustment strategy using Bernoulli mapping is introduced to dynamically alter the leader–follower ratio throughout the iteration process, thereby maintaining an optimal balance between global exploration and local exploitation. (2) A co-direction leader update strategy is developed, integrating both

food-source guidance and historical elite information, which effectively breaks the reliance on a single search direction. (3) A chaotic logistic map-based follower update strategy is implemented to replace the rigid one-way message passing, enabling followers to exchange information with historical optima to successfully escape local traps.

Together, these specific modifications significantly improve both convergence speed and Pareto solution diversity. Furthermore, tailored discrete encoding strategies and a specialized fitness function incorporating the scenario-based regret constraints are developed to suit the discrete multimodal routing problem. The complete workflow of the proposed LMSSA is illustrated in Figure 3.

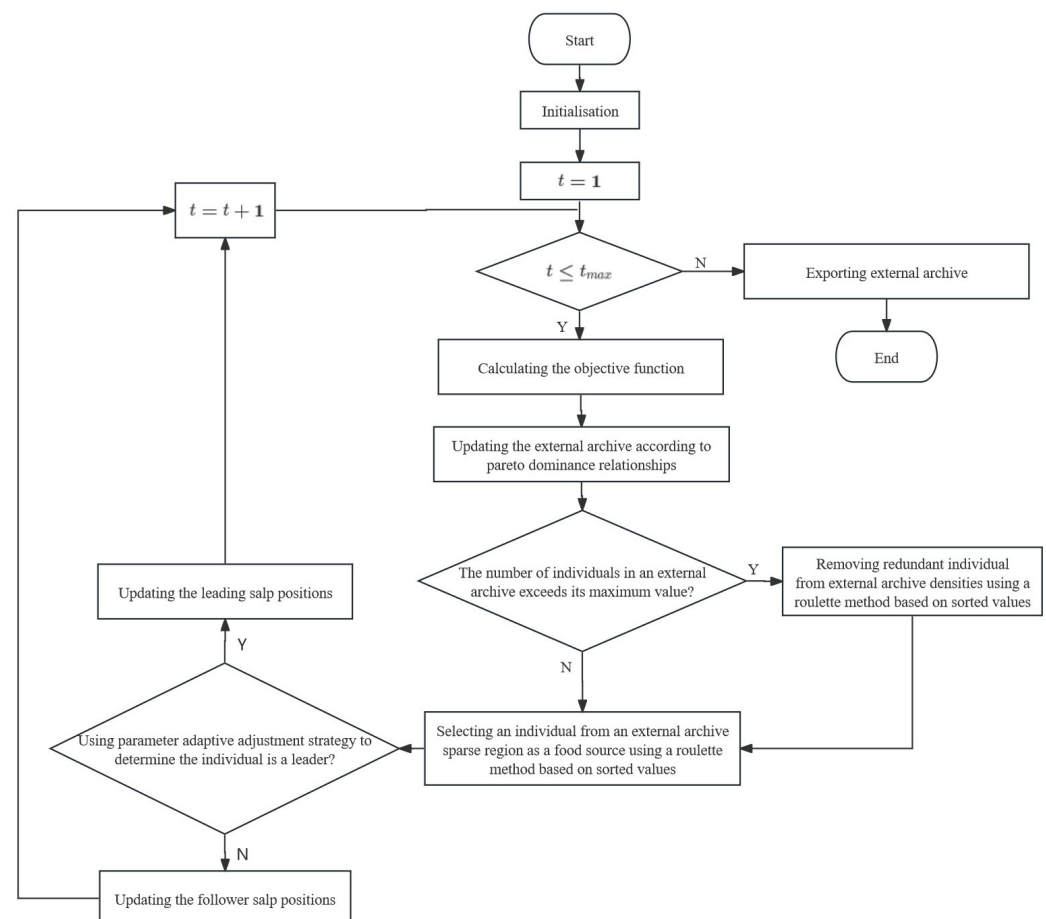


Figure 3. The proposed algorithm flow diagram.

4.1. Individual Encoding

Multimodal transport path planning is a discrete combinatorial optimization problem in which both the sequence of nodes and the transportation mode between adjacent nodes must be decided simultaneously. To effectively represent such solutions within the LMSSA framework, a two-tier natural number encoding scheme is adopted.

The first tier encodes the transportation route using a sequence of n nodes, where n is the total number of nodes visited from the origin to the destination (including both). The second tier encodes the transportation mode using a sequence of length $n - 1$, with each element indicating the specific mode (road, rail, or waterway) used to travel between two consecutive nodes in the route. This layered structure ensures that both routing and mode selection decisions are simultaneously represented in a single individual, which is essential for solving the multimodal problem.

The complete encoding of an individual is illustrated in Figure 4. The first n positions represent the node sequence, while the subsequent $n - 1$ positions represent the corresponding

transportation modes. This encoding scheme is intuitive, ensures feasibility through simple repair mechanisms if needed, and is particularly compatible with the position update operators developed in the proposed LMSSA. Moreover, compared with binary or permutation-based encodings, the two-tier natural number representation significantly reduces the complexity of decoding and constraint handling in large-scale multimodal networks.

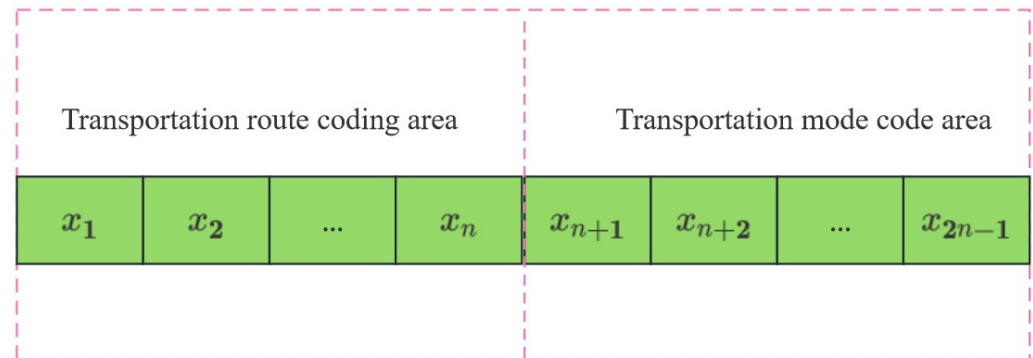


Figure 4. Individual coding rules for each salp.

4.2. Fitness Function Definition

Because metaheuristic algorithms cannot directly process rigid hard constraints, the regret constraints established in the scenario-based stochastic model (Section 3.5) must be integrated into the algorithmic search process. To properly achieve this, a static penalty function approach is employed. By introducing a large penalty term into the objective functions, any violation of the regret limits is heavily penalized, thereby guiding the salp swarm toward robust and feasible regions. The precise formulations for the converted fitness functions F_1 (for cost) and F_2 (for carbon emissions) are articulated as follows:

$$F_1 = \sum_{s=1}^S p_s \cdot C_s + f \cdot \left\{ \sum_{s=1}^S \max\{0, C_s - (1 + \gamma)C_s^*\} \right\} \quad (24)$$

$$F_2 = \sum_{s=1}^S p_s \cdot E_s + f \cdot \left\{ \sum_{s=1}^S \max\{0, E_s - (1 + \gamma)E_s^*\} \right\} \quad (25)$$

where f is a strictly large positive penalty coefficient, and γ is the identical regret factor defined in the mathematical model, which controls the maximum allowable deviation from the scenario-specific optimum.

4.3. Parameter Adaptive Adjustment Strategy

In the standard salp swarm algorithm, the foremost individual of the chain acts as the leader, while the remaining $N - 1$ individuals act as followers. However, a statically fixed ratio of leaders to followers can significantly impair search efficiency. An excessive number of followers leads to an overly detailed local search, making the algorithm prone to stagnation in local optima, whereas insufficient leaders restrict the global exploration capability.

To resolve this imbalance, this paper proposes a dynamic population allocation strategy that adaptively adjusts the leader–follower ratio as the iterations progress. Specifically, the strategy ensures that the number of leaders nonlinearly decreases, while the number of followers correspondingly increases. During the early iterations, a larger proportion of individuals execute the leader position-updating mechanism to enhance the algorithm's global pioneering ability. In the later iterations, the majority of individuals transition to the follower position-updating mechanism to intensify local exploitation. The formula governing the number of leaders r at the current iteration t is designed as follows:

$$r = \text{round} \left(N \cdot \left(u \cdot \tan \left(\frac{1}{g} \left(\pi - \frac{\pi \cdot t}{t_{\max}} \right) \right) + a \cdot Z_t \right) \right) \quad (26)$$

where r is the calculated number of leaders (rounded to the nearest integer), making the number of followers precisely $N - r$. N denotes the total population size of the swarm, t denotes the current iteration number, and $t_{\max}$ denotes the maximum number of iterations. The parameter g is an adjustment coefficient set to 4, while u and a are control parameters empirically set to 0.7 and 0.2, respectively [58]. Furthermore, to inject beneficial randomness and prevent premature convergence, Z_t represents a chaotic variable generated by a Bernoulli mapping at iteration t . To avoid notation conflicts with the transport mode indices, the Bernoulli mapping evolution is formally defined using the iteration index t :

$$Z_{t+1} = \begin{cases} Z_t / (1 - c), & Z_t \in (0, 1 - c] \\ (Z_t - 1 + c) / c, & Z_t \in (1 - c, 1] \end{cases} \quad (27)$$

where c is the critical chaos parameter, which is rigorously set to 0.4 [57,59].

4.4. Updating the Leading Salp Position Strategy

The standard salp swarm algorithm fundamentally relies on a unidirectional message-passing mechanism. Each follower salp only receives positional information from the preceding individual without any backward feedback. This strictly linear communication chain leads to a slow propagation of information throughout the swarm, significantly reducing the convergence speed. Furthermore, during the global exploration phase, the leaders rely solely on tracking a single food source (the global best). This singular directional focus makes the population highly susceptible to premature convergence and stagnation if the food source falls into a local optimum.

To explicitly address this algorithmic limitation and diversify the global search directions, a co-direction leader update strategy is proposed in this study. Instead of relying uniquely on the food source, the improved strategy introduces a dual-source information exchange mechanism. It intelligently directs the population movement by allowing the current leader to learn from either the food source or its own historical elite position from the previous iteration. Given the discrete nature of the multimodal routing problem, this positional update cannot utilize continuous mathematical addition; instead, it is executed using a position-based crossover (PBX) operator. The mathematical logic for the leader update is formulated as follows:

$$X_i(t+1) = \begin{cases} PBX(X_i(t), X_\alpha(t)), & 0 \leq r_1 < 0.5 \\ PBX(X_i(t), X_i(t-1)), & 0.5 \leq r_1 \leq 1 \end{cases} \quad (28)$$

where $X_i(t+1)$ and $X_i(t)$ represent the discrete encoded position sequence of the i -th leading salp at iterations $t+1$ and t , respectively. $X_\alpha(t)$ denotes the position sequence of the food source (i.e., a randomly selected non-dominated Pareto optimum from the external archive), and $X_i(t-1)$ represents the historical elite position of the i -th individual from the preceding iteration. r_1 is a uniformly distributed random variable generated in the interval $[0, 1]$.

PBX represents the position-based crossover operation, as structurally illustrated in Figure 5. The specific execution steps are as follows: First, several coding positions in the first parent individual (which may be spatially discontinuous) are randomly selected, and their genetic codes are directly copied to the exact same positions in the offspring individual. Subsequently, the remaining missing nodes are sequentially retrieved from the second parent individual. These retrieved codes are then filled into the empty positions of

the offspring in their original order, thereby preserving a valid and strictly feasible routing sequence without generating duplicated or missing transit nodes.

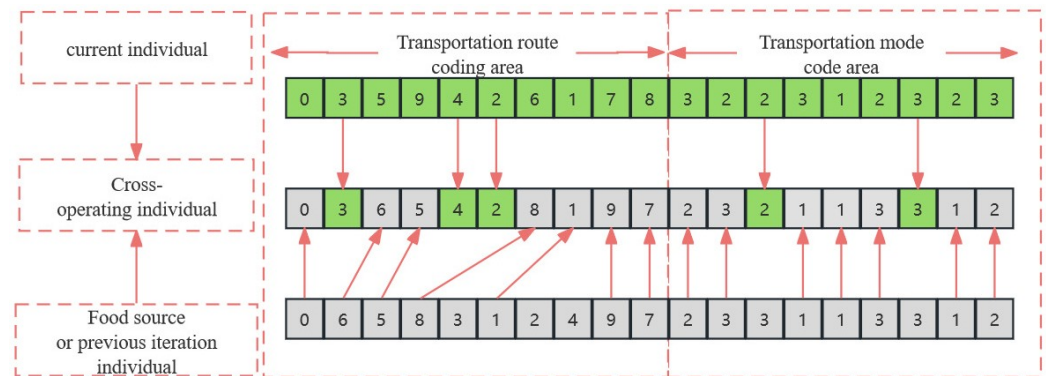


Figure 5. Leading salp position update strategy.

4.5. Updating the Follower Salp Position Strategy

In the standard salp swarm algorithm, the position update of a follower salp strictly depends on its own current position and the position of the immediately preceding individual. This rigid, single-chain dependency inherently lacks broader information exchange with the rest of the swarm. Consequently, if a preceding follower falls into a local optimum, the subsequent followers will inevitably replicate this flawed trajectory, leading to premature stagnation of the entire population.

To definitively resolve this local entrapment and enhance the local exploitation capability, a dual-guidance strategy is proposed for the followers. Instead of deterministically following the immediate predecessor, a follower is now dynamically guided by either its preceding individual or the historically optimal follower. Furthermore, to dictate this selection process with high unpredictability and ergodicity, a chaotic logistic map is integrated into the update mechanism, which effectively prevents the swarm from becoming trapped in local optimal solutions.

The logistic mapping generates a sequence of chaotic variables distributed between 0 and 1. If the generated chaotic variable is less than 0.5, the current follower performs a crossover operation with its immediate predecessor; otherwise, it crosses over with the optimal follower individual identified in the current iteration. The mathematical formulation of this discrete follower update is rigorously defined as follows:

$$X_i(t+1) = \begin{cases} OX(X_i(t), X_{i-1}(t)), & r_{t+1} < 0.5 \\ OX(X_i(t), X_{best}(t)), & r_{t+1} \geq 0.5 \end{cases} \quad (29)$$

where $X_{i-1}(t)$ denotes the discrete position sequence of the preceding follower, and $X_{best}(t)$ represents the optimal follower individual discovered up to the current iteration t . OX denotes the Order-Based Crossover operation, as graphically illustrated in Figure 6. The OX mechanism is executed by randomly selecting a continuous routing segment bounded by a start and an end position in the first parent individual. This selected segment is directly inherited by the offspring at the exact same spatial positions. Subsequently, the missing routing nodes are sequentially scanned from the second parent individual and inserted into the remaining empty positions of the offspring. This discrete operation explicitly guarantees that the generated transportation route remains strictly valid without any node duplication or omission.

Additionally, r_{t+1} is the chaotic variable generated via the logistic map [59], which is iteratively formulated as follows:

$$r_{t+1} = R \cdot r_t \cdot (1 - r_t) \quad (30)$$

where the control parameter R is strictly set to 4 to ensure the system operates in a fully chaotic state, and the initial value r_0 is a randomly generated number within the interval $(0,1)$ [57,59].

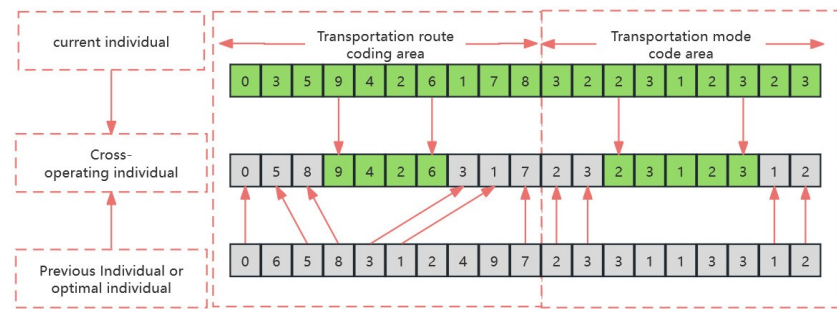


Figure 6. Following salp position update strategy.

5. Case Study Analysis

5.1. Numerical Results in Instances

To rigorously evaluate the performance of the proposed algorithm across different problem sizes, a comprehensive set of test instances is generated, adopting a methodology similar to Resat and Turkey [51]. In our computational experiments, the multimodal transport network is systematically built with 8 nodes for small-scale instances; 20 and 30 nodes for medium-scale instances; and 50 and 100 nodes for large-scale instances. For each network scale, 10 independent instances are randomly generated, yielding a total of 50 instances. The detailed characteristics of these test sets are summarized in Table A1.

5.1.1. Justification for Parameter Choices and Scenario Generation

To address the specific requirements of the multimodal routing model, the initial parameters must be explicitly justified to ensure the practical relevance of the study. The allowable delivery time window for the transported goods is strictly set between 55 and 65 h. To prevent violations, unit storage costs incurred by early arrivals are set to 50 yuan/h·TEU, while unit penalty costs for delayed arrivals are set significantly higher at 95 yuan/h·TEU. Furthermore, recognizing that fuel conversion factors vary slightly across different organizations, this paper uniformly adopts the European carbon emission standard for the calculation of carbon emissions, utilizing a fixed fuel conversion factor of 2.62. The specific operational parameters related to the three transport modes (road, rail, and waterway) are detailed in Tables A2–A4.

To incorporate demand uncertainty, a scenario-based methodology is employed. The baseline transportation demand is conservatively set at 24 TEU, which reflects the typical daily cargo consolidation volume for small-to-medium enterprises operating in Chinese ports. The five discrete demand scenarios, corresponding to a $\pm 20\%$ fluctuation range around this baseline, are illustrative values intended to represent a realistic range of short-term demand variability commonly discussed in the multimodal logistics literature, rather than figures extracted from a specific proprietary dataset. Similarly, the seasonal probability distributions in Table 2 are illustrative weightings designed to reflect the qualitative pattern of demand seasonality, rather than estimates derived from a specific cited dataset. Based on this statistical observation, five discrete transportation scenarios are constructed: 20 TEU (-16.7%), 22 TEU (-8.3%), 24 TEU (baseline), 26 TEU ($+8.3\%$), and 28 TEU ($+16.7\%$).

To assess the sensitivity of the proposed framework to these choices, the case study varies several of these parameters: Tables 3 and 4 report results across the full range of demand scenarios, Figure 7 examines sensitivity to the regret coefficient, and Figure 8 examines sensitivity to the seasonal probability weighting in Table 2. Across all these variations, the qualitative conclusions of the study remain consistent, suggesting that the

framework's practical insights are not critically dependent on the exact numerical values chosen for these parameters.

The occurrence probability p_s for each specific scenario is likewise illustrative rather than dataset-derived, and is qualitatively informed by seasonal demand characteristics. For example, scenarios with high demand (+8.3% and +16.7%) are assigned higher probabilities during peak shopping festivals or harvest seasons, whereas lower-demand scenarios are statistically favored during off-season periods. These illustrative probability weightings are intended only to reflect a qualitative seasonal pattern, consistent with the demand baseline and fluctuation range described above. This probabilistic assignment effectively integrates stochastic programming principles with robust regret control. The regret coefficient γ , representing the decision-maker's tolerance for worst-case deviation, is set to 0.2 and 0.3 to systematically examine the trade-off between economic efficiency and solution conservatism.

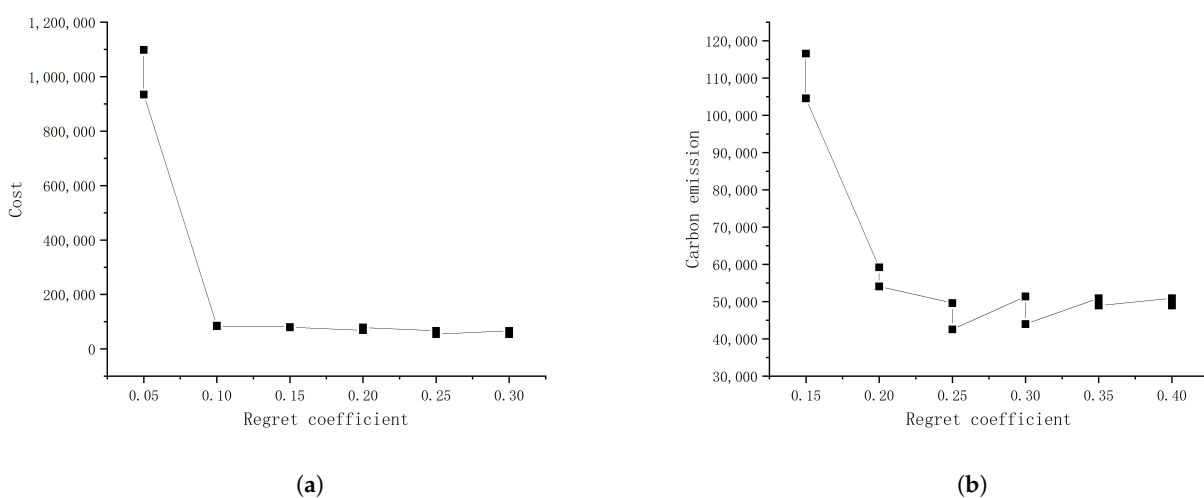


Figure 7. Relationship between varying regret coefficients and expected optimal solutions. (a) Regret coefficient vs. expected total costs. (b) Regret coefficient vs. expected carbon emissions.

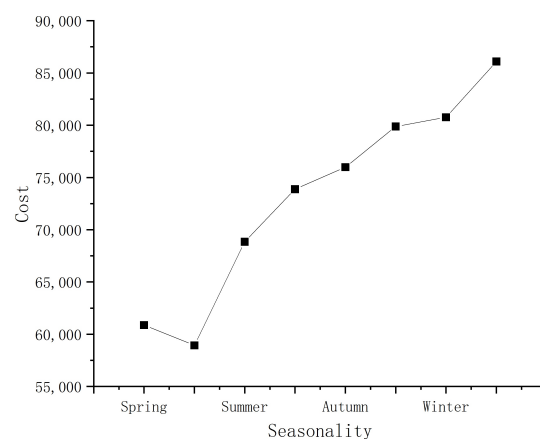


Figure 8. Dynamic escalation of expected total costs across seasonal transport scenarios.

Regarding algorithmic hyperparameters, the population size is fixed at $N = 50$ and the maximum number of iterations at $t_{\max} = 100$. The population size and maximum iteration number adopted in this study are consistent with typical settings used in salp swarm algorithm and related swarm intelligence studies [45,54,55], which commonly employ comparable population sizes and iteration budgets for combinatorial optimization problems of similar scale. Finally, the actual-to-design traffic capacity ratio (f/c) on road links is varied

within the range of $[0, 3]$ to simulate varying degrees of traffic congestion. Mode capacities are constrained as follows: 2 TEU for trucks, 50 TEU for trains, and 200 TEU for cargo ships.

Table 2. Seasonally varying probability distributions assigned to distinct transport demand scenarios.

Seasonality	Occurrence Probability (p_s) for Demand Scenarios				
	20 TEU	22 TEU	24 TEU	26 TEU	28 TEU
Spring	0.30	0.30	0.20	0.10	0.10
Summer	0.20	0.20	0.20	0.20	0.20
Autumn	0.10	0.10	0.20	0.30	0.30
Winter	0.10	0.10	0.10	0.30	0.40

Table 3. Comparison of results between deterministic and uncertain scenarios.

Q	RC1	RE1	RC1%	RE1%	RC2	RE2	RC2%	RE2%
20	35,138	49,609	5.55%	4.25%	41,027	40,912	19.89%	-
22	49,938	50,508	5.31%	4.67%	57,670	40,941	18.52%	-
24	66,790	51,406	4.75%	5.10%	76,592	40,969	17.18%	-
26	85,694	52,304	4.40%	5.52%	97,795	40,998	16.32%	-
28	121,280	41,030	15.79%	-	106,650	53,200	4.23%	5.93%

Table 4. Optimal solutions under isolated deterministic demand scenarios.

Q	Time Window	Transport Route	Transport Mode	Solution C	Solution E
20	55,65	27,16,2,3,1	2,3,1,1	34,453	69,843
20	55,65	27,16,2,1	1,3,2	33,078	72,719
20	55,65	27,16,2,1	2,3,2	29,396	78,541
20	55,65	27,13,12,2,1	1,1,3,2	35,138	49,609
20	55,65	27,13,12,2,1	1,1,3,1	41,027	40,912
22	55,65	27,16,2,3,1	2,3,1,1	49,185	70,450
22	55,65	27,16,2,1	1,3,2	47,672	73,614
22	55,65	27,16,2,1	2,3,2	41,521	80,018
22	55,65	27,13,12,2,1	1,1,3,2	49,938	50,508
22	55,65	27,13,12,2,1	1,1,3,1	57,670	40,941
24	55,65	27,16,2,1	2,3,2	56,240	81,495
24	55,65	27,16,2,1	2,3,1	66,042	71,058
24	55,65	27,16,2,1	1,3,2	64,318	74,508
24	55,65	27,13,12,2,1	1,1,3,2	66,790	51,406
24	55,65	27,13,12,2,1	1,1,3,1	76,592	40,969
26	55,65	27,16,2,1	1,3,2	83,016	75,403
26	55,65	27,16,2,1	2,3,2	72,782	82,972
26	55,65	27,13,12,2,1	1,1,3,2	85,694	52,304
26	55,65	27,13,12,2,1	1,1,3,1	97,795	40,998
26	55,65	27,16,2,3,1	2,3,1,1	84,803	71,665
28	55,65	27,13,12,2,1	1,1,3,1	121,280	41,030
28	55,65	27,13,12,2,1	1,1,3,2	106,650	53,200
28	55,65	27,16,2,1	1,3,2	103,770	76,300
28	55,65	27,16,2,1	2,3,2	91,150	84,450
28	55,65	27,16,12,2,1	2,2,3,2	105,190	69,150

5.1.2. Algorithm Evaluation Criteria and Ablation Study

To scientifically verify the effectiveness of the claimed improvements and evaluate the algorithm's performance, an ablation study is strictly conducted. Three simplified variants of the proposed algorithm are constructed for comparison:

- LMSSA-1: Excludes the leader–food-source co-guiding mechanism (reverting to singular food-source reliance).
- LMSSA-2: Excludes the parameter adaptive adjustment strategy (reverting to a fixed leader–follower ratio).
- LMSSA-3: Excludes the follower chaotic mapping optimization strategy (reverting to deterministic predecessor dependence).

Each algorithm (including the baseline MSSA and the complete LMSSA) is executed independently for 10 runs to eliminate stochastic bias, with all other computational conditions strictly identical.

To provide a comprehensive assessment of multi-objective algorithmic performance, four distinct evaluation metrics are explicitly defined: (1) the total number of Pareto-optimal solutions successfully found within the maximum iterations; (2) the specific iteration count at which the first Pareto-optimal solution is identified (reflecting initial convergence speed); (3) whether the complete set of true optimal solutions is successfully located (reflecting global search capability); and (4) the average CPU computational time in seconds per independent run.

The detailed optimization results and performance comparisons against the proposed LMSSA are systematically presented in Tables 5–9. Furthermore, the dynamic convergence curves illustrating the relationship between the number of discovered optimal solutions and the number of algorithmic iterations are plotted in Figures 9–13.

Table 5. Computational results for eight nodes.

	Route	Mode	Total Costs	Carbon Emissions	Optimal Solution	Iteration Number	Time
LMSSA	8,2,3,1	3,1,1	8656	63,969	Yes	9	0.45
LMSSA	8,6,2,1	1,3,1	69,180	40,927	Yes	17	0.85
LMSSA	8,2,1	3,1	11,202	63,932	Yes	9	0.45
LMSSA-1	8,2,3,1	3,1,1	8656	63,969	Yes	13	0.65
LMSSA-1	8,6,2,1	1,3,1	69,180	40,927	Yes	13	0.65
LMSSA-1	8,2,1	3,1	11,202	63,932	Yes	13	0.65
LMSSA-2	8,2,3,1	3,1,1	8656	63,969	Yes	15	0.75
LMSSA-2	8,2,1	3,1	11,202	63,932	Yes	15	0.75
LMSSA-3	8,2,1	3,1	11,202	63,932	Yes	11	0.55
LMSSA-3	8,6,2,1	1,3,1	69,180	40,927	Yes	11	0.55
LMSSA-3	8,2,3,1	3,1,1	8656	63,969	Yes	22	1.1
MSSA	8,2,3,1	3,1,1	8656	63,969	Yes	19	0.95
MSSA	8,6,2,1	1,3,1	69,180	40,927	Yes	19	0.95

Table 6. Computational results for 20 nodes.

	Route	Mode	Total Costs	Carbon Emissions	Optimal Solution	Iteration Number	Time
LMSSA	20,8,11,5,3,1	1,1,1,1,1	45,390	574	Yes	27	1.35
LMSSA	20,8,11,5,3,1	1,2,1,1,1	25,294	1651	Yes	24	1.2
LMSSA	20,8,11,5,1	1,2,1,1	26,755	1635	Yes	16	0.8
LMSSA	20,8,11,5,1	1,1,1,1	47,252	558	Yes	5	0.25
LMSSA-1	20,8,11,5,1	1,2,1,1	26,755	1635	Yes	15	0.75
LMSSA-1	20,8,11,5,1	1,1,1,1	47,252	558	Yes	15	0.75
LMSSA-2	20,8,11,5,2,1	1,2,1,1,1	27,547	1642	No	18	-
LMSSA-2	20,8,11,5,2,1	1,1,1,1,1	46,745	648	No	18	-
LMSSA-2	20,8,11,5,1	1,1,1,1	47,252	558	Yes	18	0.9
LMSSA-2	20,8,11,5,3,1	1,2,1,1,1	25,294	1651	Yes	18	0.9
LMSSA-3	20,8,11,5,3,1	1,1,1,1,1	45,390	574	Yes	33	1.65
LMSSA-3	20,8,11,5,3,1	1,2,1,1,1	25,294	1651	Yes	27	1.35
LMSSA-3	20,8,11,5,1	1,2,1,1	26,755	1635	Yes	20	1
LMSSA-3	20,8,11,5,1	1,1,1,1	47,252	558	Yes	20	1
MSSA	20,16,2,1	2,3,2	41,396	68,699	No	31	-
MSSA	20,16,2,1	1,3,1	43,436	66,059	No	31	-
MSSA	20,16,2,1	2,3,1	45,908	65,539	No	31	-
MSSA	20,8,11,5,1	1,1,1,1	47,252	558	Yes	31	1.55

Table 7. Computational results for 30 nodes.

	Route	Mode	Total Costs	Carbon Emissions	Optimal Solution	Iteration Number	Time
LMSSA	27,13,12,2,1	1,1,3,2	68,842	44,129	Yes	37	1.85
LMSSA	27,13,12,2,1	1,1,3,1	78,872	40,969	Yes	22	1.1
LMSSA	27,16,2,1	1,3,2	66,370	67,231	Yes	7	0.35
LMSSA	27,16,2,1	2,3,1	68,094	66,188	Yes	7	0.35
LMSSA	27,16,2,1	2,3,2	58,218	69,347	Yes	7	0.35

Table 7. Cont.

	Route	Mode	Total Costs	Carbon Emissions	Optimal Solution	Iteration Number	Time
LMSSA-1	27,16,2,1	2,3,2	58,218	69,347	Yes	11	0.55
LMSSA-1	27,16,2,1	2,3,1	68,094	66,188	Yes	11	0.55
LMSSA-1	27,16,2,1	1,3,2	66,370	67,231	Yes	11	0.55
LMSSA-1	27,16,12,2,1	1,1,3,2	69,108	44,130	No	31	-
LMSSA-1	27,16,12,2,1	1,1,3,1	79,138	40,977	No	31	-
LMSSA-2	27,16,2,1	2,3,2	58,218	69,347	Yes	15	0.75
LMSSA-2	27,16,2,1	1,3,2	66,370	67,231	Yes	15	0.75
LMSSA-2	27,16,2,1	1,3,1	79,537	64,072	No	15	-
LMSSA-2	27,16,2,1	2,3,1	68,094	66,188	Yes	15	0.75
LMSSA-3	27,13,12,2,1	1,1,3,1	78,872	40,969	Yes	58	2.9
LMSSA-3	27,13,12,2,1	1,1,3,2	68,842	44,129	Yes	34	1.7
LMSSA-3	27,16,2,1	2,3,2	58,218	69,347	Yes	13	0.65
LMSSA-3	27,16,2,1	2,3,1	68,094	66,188	Yes	13	0.65
LMSSA-3	27,16,2,1	1,3,2	66,370	67,231	Yes	13	0.65
MSSA	27,16,2,3,1	2,3,1,1	69,569	66,187	No	54	-
MSSA	27,16,14,2,1	1,1,3,2	79,456	46,111	No	54	-
MSSA	27,16,14,2,1	1,1,3,1	82,254	42,951	No	54	-
MSSA	27,16,2,1	1,3,2	66,370	67,231	Yes	54	2.7
MSSA	27,16,2,1	2,3,2	58,218	69,347	Yes	54	2.7

Table 8. Computational results for 50 nodes.

	Route	Mode	Total Costs	Carbon Emissions	Optimal Solution	Iteration Number	Time
LMSSA	50,31,35,5,1	1,1,1,1	76,321	54,782	Yes	44	2.2
LMSSA	50,31,21,1	1,1,2	70,934	56,481	Yes	29	1.45
LMSSA	50,40,5,1	1,2,1	81,814	51,392	Yes	14	0.7
LMSSA	50,31,23,21,1	1,3,1,1	83,892	50,579	Yes	14	0.7
LMSSA	50,42,39,21,1	1,2,3,1	70,769	57,326	Yes	24	1.2
LMSSA-1	50,31,21,1	1,1,2	70,934	56,481	Yes	18	0.9
LMSSA-1	50,40,5,1	1,2,1	81,814	51,392	Yes	18	0.9
LMSSA-1	50,31,23,21,1	1,3,1,1	83,892	50,579	Yes	28	1.4
LMSSA-2	50,31,23,21,1	1,3,1,1	83,892	50,579	Yes	22	1.1
LMSSA-2	50,40,5,1	1,2,1	81,814	51,392	Yes	22	1.1
LMSSA-2	50,31,21,1	1,1,2	70,934	56,481	Yes	22	1.1
LMSSA-2	50,40,5,21,1	1,1,1,3	70,871	57,603	No	41	-
LMSSA-3	50,31,35,5,1	1,1,1,1	76,321	54,782	Yes	61	3.05
LMSSA-3	50,31,21,1	1,1,2	70,934	56,481	Yes	46	2.3
LMSSA-3	50,40,5,1	1,2,1	81,814	51,392	Yes	24	1.2
LMSSA-3	50,31,23,21,1	1,3,1,1	83,892	50,579	Yes	24	1.2
LMSSA-3	50,42,39,21,1	1,2,3,1	70,769	57,326	Yes	34	1.7
MSSA	50,31,23,21,1	1,3,1,1	83,892	50,579	Yes	46	2.3
MSSA	50,40,5,1	1,2,1	81,814	51,392	Yes	56	2.8
MSSA	50,31,23,5,1	1,1,2,1	71,634	56,509	No	70	-
MSSA	50,40,5,21,1	1,1,1,3	70,871	57,603	No	72	-

Table 9. Computational results for 100 nodes.

	Route	Mode	Total Costs	Carbon Emissions	Optimal Solution	Iteration Number	Time
LMSSA	100,67,53,24,1	1,1,3,1	96,721	65,182	Yes	66	3.3
LMSSA	100,53,18,1	1,1,3	91,994	67,505	Yes	58	2.9
LMSSA	100,53,24,1	2,1,1	101,514	60,946	Yes	28	1.4
LMSSA	100,54,32,1	1,1,1	113,314	58,702	Yes	28	1.4
LMSSA-1	100,53,24,1	2,1,1	101,514	60,946	Yes	36	1.8
LMSSA-1	100,54,32,1	1,1,1	113,314	58,702	Yes	36	1.8
LMSSA-2	100,54,32,1	1,1,1	113,314	58,702	Yes	40	2
LMSSA-2	100,53,24,1	2,1,1	101,514	60,946	Yes	40	2
LMSSA-2	100,65,24,1	1,3,1	95,621	67,850	No	54	-
LMSSA-3	100,54,32,1	1,1,1	113,314	58,702	Yes	38	1.9
LMSSA-3	100,53,18,1	1,1,3	91,994	67,505	Yes	72	3.6
LMSSA-3	100,53,24,1	2,1,1	101,514	60,946	Yes	38	1.9
LMSSA-3	100,67,53,24,1	1,1,3,1	96,721	65,182	Yes	84	4.2
MSSA	100,54,32,1	1,1,1	113,314	58,702	Yes	81	4.05
MSSA	100,53,24,1	2,1,1	101,514	60,946	Yes	81	4.05
MSSA	100,65,24,1	1,3,1	95,621	67,850	No	83	-

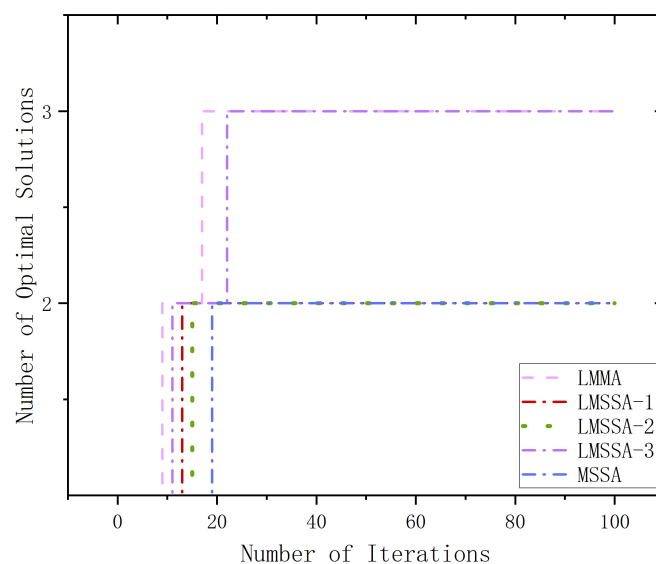


Figure 9. Comparison of the five algorithms for eight nodes.

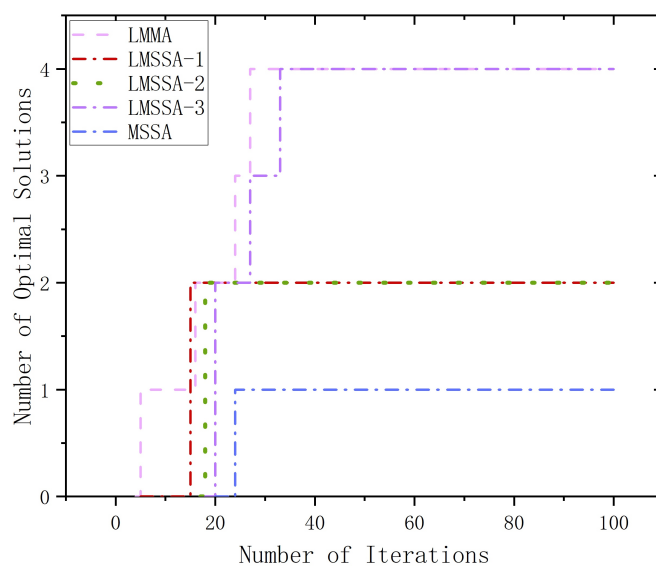


Figure 10. Comparison of the five algorithms for 20 nodes.

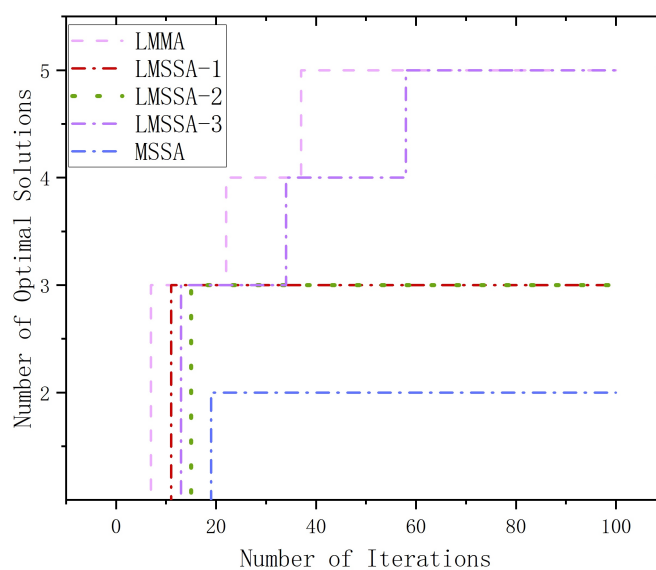


Figure 11. Comparison of the five algorithms for 30 nodes.

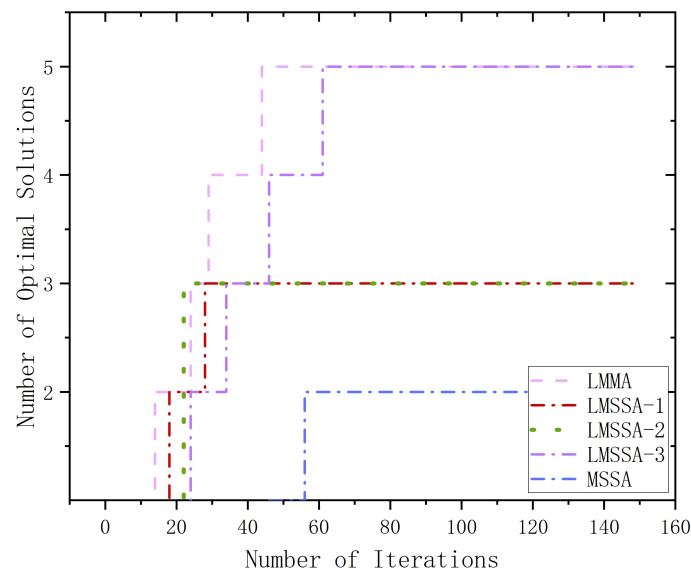


Figure 12. Comparison of the five algorithms for 50 nodes.

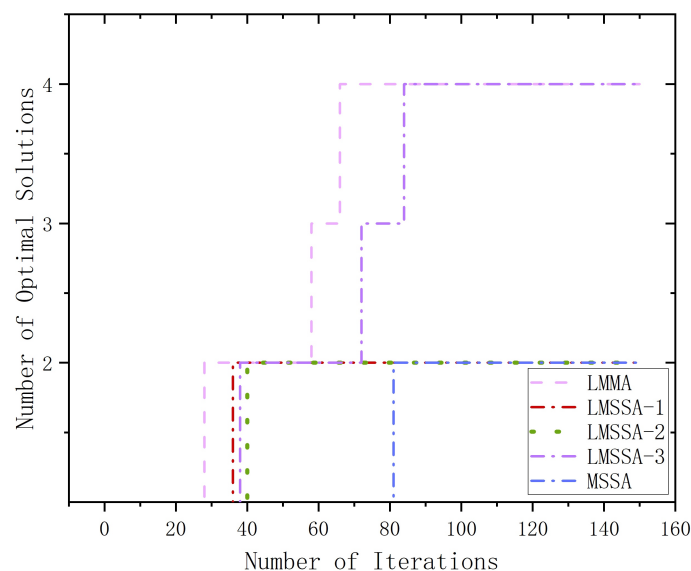


Figure 13. Comparison of the five algorithms for 100 nodes.

Based on the comprehensive numerical experiments, the performance of the proposed algorithms is systematically evaluated. Drawing from the computational results, the analysis is detailed from two distinct perspectives.

5.1.3. Analysis of Pareto-Optimal Solution Discovery

Analyzing the specific optimization outcomes presented in Tables 5–9, the following conclusions are drawn:

Small-scale instances (eight nodes): The proposed LMSSA identifies the first Pareto-optimal solution as early as the 9th iteration and successfully uncovers the complete set of true optimal solutions by the 17th iteration. In stark contrast, the baseline MSSA struggles with convergence speed, finding only two non-dominated solutions by the 19th iteration.

To substantiate the local-trap phenomenon and to provide a credible reference for evaluating algorithmic performance on the eight-node instances, we examine the complete set of non-dominated solutions discovered across all five algorithm configurations, namely LMSSA and its three ablated variants plus the baseline MSSA. Collectively, only three distinct non-dominated solutions were identified across all configurations: 8656 and

63,969, 69,180 and 40,927, and 11,202 and 63,932. Given the limited size of the feasible solution space for the eight-node network, constrained by the network topology and Assumption 2, the consistent recovery of this same three-solution set across five structurally different search procedures provides strong empirical evidence that this set closely approximates the Pareto-optimal front for the eight-node instances. We refer to this set as the reference front for the eight-node scale rather than as a formally proven optimum, since it is established through repeated independent convergence rather than through exhaustive verification.

For the medium- and large-scale instances (20–100 nodes), establishing such an accurate reference via exhaustive enumeration is computationally intractable, which is itself a direct consequence of the NP-hard complexity discussed in Section 3.6 and the central motivation for adopting a metaheuristic approach. For these instances, following standard practice in the multi-objective metaheuristic literature, the reference Pareto front is constructed as the union of all non-dominated solutions discovered across all five algorithm configurations and all independent runs; the “Optimal solution” column in Tables 6–9 indicates whether each algorithm’s final archive recovers this reference front. Notably, the same pattern validated against the accurate eight-node reference—namely, that MSSA frequently fails to recover the complete reference front (marked “No” in Tables 6–9) while LMSSA consistently does (marked “Yes”)—persists across every larger scale, reinforcing the conclusion that the proposed enhancements effectively mitigate the local-trap issue identified in the baseline algorithm.

Medium-scale instances (20 and 30 nodes): LMSSA maintains a distinct superiority. For the 20-node problem, it locates the initial optimal solution in the 5th iteration and fully maps the Pareto front by the 27th iteration, whereas MSSA finds only a single optimal solution by the 31st iteration. Similarly, for the 30-node problem, LMSSA locates three optimal solutions by the 7th iteration and the complete set by the 37th iteration, vastly outperforming MSSA, which yields only two optimal solutions by the 54th iteration.

Large-scale instances (50 and 100 nodes): The robust scalability of LMSSA becomes highly evident. In the 50-node network, LMSSA discovers two optimal solutions by the 14th iteration and the complete set by the 44th, compared to MSSA’s three solutions at the 70th iteration. In the most complex 100-node scenario, LMSSA retrieves the complete Pareto front by the 66th iteration, while MSSA manages to find only two optimal solutions by the 81st iteration. These results unequivocally demonstrate LMSSA’s exceptional search efficiency and robustness in handling high-dimensional multimodal networks.

Ablation variants (LMSSA-1, LMSSA-2, LMSSA-3): The isolated variants consistently yield more satisfactory Pareto fronts than the standard MSSA. This empirically validates that the introduction of both the parameter adaptive adjustment strategy and the modified position-updating strategies independently contribute to identifying highly satisfactory multimodal routing schemes.

5.1.4. Analysis of Algorithmic Convergence and Ablation Effectiveness

To explicitly justify the claimed algorithmic improvements, the dynamic convergence behaviors illustrated in Figures 9–13 are analyzed.

The standard MSSA frequently suffers from premature convergence, falling into local optima within a limited number of iterations and fundamentally failing to explore the complete solution space.

Comparing the fully integrated LMSSA with its variants (LMSSA-1 and LMSSA-2) and the baseline MSSA, it is empirically evident that adopting the co-direction leader update strategy (which simultaneously utilizes food-source and historical elite guidance) effectively resolves the algorithm’s vulnerability to local entrapment.

Comparing LMSSA and LMSSA-3 against the baseline MSSA reveals that integrating the chaotic logistic mapping into the follower update strategy significantly accelerates the global convergence rate, resolving the traditional algorithm's notoriously slow optimal discovery process.

In conclusion, these rigorous comparative analyses prove the effectiveness of the proposed LMSSA. The tailored modifications successfully achieve a dynamic balance between global exploration and local exploitation capabilities, significantly elevating the optimization performance over the standard MSSA. Ultimately, the proposed algorithm proves to be a highly reliable and computationally efficient solver for complex, discrete multimodal transportation problems of varying practical scales.

5.1.5. External Algorithmic Comparison

To address the scope of the algorithmic comparison and the absence of standard multi-objective performance metrics in the original evaluation, this section presents a supplementary comparison of LMSSA against two widely used multi-objective metaheuristics, NSGA-II and MOEA/D.

Four new test instances with 15, 30, 50, and 100 nodes were generated following the same network-construction methodology described in Section 5.1.1, with parameters consistent with Tables A2–A4. Consistent with the reference-front construction already used for the main ablation study in Tables 6–9, the reference front for each supplementary instance is taken as the union of all non-dominated solutions discovered across the three algorithms and all 30 independent runs. Exhaustive enumeration was not pursued for these instances, since it is computationally intractable at these scales for the same reasons discussed in Section 3.6, and the reference front reported here should be understood as an approximate rather than a formally verified optimum.

All three algorithms were implemented using an identical population size of 50, an iteration budget of 100, and identical underlying route and mode variation operators, and each algorithm was independently run 10 times per instance. Four standard metrics were computed following definitions established in the multi-objective optimization literature: the Hypervolume ratio relative to the true Pareto front, the Inverted Generational Distance, the Spacing metric, and the Spread metric. The results are summarized in Table 10.

Table 10. External comparison of LMSSA against NSGA-II and MOEA/D on supplementary instances, using an approximate union-based reference front (mean over 10 independent runs).

Scale	Algorithm	HV Ratio	IGD	Spacing	Spread	Complete-Front Rate
15 nodes	LMSSA	0.999	0.0009	0.175	0.450	9/10
15 nodes	NSGA-II	0.992	0.0256	0.153	0.395	6/10
15 nodes	MOEA/D	0.930	0.1253	0.088	0.423	2/10
30 nodes	LMSSA	0.986	0.0157	0.238	0.568	7/10
30 nodes	NSGA-II	0.986	0.0262	0.217	0.574	7/10
30 nodes	MOEA/D	0.907	0.1723	0.154	0.760	0/10
50 nodes	LMSSA	0.998	0.0145	0.061	0.371	6/10
50 nodes	NSGA-II	0.947	0.0986	0.079	0.382	2/10
50 nodes	MOEA/D	0.910	0.1548	0.082	0.414	0/10
100 nodes	LMSSA	0.970	0.1240	0.162	0.570	6/10
100 nodes	NSGA-II	0.959	0.1201	0.244	0.569	3/10
100 nodes	MOEA/D	0.908	0.2700	0.093	0.629	1/10

On the 100-node instances, all three algorithms achieve a complete-front recovery rate of zero out of ten runs, reflecting the substantially larger combinatorial search space at this scale. LMSSA nonetheless retains the highest Hypervolume ratio at this scale, indicating that, although none of the algorithms fully recover the reference front within the given iteration budget, LMSSA's archive remains the closest in coverage and convergence among the three.

LMSSA achieves the highest Hypervolume ratio across all four instance scales, indicating that its archives most closely approximate the true Pareto front in terms of both convergence and coverage. LMSSA also achieves the lowest Inverted Generational Distance on three of the four scales and the highest complete-front recovery rate, defined as the proportion of runs in which an algorithm's archive recovers the entire true Pareto front, on three of the four scales. NSGA-II performs comparably to LMSSA on the 30-node instance, where the two algorithms tie on both the Hypervolume ratio and the complete-front recovery rate, and remains competitive across the other scales. MOEA/D consistently exhibits lower Hypervolume ratios and higher Inverted Generational Distance values, reflecting its comparatively slower convergence on this discrete, combinatorial routing problem under the present operator configuration. Regarding Spacing, no algorithm exhibits a consistent advantage across scales: each of the three algorithms attains the lowest (best) Spacing value on at least one instance size. The Spread metric shows a milder pattern, with MOEA/D recording the highest (least uniform) Spread value on three of the four scales; however, this should be interpreted with caution, since Spread is sensitive to the number of solutions an algorithm has discovered, and MOEA/D's lower complete-front recovery rate means its archives generally contain fewer, more extreme solutions. This is consistent with the well-documented trade-off in multi-objective optimization between convergence to the true front and the uniformity of the distribution of the typically fewer solutions an algorithm has so far discovered.

5.2. Case Study

In this section, to verify the practical validity of the proposed model and to explore the impact of uncertain demand on container multimodal transport routing considering traffic congestion, a real-world multimodal transport system in northern China is utilized as a case study. The topology of the network structure is illustrated in Figure 14. The nodes in this network are numbered 1 to 27 sequentially. The actual transportation distances for the three available modes (road, rail, and waterway) across the network links are detailed in Table A5. All other operational parameters remain consistent with the settings defined in the previous numerical instances.

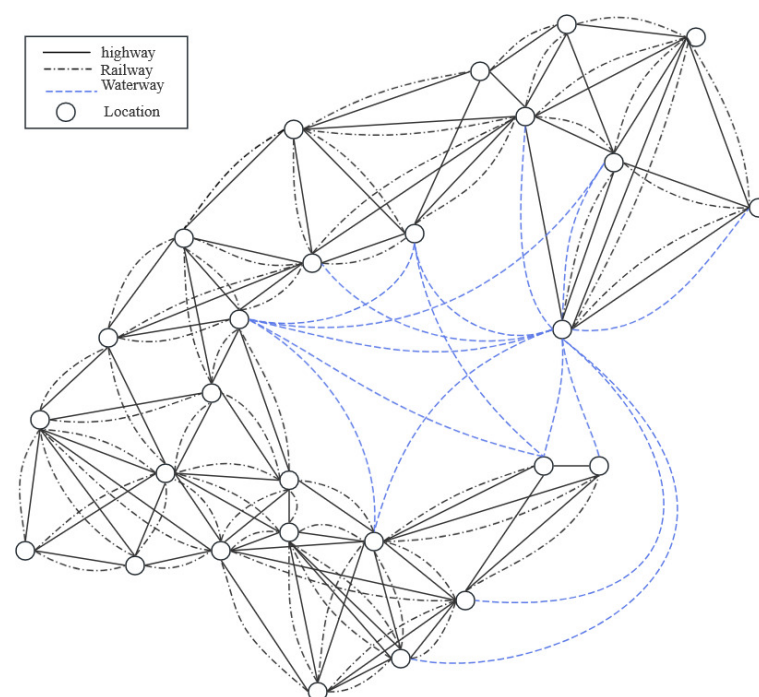


Figure 14. Multimodal transport network in north-eastern China.

5.2.1. Computational Results and Analysis

To identify a highly reliable and economically viable routing solution across all possible demand fluctuations, the regret coefficients γ in the proposed scenario-based stochastic model are set to 0.2 and 0.3, respectively.

To systematically analyze the performance of the proposed method, the evaluations are divided into three parts. First, the optimal transport routes, modes, costs, and emissions under each isolated, deterministic demand scenario are presented in Table 4. Second, the strategic routing decisions generated by our proposed regret-constrained stochastic approach are presented in Table 11. Finally, to evaluate the reliability of these strategic decisions, the proposed routing schemes were tested against the five different real-world freight volume scenarios. The corresponding expected total costs and carbon emissions were compared with the perfect-information deterministic solutions, with the comparative results detailed in Table 3.

Table 11. Optimal routing solutions under the proposed scenario-based model with regret constraints.

	Q	Time Window	Transport Route	Transport Mode	Regret-Based Solution C	Regret-Based Solution E
R1	20–28	55,65	27,13,12,2,1	1,1,3,2	68,842	51,406
R2	20–28	55,65	27,13,12,2,1	1,1,3,1	78,872	40,969

Based on the obtained solutions and comparative data presented in Tables 3, 4 and 11, we systematically observe the following insights:

1. As the transport demand fluctuates within the range of 20 to 28 TEU, the optimal multimodal transport routes, transport modes, total costs, and carbon emissions undergo significant shifts. This highlights the extreme sensitivity of deterministic routing schemes to demand variability and validates the necessity of considering uncertainty in multimodal transport planning.
2. The strategic solutions derived from our proposed regret-constrained model rigorously satisfy the strict 55–65 h delivery time window across all five distinct demand scenarios. This demonstrates that the proposed algorithm yields universally feasible and stable transport solutions, effectively immunizing the enterprise against unpredictable demand shocks.
3. The maximum relative deviation of the proposed scenario-based solution compared to any scenario-specific deterministic optimum is strictly bounded. As validated in the results, the deviations do not exceed the predefined regret threshold coefficients of 0.2 and 0.3. This statistically demonstrates the model's robustness and flexibility in safely meeting rigorous customer requirements.
4. The expected total costs of the regret-based solutions are marginally higher than or equal to the minimum costs obtained under perfect-information deterministic scenarios. In operations research, this marginal increase represents the “price of robustness”—a necessary and completely acceptable premium that enterprises pay to guarantee service reliability. By adopting this approach, logistics companies can avoid the severe late penalties and cargo interruptions that would inevitably occur if a deterministic plan were exposed to sudden demand surges.

5.2.2. Influence of Traffic Congestion

To rigorously investigate the cascading impact of road traffic congestion on multimodal transport decisions, scenarios with varying traffic volume-to-capacity ratios (f/c) are systematically designed. The spatial distributions of the optimal routes derived under the

proposed regret-constrained stochastic model are illustrated in Figure 15. Furthermore, the detailed multimodal transport schemes (including routing and mode selections) under different congestion severity levels are summarized in Table 12.

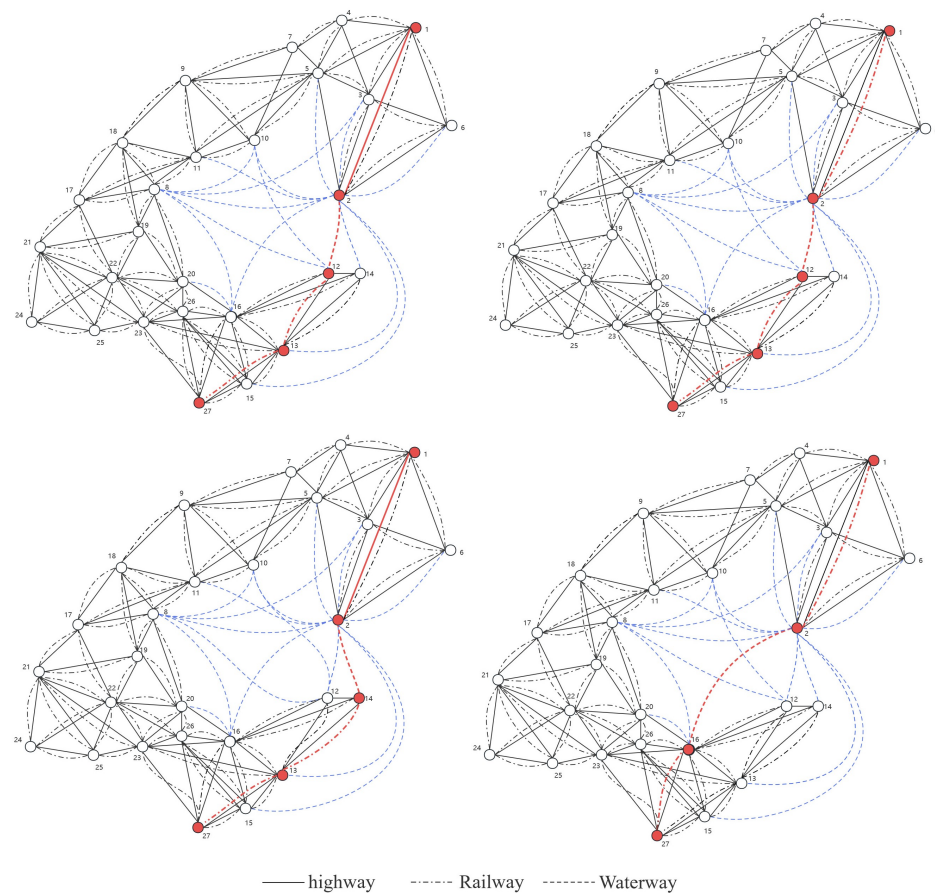


Figure 15. Optimal multimodal routes under the proposed regret-constrained scenario approach.

Table 12. Optimal routing schemes under varying road traffic congestion scenarios.

f/c Ratio	Demand	Time Window	Transport Route	Transport Mode	Total Cost	Carbon Emissions
0.5	20–28	55–65	27,13,12,2,1	1,1,3,1	78,872	40,969
0.5	20–28	55–65	27,13,12,2,1	1,1,3,2	68,842	44,129
1.1	20–28	55–65	27,13,12,2,1	1,1,3,2	71,107	46,582
1.2	20–28	55–65	27,13,14,2,1	1,1,3,2	73,840	49,418
1.25	20–28	55–65	27,13,14,2,1	1,1,3,2	74,434	49,890
1.5	20–28	55–65	27,16,2,1	1,3,1	76,400	64,072
2.5	20–28	55–65	27,16,2,1	1,3,1	76,400	64,072

Based on the numerical results in Table 12, it is evident that under low to moderate congestion levels (e.g., $f/c \leq 1.1$), the physical multimodal transport route remains unchanged. However, the corresponding time-related costs and carbon emissions increase monotonically due to the nonlinear speed reduction dictated by the Bureau of Public Roads (BPR) function.

Conversely, when the level of traffic congestion becomes severe (e.g., $f/c \geq 1.2$), the original routing scheme may either violate the strict delivery time window or incur exorbitant penalty costs, rendering it suboptimal or entirely infeasible. Consequently, the algorithm generates an alternative multimodal transport scheme to effectively bypass the heavily congested road links. Moreover, it is notably observed that as road congestion intensifies, the model strategically shifts toward rail and waterway transport modes. The

underlying operational rationale is that rail and waterway modes operate on dedicated infrastructures, providing highly reliable transit times and significantly shielding the supply chain operations from unpredictable road traffic disruptions.

5.2.3. Influence of Time Windows

To systematically investigate the sensitivity of the multimodal transport network to delivery time constraints, four distinct time window configurations were designed: unconstrained (denoted as “-”), broadly constrained (50–70 h), moderately constrained (55–65 h), and strictly constrained (55–60 h). The Pareto-optimal routing solutions generated under varying time constraints and congestion levels are summarized in Table 13.

As illustrated in Table 13 and visually supported by Figure 16, delivery time constraints exert a profound impact on both mode selection and total objective values. When time windows are completely relaxed (unconstrained), the algorithm successfully identifies baseline routes with minimal transport costs and carbon emissions. However, as the time window progressively narrows (e.g., from 50–70 h to 55–60 h), the temporal flexibility of the supply chain severely decreases. To strictly satisfy the narrowing delivery requirements and avoid early-arrival storage costs (P_e) or delayed-arrival penalties (P_l), the algorithm is forced to select faster, albeit more economically and environmentally expensive, transport configurations.

Particularly noteworthy is the extreme scenario combining strict time constraints (55–60 h) with heavy traffic congestion ($f/c = 2.5$), as observed in the final row of Table 13. In this instance, the total costs and emissions explode to an astronomical magnitude. From a mathematical modeling perspective, this extreme surge explicitly reflects the activation of the massive penalty terms established in the fitness functions. It physically indicates that under severe traffic delays, no feasible transport route exists that can successfully deliver the cargo within the narrow 5 h window, thereby rendering the strict requirement virtually impossible without incurring prohibitive penalty losses.

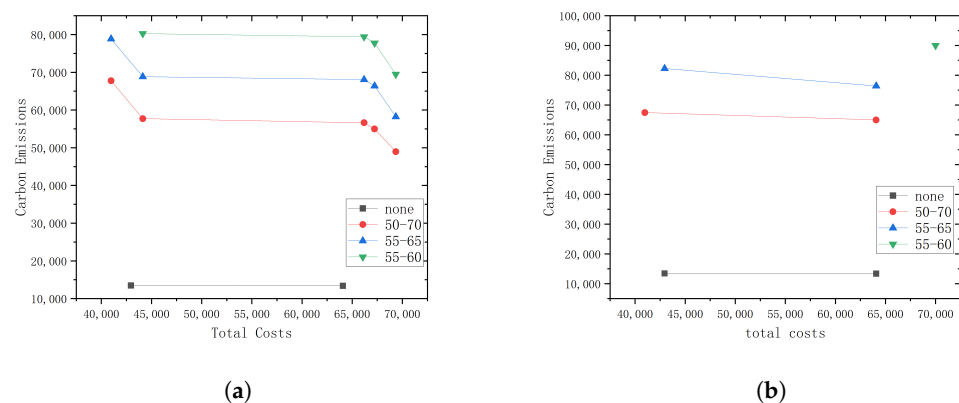


Figure 16. Optimal solutions under different time windows. (a) Low congestion ($f/c = 0.5$). (b) Heavy congestion ($f/c = 2.5$).

From a practitioner’s perspective, this case should be interpreted as infeasible rather than as an extremely costly but viable option, since no transport plan can simultaneously satisfy the 55–60 h delivery requirement and the $f/c = 2.5$ congestion level. Decision-makers facing such a combination of constraints would need to relax the delivery time window, postpone shipment until congestion subsides, or accept a documented service failure. The numerical value originally reported in this case serves only as an internal signal within the optimization algorithm and should not be used as a basis for cost or emissions accounting.

Table 13. Optimal routing schemes under varying delivery time windows.

Time Window	f/c Ratio	Demand	Transport Route	Transport Mode	Total Cost	Carbon Emissions
-	0.5	20–28	27,16,14,2,1	1,1,3,1	13,474	42,951
-	0.5	20–28	27,16,2,1	1,3,1	13,396	64,072
50–70	0.5	20–28	27,16,2,3,1	2,3,1,1	56,620	66,187
50–70	0.5	20–28	27,16,12,2,1	1,1,3,2	57,708	44,130
50–70	0.5	20–28	27,16,12,2,1	1,1,3,1	67,738	40,970
50–70	0.5	20–28	27,16,2,1	1,3,2	54,970	67,231
50–70	0.5	20–28	27,16,2,1	2,3,2	48,971	69,347
55–65	0.5	20–28	27,16,2,1	2,3,1	68,094	66,188
55–65	0.5	20–28	27,16,2,1	2,3,2	58,218	69,347
55–65	0.5	20–28	27,16,2,1	1,3,2	66,370	67,231
55–65	0.5	20–28	27,13,12,2,1	1,1,3,1	78,872	40,969
55–65	0.5	20–28	27,13,12,2,1	1,1,3,2	68,842	44,129
55–60	0.5	20–28	27,16,2,3,1	2,3,1,1	79,420	66,187
55–60	0.5	20–28	27,13,12,2,1	1,1,3,2	80,242	44,129
55–60	0.5	20–28	27,16,2,1	1,3,2	77,770	67,231
55–60	0.5	20–28	27,16,2,1	2,3,2	69,464	69,347
-	2.5	20–28	27,13,14,2,1	1,1,3,1	13,474	42,944
-	2.5	20–28	27,16,2,1	1,3,1	13,396	64,072
50–70	2.5	20–28	27,13,12,2,1	1,1,3,1	67,472	40,969
50–70	2.5	20–28	27,16,2,1	1,3,1	65,000	64,072
55–65	2.5	20–28	27,16,14,2,1	1,1,3,1	82,254	42,951
55–65	2.5	20–28	27,16,2,1	1,3,1	76,400	64,072
55–60	2.5	20–28	27,16,2,1	1,3,1	Infeasible [†]	Infeasible [†]

[†] No feasible route exists that satisfies the 55–60 h delivery time window under severe congestion ($f/c = 2.5$). The reported value corresponds to the activation of the penalty term in Equations (24) and (25); it is a mathematical artifact of the metaheuristic's fitness function used to guide the search away from infeasible regions, rather than a meaningful cost or emission figure, and should not be interpreted as a viable operational outcome.

5.2.4. Influence of Different Regret Coefficients

The regret coefficient γ plays a pivotal role in bridging stochastic expectations with robust scenario-control in the proposed optimization framework. The dynamic relationship between varying regret coefficients and the optimal expected objective values is systematically illustrated in Figure 7.

As graphically demonstrated, when the predefined regret coefficient γ is extremely restrictive (i.e., close to 0), the customer's tolerance for worst-case deviations from any individual scenario's isolated optimum is critically low. In this highly conservative state, the algorithm is forced to search for a universally perfect routing scheme that performs optimally under all possible demand fluctuations simultaneously. Mathematically, this triggers excessively large expected costs and carbon emissions, and in extreme cases, the heavily constrained feasible region may shrink to an empty set, resulting in no feasible solution to the model.

Conversely, as the regret coefficient γ gradually increases, the strict bounds of the regret constraints are relaxed. The decision-maker implicitly accepts a marginally higher degree of performance variation across different demand scenarios. Consequently, the algorithm identifies more flexible routing strategies, and both the expected total cost and expected carbon emission values exhibit a clear monotonically decreasing trend. However, once the regret coefficient γ surpasses a certain threshold, the regret constraints are completely non-binding. At this saturation point, the optimal stochastic solution converges and stabilizes without further changes.

From a managerial perspective, these analytical results validate the immense flexibility of the proposed regret-constrained methodology. Decision-makers can actively calibrate the regret coefficient γ to strike a personalized, optimal balance between strict solution robustness and long-term economic and environmental efficiency.

5.2.5. Influence of Different Demand Scenario Probabilities

To explicitly justify the assignment of occurrence probabilities (p_s) across discrete scenarios, seasonal and temporal variations in logistics demand are profoundly analyzed. Empirical evidence from the freight transportation literature corroborates the existence of such seasonally driven demand fluctuations at a comparable magnitude. For instance, a 30-year analysis of cargo throughput and freight rates across major shipping sectors reports monthly variance ranging from 0.005 (container) to 0.064 (dry bulk), with year-on-year freight rate variance reaching as high as 0.653 during peak demand periods [60]. This magnitude of fluctuation lends empirical support to the scenario probability settings adopted in this study, which span from 0.10 to 0.40 across seasons. As structurally mapped in Table 2, the probability distributions of transport volumes inherently fluctuate. During peak periods such as the agricultural harvest season (autumn) or holiday shopping festivals (winter), the probability mass heavily shifts toward high-capacity scenarios (e.g., 26 TEU and 28 TEU). Conversely, during off-season logistics cycles (spring), the occurrence probability is predominantly concentrated in low-demand scenarios (e.g., 20 TEU and 22 TEU).

The cascading impact of these seasonally shifting probability distributions on the expected total transport costs is explicitly demonstrated in Figure 8. As the statistical weight dynamically transitions from low-demand to high-demand scenarios across the four seasons, the expected multimodal transportation costs exhibit a significant exponential escalation. From a mathematical optimization perspective, this surge in cost is fundamentally driven by the increased weighting (p_s) of high-freight scenarios within the stochastic objective function. To strictly satisfy the delivery time windows under massive cargo volumes and prevent severe delayed-arrival penalties, the algorithmic model is mathematically forced to bypass cheaper, slower transport modes in favor of higher-capacity, faster, yet more expensive logistical configurations.

From a strategic managerial standpoint, this analysis empirically validates the absolute necessity of incorporating stochastic probabilities into multimodal routing optimization. If enterprises blindly rely on a static, deterministic baseline model (e.g., assuming a uniform probability distribution like the summer scenario year-round), they will critically misallocate transportation resources during peak seasons, resulting in catastrophic service failures and extreme penalty losses. Therefore, a highly adaptable stochastic framework—one that meticulously calibrates scenario probabilities against real-world seasonal shifts—is essential for maintaining both economic competitiveness and operational resilience in modern multimodal logistics.

6. Conclusions and Future Perspectives

To address the critical challenge of multi-objective multimodal transport route planning under highly complex and unpredictable environments, this study comprehensively investigates the intricate impacts of demand uncertainty and road traffic congestion. An integrated multi-objective optimization model is formulated to simultaneously minimize expected total transport costs and carbon emissions. To successfully navigate this NP-hard discrete combinatorial problem, an improved multi-objective salp swarm algorithm (LMSSA) is meticulously proposed and rigorously compared against the standard algorithm through extensive ablation studies. Finally, the practical feasibility, economic viability, and environmental sustainability of the proposed methodology are validated using varying-scale numerical instances and a real-world multimodal logistics network in northern China.

The core conclusions drawn from this study are summarized as follows:

1. Improved Algorithm Optimization Capabilities: Compared to standard baseline algorithms, the LMSSA proposed in this paper effectively enhances global search and

local exploration capabilities by introducing adaptive parameter tuning, co-directional leader updates, and chaotic follower mapping. Experimental results demonstrate that this algorithm significantly improves convergence efficiency and effectively mitigates the issues of local optima and premature convergence. Consequently, it exhibits greater stability and adaptability when solving large-scale, discrete, multi-constraint, multimodal route optimization problems.

2. **Robust Decision-Making in Uncertain Environments:** This paper employs a scenario-based stochastic optimization method and incorporates a regret constraint to establish a more balanced modeling framework that strikes a balance between the utilization of demand forecast information and risk control. This method ensures that transportation plans maintain a high degree of feasibility and consistency across various discrete demand scenarios and delivery time constraints, thereby enhancing the stability and robustness of corporate decision-making in complex market environments.
3. **Green Coordinated Transportation under Congestion Conditions:** By incorporating the nonlinear dynamic characteristics of road traffic congestion into the calculation of travel time and carbon emissions, this study has obtained route optimization results that more closely reflect real-world operating conditions. The research indicates that congestion simultaneously affects travel time, cost, and emission levels; based on this, the model can guide a more rational dynamic allocation of freight flows across different modes of transportation, particularly promoting the use of low-carbon modes such as rail and water transport when road conditions deteriorate.
4. **Time Constraints and Supply Chain Resilience:** Against a backdrop of fluctuating demand, transportation disruptions, and increasingly stringent time requirements, delivery time windows not only influence the choice of transport mode but also directly impact intermodal transfer efficiency, customer service levels, and supply chain resilience. Ignoring the interdependence between time windows and dynamic traffic conditions can easily lead to delays, resource misallocation, and network operational imbalances. Therefore, incorporating strict time constraints into multimodal route optimization models is key to enhancing the feasibility and resilience of transport solutions.
5. **Policy Coordination and Digital Intelligent Low-Carbon Transition:** Against the backdrop of the ongoing advancement of the “dual carbon” goals and the digital intelligent transformation of logistics, the dynamic optimization framework proposed in this paper not only reduces resource waste caused by demand uncertainty and sudden congestion but also provides quantitative support for green scheduling, carbon emissions accounting, and coordinated decision-making. This framework helps enterprises achieve coordinated optimization among costs, timeliness, resilience, and emission reduction performance, thereby providing a decision-making basis for green supply chain management and low-carbon transportation practices.

In future research, several directions can further extend the practical relevance and theoretical scope of this study. First, the current mathematical formulation can be refined to enhance its operational practicality by incorporating fixed departure schedules and exact timetable constraints for rail and waterway transport. In particular, incorporating timetable-based waiting times for intramodal railway line transfers, which can affect the total transport time and its interaction with the delivery time window constraints, represents an important direction for model refinement. Second, the present study deliberately excludes operational risk factors such as severe weather conditions, cargo damage, and vehicle breakdowns in order to focus on the core interactions among transportation cost, carbon emissions, demand uncertainty, and traffic congestion. Extending the proposed regret-constrained framework to jointly account for both demand uncertainty and such operational disruption risks represents a valuable avenue for future work, further enhanc-

ing the resilience of the resulting transportation decisions. Finally, the highly adaptable LMSSA metaheuristic can be extended to tackle other complex combinatorial optimization problems within the broader field of green supply chain management and vehicle routing under deep uncertainty.

Author Contributions: Conceptualization, L.Q., C.S. and L.M.; methodology, L.Q., C.S. and L.M.; software, L.Q. and C.S.; visualization, L.Q. and C.S.; validation, L.Q., C.S. and L.M.; formal analysis, L.Q., C.S. and L.M.; investigation, L.Q., C.S. and L.M.; data curation, L.Q. and C.S.; writing—original draft preparation, L.Q. and C.S.; writing—review and editing, L.Q., C.S. and L.M.; supervision, C.S. and L.M.; project administration, C.S. and L.M.; funding acquisition, C.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Humanities and Social Science Fund of Ministry of Education of China under a grant [grant number 24YJC630175], and Shanghai Sailing Program under a grants [grant number 24YF2730100], and the Postdoctoral Fellowship Program of CPSF under a grants [grant number GZC20231675].

Data Availability Statement: The data used to support the findings of this study are included within the article.

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

Appendix A

Table A1. Instance characteristics.

Scale	Set	Node	Number
Small-size instance	1	8	10
Medium-size instance	2	20	10
	3	30	10
Large-size instance	4	50	10
	5	100	10
Total number of cases			50

Table A2. Parameters related to each transport mode.

	Speed (km/h)	Price (yuan/TEU*km)	Capacity (TEU)
Truck	80	9.065	2
Train	60	3.25	50
Ship	30	1.684	200

Table A3. Transformed parameters related to each transport mode.

	Time (h/TEU)	Cost (yuan/TEU)	Carbon Emission (KG/TEU)
Truck–Train	0.7	165	4.013
Truck–Ship	1.2	225	4.015
Train–Ship	1.5	275	4.015

Table A4. Parameters related to ships.

	Main Machine Power (kw)	Auxiliary Engine Power (kw)	Design Speed (km/h)
Ship	21,657	4565	25.6

Table A5. Transportation distances for the three transportation modes.

Start	Terminal	Truck (km)	Train (km)	Ship (km)	Start	Terminal	Truck (km)	Train (km)	Ship (km)
1	2	400	378	-	21	22	210	217	-
1	3	179	185	-	21	23	314	330	-
1	4	201	218	-	21	24	169	204	-
1	5	242	235	-	21	25	263	279	-
1	6	238	241	-	19	22	118	120	-
4	5	150	138	-	19	21	259	228	-
4	7	141	134	-	19	20	203	191	-
4	3	185	197	-	22	24	260	277	-
3	5	160	169	-	22	25	162	165	-
3	8	-	-	492	22	23	133	127	-
3	6	277	268	-	22	26	208	215	-
7	9	268	275	-	22	20	196	223	-
7	5	82	98	-	12	16	258	242	-
7	10	269	279	-	12	14	85	90	-
5	10	197	213	-	12	13	234	240	-
5	9	417	352	-	16	23	207	222	-
5	11	357	336	-	16	26	112	115	-
2	12	-	-	165	16	27	260	253	-
2	8	-	-	530	16	28	384	390	-
2	13	-	-	514	16	15	175	202	-
2	10	-	-	310	16	13	158	171	-
2	5	380	378	232	13	23	365	351	-
2	14	-	-	173	13	27	277	298	-
2	6	320	304	294	13	28	428	445	-
2	15	-	-	648	13	15	148	135	-
2	16	-	-	259	15	26	266	296	-
2	11	-	-	351	15	27	142	161	-
2	3	217	217	389	15	23	322	320	-
10	12	-	-	318	14	13	264	280	-
10	11	150	138	-	14	16	324	344	-
10	8	-	-	248	20	23	146	157	-
11	8	132	153	-	20	26	84	82	-
11	17	288	289	-	20	16	182	177	-
11	18	178	208	-	24	30	257	265	-
10	9	225	222	-	24	29	285	287	-
9	11	203	185	-	24	25	136	154	-
9	18	247	225	-	25	29	174	171	-
18	17	178	169	-	25	28	169	244	-
18	8	151	136	-	23	25	129	149	-
18	19	217	198	-	23	28	215	218	-
8	17	202	182	-	23	27	236	259	-
8	19	119	114	-	26	23	110	98	-
8	20	222	249	-	26	28	278	279	-
8	12	-	-	378	26	27	237	240	-
8	16	-	-	276	27	28	208	218	-
17	21	135	143	-	28	29	123	141	-
17	22	234	246	-	29	30	207	206	-

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