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Dynamic Optimization of Multi-Object Game Decision-Making in Logistics and Supply Chain Driven by Mathematical Generative Models

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SUMMARY: *Against the backdrop of economic globalization, supply chain management has emerged as a critical strategic tool for enterprises to enhance their competitiveness. This paper briefly analyzes the multi-agent game dynamics within logistics and supply chains, and based on this analysis, constructs a mathematical generative model with operational costs and customer satisfaction as optimization objectives. To effectively solve the model, the honeypot algorithm is modified. The performance of the improved honeypot algorithm is evaluated by computing convergence curves and mean-variance metrics for 10 benchmark functions, followed by case studies. The mean values of the improved algorithm are generally lower than those of the comparison algorithms across all functions, ranging from 2.89E-10 to 5.58E-9, while exhibiting superior convergence. The optimal solution identified allocated regional shares of 56.32%, 26.88%, and 16.80% to the three logistics service providers. Compared to the original plan, this solution reduced operational costs by 38.57% and increased customer satisfaction by 28.16%, validating the effectiveness of the dynamic optimization model. This provides enterprises with a decision-optimization method for logistics and supply chain management.*

KEYWORDS: *Mathematical generation model; Logistics and supply chain; Honeypot algorithm; Dynamic optimization*

1 Introduction

With the advancement of globalization and e-commerce, the importance of the logistics industry has become increasingly prominent. Modern logistics connects production on one end and consumption on the other, highly integrating and merging service functions such as transportation, warehousing, distribution, delivery, and information management. It serves as a vital pillar for extending industrial chains, enhancing value chains, and building supply chains. Logistics plays a pioneering, foundational, and strategic role in constructing a modern circulation system, fostering a robust domestic market, driving high-quality development, and building a modern economic system [1-3]. Simultaneously, the logistics industry underpins the development of other sectors. For instance, manufacturing relies on logistics for supply chain management of raw materials and components, as well as transportation and warehousing of finished goods; retail depends on logistics for product distribution and after-sales services; and

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the pharmaceutical industry requires logistics for drug transportation and storage, among other functions [4]. Consequently, the advancement and enhancement of logistics can stimulate the growth and revitalization of other industries.

In 2022, China's total social logistics volume reached 347.6 trillion yuan, marking a 3.4% year-on-year increase. The scale of logistics demand continued to expand, achieving stable growth. Concurrently, total social logistics costs amounted to 17.8 trillion yuan, rising 4.4% year-on-year. This represented 14.7% of GDP, an increase of 0.1 percentage points compared to the previous year [5]. Amid complex and severe international conditions and factors like the pandemic, the logistics industry accelerated improvements in operational efficiency and the responsiveness of Logistics Service Supply Chains (LSSC), entering a strategic transition period from high-speed growth to high-quality development [6]. LSSC is a system comprising Logistics Service Providers (LSP), Logistics Service Integrators (LSI), and customers [7-9]. The LSSC is characterized by LSPs providing various logistics service functions, while LSIs integrate different logistics service providers and coordinate with customers[10]. This vertically integrated collaboration model enhances enterprises' ability to navigate uncertain markets and improves their flexibility. Through LSSC, enterprises can respond more effectively to market changes and deliver flexible, efficient logistics services.

However, like other supply chain alliances, LSSCs also exhibit instability. To maximize their own profits, member companies may conceal or refuse to share information they possess, leading to insufficient communication and information exchange within the LSSC. This inadvertently increases the overall operational costs of the supply chain [11]. In recent years, evolutionary game theory has advanced researchers' understanding of interactions among enterprises within supply chain networks. Companies in these networks can evaluate the effectiveness of different strategies through game processes and make corresponding decisions based on outcomes [12]. Consequently, how to foster long-term cooperation among chain enterprises and how to reasonably allocate supply chain benefits to achieve a win-win situation are both worthy of exploration.

Evolutionary game theory serves as a methodology for studying interactions and optimizing strategies among participants, finding extensive application in economic domains including service supply chains. Current scholarly research on LSSC games primarily focuses on profit distribution, multi-agent coordination within supply chains, and strategy selection. Relevant domestic and international studies pertaining to this paper can be categorized as follows:

(1) Research on Profit Distribution Games in LSSCs.

Lu, F et al. [13] proposed an improved LSSC profit distribution model based on the BO framework, incorporating fairness preferences and inequality aversion to maximize member benefits and achieve equilibrium within the chain. Chen, Z. and Kong, J.[14] employed evolutionary game theory (symmetric and asymmetric game models) to examine resource-sharing decision processes among logistics enterprise alliances. They investigated the influence of factors such as enterprise scale and profit distribution on member decisions, ultimately proposing an improved income distribution model based on the Raiffa solution. Zhou, L et al. [15] employed evolutionary game theory to simulate and analyze strategic interactions among Logistics Service Providers (LSP), Professional Service Companies (PSC), and Customers (C) in “last-mile delivery services.” They determined that optimal profit distribution and optimal cost-sharing coefficients form the foundation for sustaining supply chains. Su, X et al. [16] proposed a game model for horizontal and vertical enterprise network embedding behaviors using biological evolutionary dynamics. The study revealed that network embedding strategies are related to the specific investment costs and cooperative profits of member enterprises within supply chain networks. He, C and Liu, W [17] developed a dynamic game model for a three-tier LSSC to design coordinated contracts among chain members. These contracts aim to maximize members' expected profits through options, cost-sharing, and revenue-sharing mechanisms, ensuring mutual benefits for all participants. Han, R and Yang, M[18] designed a fairer profit distribution scheme under the carbon neutrality framework, coordinating multiple stakeholders (government and LSSC members). They analyzed multi-agent interactions and the impact of different schemes on cooperation and stability through a tripartite evolutionary game model.

(2) Multi-agent coordination in LSSCs.

Zhong, Y et al. [19] applied Stackelberg game theory to study multi-agent coordination in e-commerce LSSCs, using case studies to analyze the feasibility of coordination strategies. Haque, M et al. [20] employed a two-level Nash game strategy to manage decentralized LSSCs, aiming to enhance supply chain sustainability by strengthening coordination among agents and reducing carbon emissions during transportation. Rezaei, S. and Behnamian, J. [21] proposed a cooperative supply chain network strategy for multi-agent green transportation using game theory. This approach leverages dynamic competitive structures and decentralized decision algorithms to expand green transportation coverage and enhance market competitiveness. Liu, W et al. [22] constructed a Stackelberg game model based on the mutual influence and constraints between manufacturers and logistics service providers during intelligent logistics transformation. By formulating appropriate contracts, LSPs can reduce service costs, thereby achieving full coordination among supply chain members. Shi, L et al. [23] investigated timing consistency in multi-agent supply chain systems by constructing a nonlinear feedback timing control protocol. They discovered that its sufficient conditions exert a positive influence on supply chain network management. Jalbut, A. and Sichman, J. [24] extended the Beer game model using a multi-agent approach to assess the impact of trust on supply chain performance. They examined how peer recommendations and deception influence working capital and trust metrics across different agent types.

(3) Research on LSSC Strategy Selection.

Liu, W et al. [25] investigated the impact of loss aversion preferences on service capacity procurement decisions in an LSSC composed of one LSI and one LSP under demand updates. Zhang, C et al. [26] examined optimal strategies for two-tier service supply chains within a two-level game structure. By analyzing the dual-layer game structure and decision models across different scenarios, they established utility functions for members under various decision models. Wang, S. and Hu, Z. [27] examined decision choices in a two-stage logistics service supply chain under four power structures. Findings revealed that centralized decision-making achieved the highest metrics for service level, market demand, and overall profit, followed by the vertical Nash equilibrium decision model. Wang, G et al.[28] examined service provider selection and order allocation for different procedures under mass customization logistics service models. They formulated a nonlinear mixed-integer multi-objective optimization model to simultaneously determine optimal supplier selection strategies, order allocation strategies, and the optimal CODP (Customer Order Decoupling Point) location through quantitative methods. Building upon prior research, Yoo, S. and Cheong, T.[29] analyzed factors influencing supply chain performance to construct supply chain quality incentive decisions. They discussed the impact mechanisms of different incentive decisions on the performance of supply chain members.

In summary, current research on LSSCs primarily focuses on profit distribution games, multi-agent coordination, and strategy selection during their evolutionary processes. By constructing various evolutionary game models to simulate LSSC evolution, researchers aim to optimize the evolutionary trajectories of entities within the chain. However, these studies predominantly consider only the characteristic changes of individual entities within LSSCs, overlooking the fact that LSSCs themselves constitute complex systems reflecting real-world market dynamics. Therefore, within this intricate LSSC framework, the dynamic optimization processes of each entity must also account for multiple external factors to describe changes in network characteristics, warranting in-depth academic research and ongoing exploration.

This study focuses on suppliers, distributors, and customers as the core entities for problem description and model assumptions. Capacity constraints are imposed as limiting conditions, with the optimization objectives being the minimization of total operational costs and the maximization of customer satisfaction. A digital generative model for the dynamic optimization of multi-agent decision-making in logistics and supply chains is constructed. During the initialization phase of the honeypot algorithm, a sine chaotic mapping and population filtering mechanism are employed. An elite-guided subpopulation mechanism is introduced during population iteration. A local search method based on Lévy flight is proposed to expand the search scope. Subsequently, the balance factor is refined to enhance the honeypot algorithm. The proposed model is solved using this improved honeypot algorithm. Subsequently, the proposed algorithm is evaluated using 10 benchmark functions and compared with MFO, WOA, PSO, and GOA to investigate the performance of the improved honeypot algorithm. Finally, using the logistics service provider selection and logistics demand allocation problem of a fresh produce enterprise as an example, the proposed model is applied for solution analysis to obtain the comprehensive optimal solution, demonstrating the model's validity and optimization effectiveness.

2 The Game-Theoretic Relationships Among Multiple Stakeholders in Logistics and Supply Chains

In constructing a dynamic optimization model for multi-agent game-theoretic decision-making within logistics and supply chains, this paper recognizes that the interconnectivity among game systems significantly influences the overall evolutionary stability of the system. Therefore, it analyzes the game relationships between various agents in logistics and supply chains to facilitate clearer subsequent model construction and analysis.

Logistics enterprises primarily handle the delivery of consumer-ordered goods from suppliers to end-users. The efficiency and cost of logistics directly impact consumer shopping experiences, necessitating cooperative relationships between logistics providers, suppliers, and merchants. Logistics firms must deliver reliable services to meet the demands of suppliers, e-commerce merchants, and consumers. However, logistics companies may be driven by profit motives to reduce their own costs by offering substandard services. This risks diminishing the willingness of suppliers and merchants to collaborate, as well as causing reputational damage from negative consumer reviews, which can lead to a decline in order volume. Suppliers are responsible for the entire product lifecycle, including production, manufacturing, sales, and after-sales service. The quality of their products and services directly impacts the credibility and image of distributors, while also significantly influencing the consumer experience. Consumers represent the end-users within the entire logistics and supply chain system. Their demands and purchasing behaviors influence the profitability and competitive strategies of platforms and merchants.

Within this interdependent strategic landscape, each entity's decision-making process influences others. Suppliers must offer appealing products and exceptional customer service, logistics firms require reliable operations to secure partnerships with suppliers and distributors for increased business volume, while consumer demand drives the entire system. These relationships are complex and dynamic, shaped by market competition, policy shifts, evolving consumer preferences, changing user demands, and regulatory frameworks.

3 Dynamic Optimization Models in Logistics and Supply Chain Management

In practical applications of logistics and supply chain networks, researchers can address optimization challenges through mathematical modeling, simulation, data-driven approaches, and game theory models. This paper constructs a dynamic optimization digital generation model based on multi-agent decision-making within logistics and supply chains, employing intelligent optimization algorithms for solution.

3.1 Problem Description and Model Assumptions

3.1.1 Problem Description

This chapter presents a dynamic optimization model for multi-agent decision-making in logistics and supply chains, aiming to simultaneously optimize the total operational cost and customer satisfaction under capacity constraints. Figure 1 illustrates the problem model. This model involves three supply chain members (suppliers, distributors, and customers) and four phases: customers sending demand to distributors, distributors placing orders with suppliers, suppliers supplying products to distributors, and distributors shipping products to customers. The problem model's workflow spans multiple time cycles.

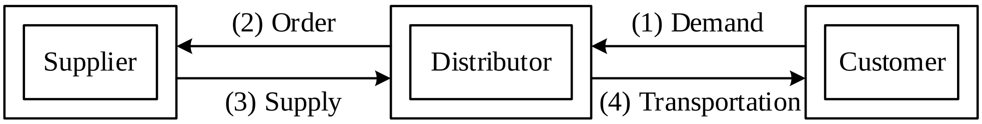


Figure 1: Schematic diagram of the inter-problem model

All variables involved in the model are described as follows:

i — Supplier index.

k — Customer index.

S — Number of suppliers.

C — Number of customers.

S_cap_i ——Capacity of supplier i .

S_pdCost_i ——Unit production cost of supplier i .

j ——Distributor index.

t ——Time period index.

D ——Number of distributors.

T ——Number of time periods.

D_cap_j ——Capacity of distributor j .

$D\_invCost_j$ ——Unit inventory cost per product for distributor j .

$SD\_tpCost_{i,j}$ ——Unit transportation cost from Supplier i to the distributor.

$D\_inv_{j,t}$ ——Inventory level of distributor j during time period t .

$C\_dem_{k,t}$ ——Customer k 's demand quantity during time period t .

$DS\_ord_{i,j,t}$ ——Distributor j 's order quantity sent to supplier i during time period t .

$DC\_tpCost_{j,k}$ ——Unit product transportation cost from distributor j to customer k .

$D\_inv_{j,0}$ ——Distributor i 's initial inventory level Distributor j at time period t .

$DC\_tp_{j,k,t}$ ——Internal transportation of Product k quantity to the customer.

The entire process of the problem model in Figure 1 can be described as follows:

(1) Demand Phase: Each customer sends demand $C\_dem_{k,r}$ to the supply chain platform at each time period. It is important to note that while the total demand of customer k is known, the demand of customer k for each distributor remains unknown.

(2) Ordering Phase: If the distributor's current inventory quantity cannot meet customer demand, the distributor will send an order $(DS\_ord_{i,j,t})$ to the supplier. During this phase, two capacity constraints must be satisfied in total. First, within time period t , the sum of the distributor's total order quantity and existing inventory must not exceed its capacity: $(\sum_i (DS\_ord_{i,j,i}) + D\_inv_{j,t-1} \le D\_cap_j)$ Second, the supplier's total order quantity must not exceed its capacity: $(\sum_j (DS\_ord_{i,j,t}) \le S\_cap_i)$ Additionally, the production cost of the supplier should be incurred at this stage: $(Prod\_cost = \sum_i \sum_j \sum_t (S\_pdCost_i \times DS\_ord_{i,j,t})$.

(3) Supply phase: the supplier transports the product to the distributor. This stage requires the expenditure of transportation costs from the supplier to the distributor $(Tp\_cost1 = \sum_i \sum_j \sum_t (SD\_tpCost_{ij} \times DS\_ord_{ij,i}))$ and the distributor's inventory cost $(Imv\_cost = \sum_j \sum_t (D\_invCost_j \times D\_inv_{j,t}))$. In addition, this stage should also update the distributor's inventory quantity: $(D\_inv_{j,t} = D\_inv_{j,t-1} + \sum_j (DS\_ord_{i,j,t}) - \sum_k (DC\_tp_{j,k,t})$ $= \sum_l (\sum_i (DS\_ord_{i,j,t}) - \sum_k (DC_t p_{j,k,t})) + D_i nv_{j,0}, l \in \{1,...,t\})$.

(4) Transportation stage: the distributor transports the product $(DC\_tp_{j,k,t})$ to the customer. This stage should pay the cost of transportation from the distributor to the customer $(Tp\_cost2 = \sum_j \sum_k \sum_t (DC\_tpCost_{j,k} \times DC\_tp_{j,k,l}))$). Customer satisfaction is maximized when all customer needs are fully satisfied.

3.1.2 Model Assumptions

The proposed problem model is based on the following two assumptions:

(1) The supplier's production quantity equals the total order quantity.

(2) Production time at the supplier, transportation time from the supplier to the distributor, and transportation time from the distributor to the customer are ignored.

The two optimization objectives of the problem model are to minimize operating costs $(f1 = Prod\_cost + Tp\_cost1 + Inv\_cost + Tp\_cost2)$ and maximize customer satisfaction $(f2 = \sum_k \sum_t (\sum_j (DC\_tp_{j,k,t}) / C\_dem_{k,t}))$, respectively. These two objectives are mutually conflicting. The second objective can be equivalently formulated as minimizing $f2 = \sum_k \sum_i (C\_dem_{k,t}) / (\sum_j \sum_k \sum_t (DC_t p_{j,k,t}) + 1.0)$.

3.2 Construction of Digital Generation Models

Based on the above description, the final mathematical model can be described as follows:

$$
\begin{aligned}
f_1 = & \sum_{i=1}^{S} (S_p dCost_i \times \sum_{j=1}^{D}\sum_{t=1}^{T} DS_o rd_{i,j,t}) + \sum_{i=1}^{S}\sum_{j=1}^{D} SD_t pCost_{i,j} \times \sum_{t=1}^{T} DS_o rd_{i,j,t} \\
& + \sum_{j=1}^{D} D\_invCost_j \times \sum_{t=1}^{T} (\sum_{l=1}^{t} (\sum_{i=1}^{S} DS\_ord_{i,j,t} - \sum_{k=1}^{C} DC\_tp_{j,k,t}) + D\_inv_{j,0}) \\
& + \sum_{j=1}^{D}\sum_{k=1}^{C} DC_t pCost_{j,k} \times \sum_{t=1}^{T} DC_t p_{j,k,t}
\end{aligned} \tag{1}
$$

$$
f2 = \frac{\sum_{k=1}^{C}\sum_{t=1}^{T} C_d em_{k,t}}{\sum_{k=1}^{C}\sum_{t=1}^{T}\sum_{j=1}^{D} DC_t p_{j,k,t} + 1.0} \tag{2}
$$

Satisfy the following constraints:

$$
DS_o rd_{i,j,t} \geq 0 \quad \forall i \in \{1,...,S\}, \forall j \in \{1,...,D\}, \forall t \in \{1,...,T\} \tag{3}
$$

$$
DC_t p_{j,k,t} \geq 0 \quad \forall j \in \{1,...,D\}, \forall k \in \{1,...,C\}, \forall t \in \{1,...,T\} \tag{4}
$$

$$
\sum_{j=1}^{D} DS\_ord_{i,j,t} \leq S\_cap_i \quad \forall i \in \{1,...,S\}, \forall t \in \{1,...,T\} \tag{5}
$$

$$
\begin{aligned}
D_i nv_{j,t} & = D_i nv_{j,t-1} + \sum_{i=1}^{S} DS_o rd_{i,j,t} - \sum_{k=1}^{C} DC_t p_{j,k,t} \quad \forall j \in \{1,...,D\}, \forall t \in \{1,...,T\} \\
& = \sum_{l=1}^{t} (\sum_{i=1}^{S} DS_o rd_{i,j,l} - \sum_{k=1}^{C} DC_t p_{j,k,l}) + D_i nv_{j,0} \geq 0
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
& \sum_{i=1}^{s} DS_o rd_{i,j,t} + D_i nv_{j,t-1} = \sum_{i=1}^{s} DS_o rd_{i,j,t} \\
& + \sum_{l=1}^{t-1} (\sum_{i=1}^{S} DS_o rd_{i,j,l} - \sum_{k=1}^{C} DC_t p_{j,k,l}) + D_i nv_{j,0} \leq D_c ap_j \\
& \forall j \in \{1,...,D\}, \forall t \in \{1,...,T\}
\end{aligned} \tag{7}
$$

Among these, operating costs ($f1$) and customer satisfaction (equivalent to $f2$) can be calculated using equations (1) and (2), respectively. Regarding the variable domains of the problem, the decision variables $DS\_ord_{i,j,t}$ and $DC\_tp_{j,k,t}$, along with the distributor's inventory quantity ($D\_inv_{j,t}$, updated during the supply phase), must all be non-negative. This is specified in equations (3), (4), and (6). Regarding capacity constraints in the ordering phase, for supplier i, the sum of orders received from distributors should not exceed its capacity, as shown in formula (5). For distributor j, the sum of orders sent to suppliers and its current inventory should not exceed its capacity, as shown in formula (7).

3.3 Model Solving Algorithm

The Honey Badger Algorithm (HBA) simulates the honey badger's dynamic search behavior of digging and foraging for honey. Due to its minimal parameter settings and simple structure, it holds broad application prospects for solving large-scale problems. This paper proposes an improved Honey Badger Algorithm (IHBA) to solve the constructed dynamic optimization model for logistics and supply chains.

3.3.1 Honey Badger Algorithm

The HBA algorithm primarily updates the population through two main phases: the “foraging phase” and the “honey-gathering phase.” The main steps of HBA are as follows.

(1) Initialization Phase: Randomly initialize a population of N solutions (i.e., honey badgers) within a specified interval, denoted as $X=(x_1,x_2,...,x_i,...,x_N)$. The formula for generating the initial positions of solutions is shown in Equation (8):

$$x_i = lb_i + r_1 \times (ub_i - lb_i) \tag{8}$$

Here, x_i denotes the i th solution in the population, lb_i and ub_i represent the lower and upper bounds of the solution, respectively, and r_1 is a random value between 0 and 1.

(2) Define the intensity factor (I): Intensity refers to the concentration of food and its correlation with the distance to the i th honey badger. As the scent of prey becomes more pronounced, the honey badger's movement speed increases. The intensity is calculated as follows:

$$\begin{gathered} I_i = r_2 \times \frac{S}{4\pi d_i^2}, \\ S = (x_i - x_{i+1})^2, \\ d_i = x_{best} - x_i \end{gathered} \tag{9}$$

Here, r_2 is a random value between 0 and 1, S denotes the concentration strength, and d_i represents the distance between the food and the i th honey badger. Furthermore, the honey badger's optimal position x_{best} indicates the location of the food, i.e., the optimal solution.

(3) Update the density factor: The density factor α controls the balance between exploration and exploitation, gradually reducing the degree of randomization over time. The formula for defining the density factor is as follows:

$$\alpha = C \times \exp\left(\frac{-t}{t_{\max}}\right) \tag{10}$$

Here, c is a constant with a default value of 2, t represents the current iteration count, and $t_{\max}$ denotes the maximum iteration limit.

(4) Update population individual positions: The position update process primarily consists of two parts: the “digging phase” and the “foraging phase.”

Digging phase: In this phase, the honey badger's foraging behavior can be simulated by the following formula:

$$\begin{aligned} x_{new} = x_{best} + F \times \beta \times I \times x_{best} + F \times r_3 \times \alpha \times d_i \\ \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \end{aligned} \tag{11}$$

Here, x_{new} is the updated position, x_{best} is the best position found so far, β is the honey badger's foraging ability (default value: 6), and d_i is the distance between the food and the i th honey badger. Additionally, $r3, r4, r5$ are three distinct random values between 0 and 1. F is a control flag that alters the search direction, determined by formula (12):

$$F = \begin{cases} 1, & r_6 \le 0.5, \\ -1, & \text{other} \end{cases} \tag{12}$$

Among these, r_6 is a random number between 0 and 1.

Foraging Phase: During the foraging phase, the honey badger follows the guide to the beehive, with the simulation formula as follows:

$$x_{new} = x_{best} + F \times r_7 \times \alpha \times d_i \tag{13}$$

3.3.2 Initialization Phase Optimization

This section employs chaotic mappings and population filtering mechanisms to optimize the initialization phase of the IBHBA.

(1) Sine Chaotic Mapping: Chaotic mapping represents a complex dynamical approach within nonlinear systems, where certain chaotic mappings typically generate chaotic numbers through iterative functions. IBHBA employs sine chaotic mapping to replace formula (8) for population initialization. Its mathematical expression is shown in equation (14):

$$\begin{aligned} y_{i+1} = \mu \times \sin(\pi \times y_i), \\ X_i = lb_i + y_i \times (ub_i - lb_i) \end{aligned} \tag{14}$$

Among these, y_i represents the chaotic number generated by the sine chaotic map, where μ is typically set to 0.99, and X_i denotes the i th solution.

(2) Population Filtering Mechanism: When generating the initial population using chaotic mapping, solutions with extremely poor positions may arise, hindering subsequent searches for optimal solutions or slowing algorithm convergence. Therefore, IBHBA employs a population filtering mechanism to select solutions with better initial positions. During the initialization phase, twice the number of solutions are first generated. Subsequently, the top half of these solutions, selected based on calculated fitness values, are chosen as the initial population.

By integrating with the Sine chaotic map, IBHBA can generate a population closer to the optimal solution location during the initialization phase.

3.3.3 Elite-Guided Subgroup Mechanism

The original HBA considered only one optimal solution and might overlook similar suboptimal solutions with good fitness values. To address this, a subpopulation mechanism is proposed to guide different populations in simultaneously searching for better solutions. The subpopulation splitting and merging process is illustrated in Figure 2. First, the original population is sorted by fitness value. Then, using an odd-even indexing scheme, the population is divided into two subpopulations for position updates, guided respectively by the optimal and suboptimal solutions. Second, before each iteration concludes, the two subpopulations are recombined into a single population. In the subsequent iteration, the process of reordering and splitting is repeated to select new optimal and suboptimal solutions.

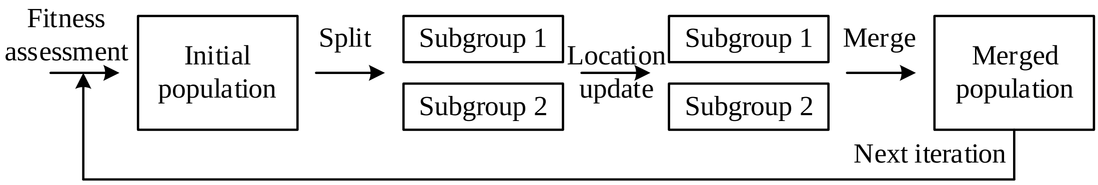


Figure 2: Schematic of the subgroup segmentation and merging process

3.3.4 Local Search Based on Lévy Flight

In HBA, each solution's position is updated based on X_{best}. If X_{best} occupies a suboptimal position, the algorithm may become trapped in local optima, degrading search performance. Therefore, to enhance search efficiency, a search technique based on Lévy flight is proposed. Levi flight is a random walk method involving heavy-tailed distributions that enables alternating short-range and long-range movements. This effectively expands the search coverage and optimizes search performance. The new position update method is shown in Equation (15):

$$x_{new} = x_{best} + Levy(\lambda) \times \alpha \times (Levy(\lambda) \times (X_A - X_B)) \tag{15}$$

Among these, X_A and X_B represent two random solutions within the population, and the Lévy walk is denoted as $Levy(\lambda)$, following the distribution:

$$Levy(\lambda) \sim u = t^{-\beta}, (1 < \beta \leq 3) \tag{16}$$

Therefore, in IBHBA, the two position update methods—the “digging mode” and the “honey-gathering mode”—are represented by formula (11) and formula (15), respectively.

3.3.5 Improved Balance Factor

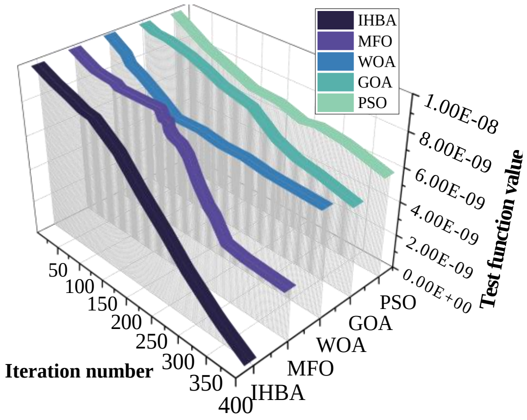
The density factor α in HBA ensures a smooth transition from the exploration phase to the exploitation phase during iteration. However, the original density factor decreases slightly too rapidly in the early stages of iteration, preventing the algorithm from reaching a larger search space during this period and potentially leading to premature convergence. To further enhance the algorithm's early exploration capability and avoid premature convergence, a modified density factor is proposed, whose mathematical formula is as follows:

$$\alpha = 1.5 \times \left(1 - \frac{t}{t_{\max}}\right)^{\frac{2t}{t_{\max}}} + 0.75 \tag{17}$$

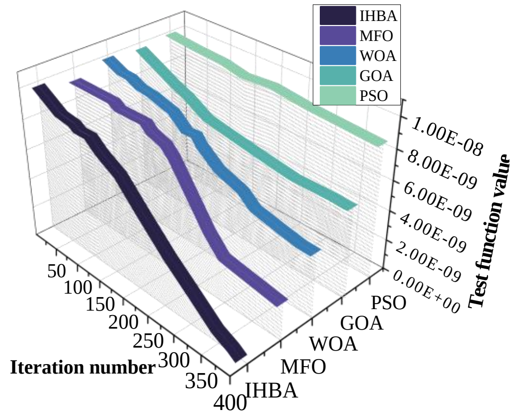
4 Case Study Analysis

4.1 Algorithm Performance Evaluation

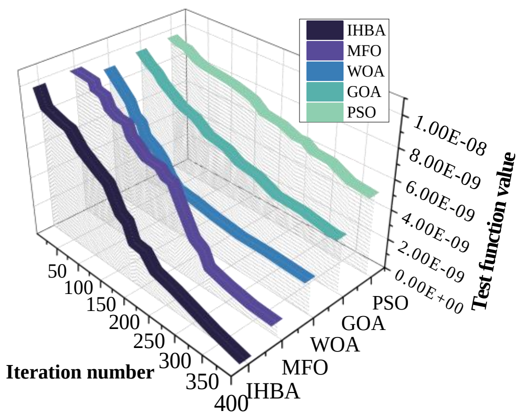
To evaluate the effectiveness of the IHBA algorithm and compare its performance with other algorithms, this paper contrasts it with PSO, MFO (Moth-to-Flame Optimization), WOA (Whale Optimization Algorithm), and GOA (Locust Optimization Algorithm). Validation was conducted by computing convergence curves and mean-variance results for 10 benchmark functions (F1–F10). Both the proposed algorithm and benchmark functions were implemented in MATLAB 2018b. Except for algorithm-specific parameter settings, the maximum iteration count was fixed at 400. The curves showing the target values of the test functions as a function of iteration count are presented in Figures 3(a) to (j). Based on the convergence trajectories and statistical analysis of optimal values for each algorithm in the figures, IHBA demonstrated the best overall performance. However, its partial optimization and convergence speed were not optimal for certain multidimensional test functions, indicating room for improvement in the algorithm's convergence phase. The mean and standard deviation of each algorithm's results were calculated based on the final outputs. The specific results are shown in Figures 4(a) to (j). The mean results of IHBA during the solution process were superior to other comparison algorithms in most cases, though not optimal in isolated instances. For test functions F1 to F10, the mean outputs of the IHBA algorithm were 5.58E-9, 5.46E-9, 3.94E-9, 5.84E-10, 6.42E-10, 2.65E-9, 2.89E-10, 9.71E-10, 1.89E-9, and 1.29E-9, respectively.



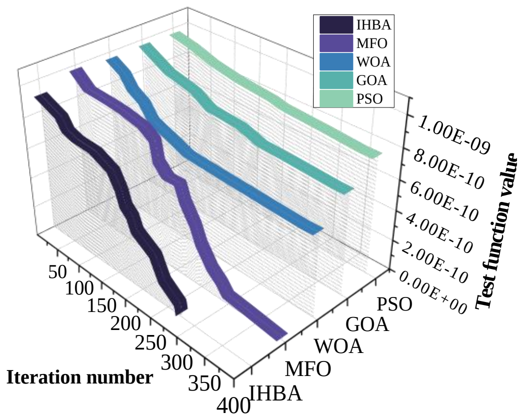
(a)F1



(b)F2



(c)F3



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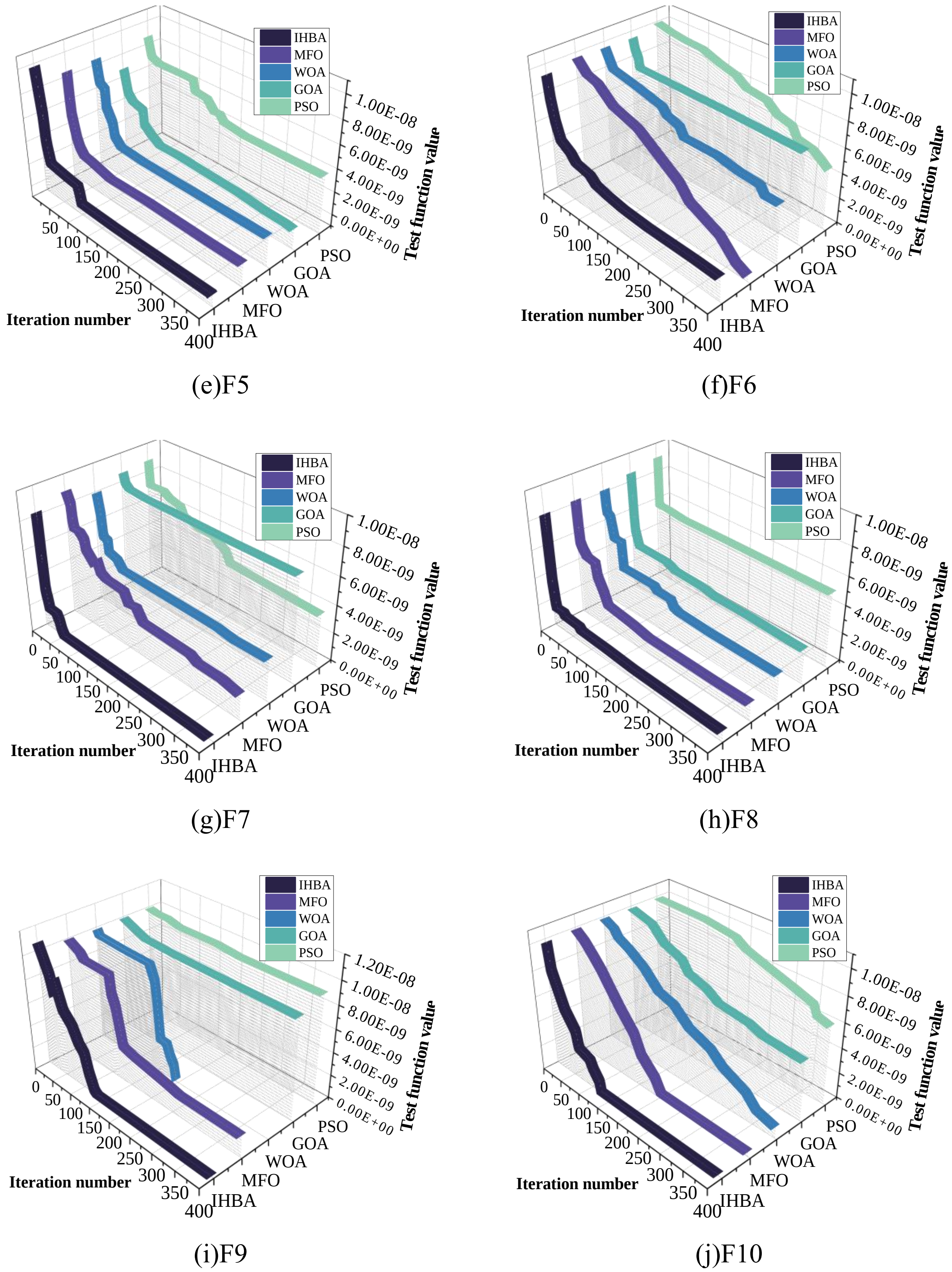
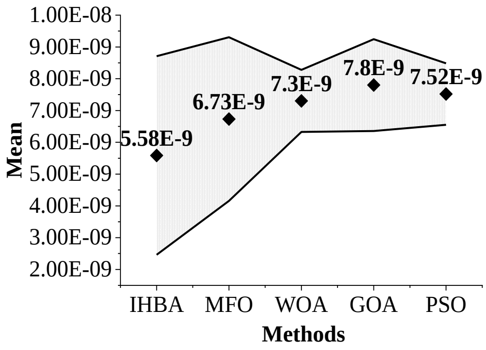
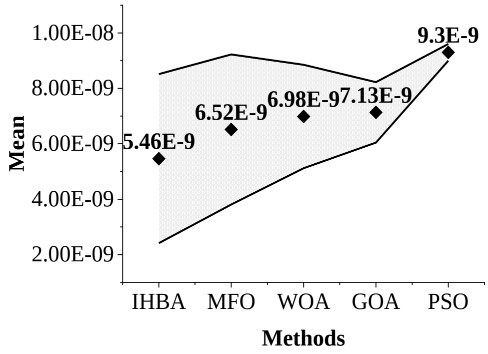


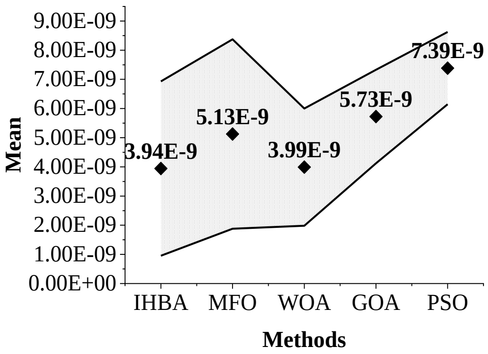
Figure 3: Change curve of the target value of test function with iterations



(a)F1



(b)F2



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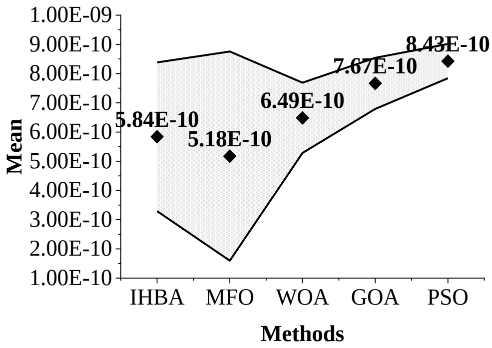

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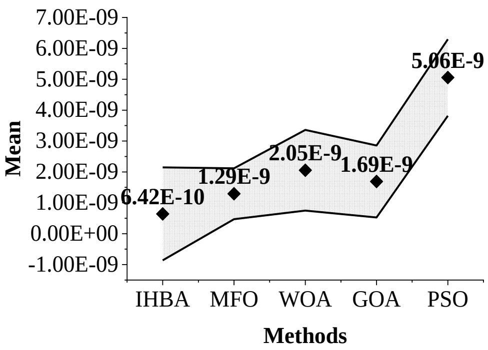
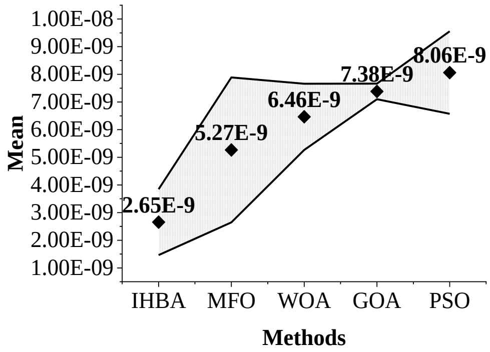
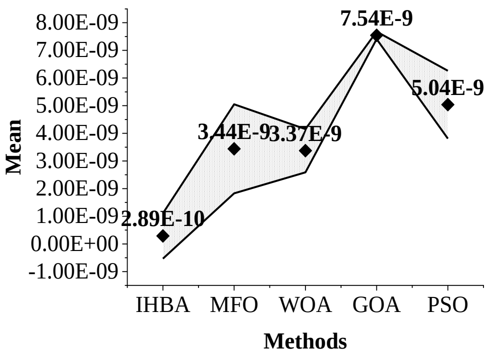


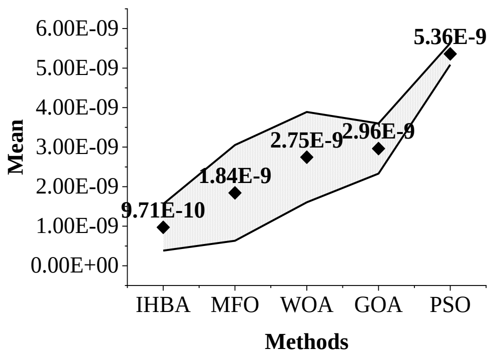
(e)F5



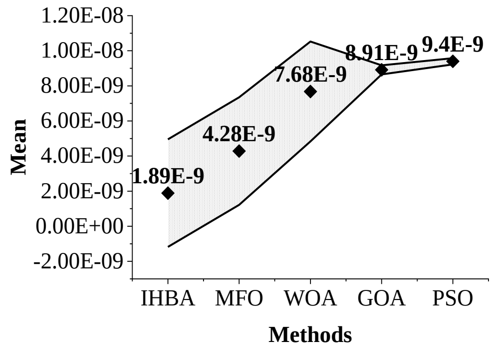
(f)F6



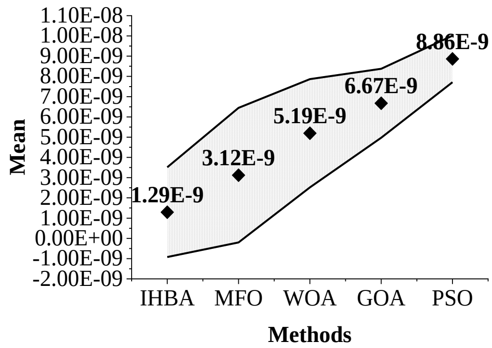
(g)F7



(h)F8



(i)F9



(j)F10

Figure 4: Average and standard deviation of running results of each algorithm

4.2 Case Study Background and Results Analysis

4.2.1 Case Study Background

A certain fresh produce enterprise is a nationally key enterprise in the industrialization of fresh agricultural products. It has established modern production and processing bases along with supporting industries in multiple provinces and cities. Currently, it has achieved full vertical integration across the entire supply chain—from upstream feed production and farming, through midstream slaughtering, processing, and packaging, to downstream cold chain logistics. Regarding its self-built logistics, the company has established a large-scale specialized highway refrigerated logistics company, forming an integrated logistics service platform encompassing refrigerated highway freight transport, warehousing, regional distribution, vehicle sales, vehicle repair, and information services. Relevant data, including logistics service and distributor demand figures, was collected from the company's annual report. Assuming 25,000 units of fresh produce need to be transported from the company's supply chain to seven regions, with three logistics service providers available, an analysis is conducted using the IHBA-based logistics and supply chain dynamic optimization model.

4.2.2 Analysis of Case Study Results

The Pareto solution sets for the HBA and IHBA algorithms are shown in Figure 5. The improved HBA algorithm demonstrates superior convergence to the traditional HBA, with more stable computational performance and locally better solutions. Additionally, changes in operational costs within the fresh produce supply chain influence customer satisfaction, exhibiting a positive proportional relationship. The operational cost and customer satisfaction results obtained by the IHBA algorithm in this study are presented in Table 1. Under the scenario of minimum operational cost, the operational cost and customer satisfaction are 10.457 billion yuan and 0.68, respectively. Under the scenario of maximum customer satisfaction, they are 18.548 billion yuan and 0.77, respectively. The overall optimal operational cost and customer satisfaction are 12.285 billion yuan and 0.72, respectively.

In practical decision-making, when the overall fresh produce supply chain environment is relatively stable, enterprises can opt for low-operating-cost solutions to maintain higher profits. When the overall environment becomes volatile or unstable, enterprises should choose solutions with higher customer satisfaction to ensure overall supply chain stability and satisfaction. In production decisions, enterprises can also make choices by setting thresholds. For instance, based on established profit targets, after deducting actual production costs, the corresponding target profit margin is derived. At this point, the optimal solution within the Pareto solution set can be selected by choosing the corresponding range of customer satisfaction values on the x-axis in Figure 5, achieving a balance between operational costs and customer satisfaction. Overall, enhancing HBA for dual-objective optimization of profit margin and resilience provides sample enterprises with more diverse supply chain and logistics options. After weighing trade-offs, decision-makers can select the most suitable strategy for corporate development.

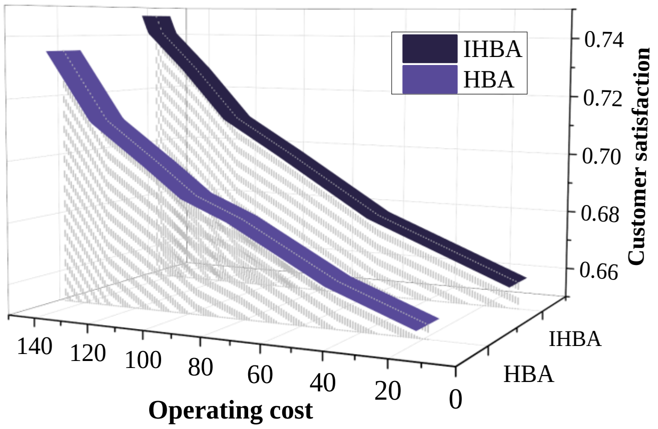


Figure 5: Pareto solution sets for two algorithms

Table 1: Operational cost and customer satisfaction results

Scheme	Operating cost(Hundred million)	Customer satisfaction
Minimum operating cost	104.57	0.68
Maximum customer satisfaction	185.48	0.77
Integrated optimum	122.85	0.72

The comprehensive optimal solution derived from the model-based solution yields the following logistics demand allocation results for each service provider, as shown in Table 2. Logistics Service Provider 1 receives the largest share of logistics demand at 56.32%, followed by Logistics Service Provider 2 at 26.88%. Regarding regional allocation, Region 6 is predominantly assigned to Logistics Service Provider 3. Region 7, with the largest share, is distributed between Logistics Service Providers 1 and 2. Regions 1, 2, 3, and 4 are primarily allocated to Logistics Service Provider 1. Therefore, when objective function preferences are identical, shippers can directly select Logistics Service Provider 1 for the logistics demand of Regions 1, 2, 3, and 4.

Furthermore, comparing membership functions across multi-objective optimization stages reveals significantly enhanced membership functions for both post-optimization objectives. This demonstrates clear optimization outcomes: reduced operational costs, improved service quality, and balanced progress across all targets. Compared to the original supply chain and logistics allocation, both objective function values show optimization: operating costs decreased by 38.57%, and customer satisfaction increased by 28.16%, demonstrating significant optimization results.

Table 2: Distribution of logistics requirements

Region	Logistics service 1	Logistics service 2	Logistics service 3
1	1000	0	0
2	3530	0	0
3	1050	0	0
4	700	0	0
5	0	0	1200
6	300	720	3000
7	7500	6000	0
Total	14080	6720	4200

5 Conclusion

For multi-agent decision-making problems in logistics and supply chains, this study explores a mathematical generative model for dynamic optimization and employs an improved honeypot algorithm for model solution. By comparing with multiple intelligent optimization algorithms, the performance of the improved honeypot algorithm is evaluated. Case studies validate the feasibility of the proposed method. In comparisons with other algorithms, the improved honeypot algorithm demonstrated the best convergence and objective function value. Its average results across 10 benchmark functions ranged from 2.89E-10 to 5.58E-9, largely lower than the average test results of other algorithms. This demonstrates the improved honeypot algorithm's superior global search capability, making it suitable for solving dynamic optimization models involving multi-party decision-making in logistics and supply chains. Using a fresh produce enterprise's logistics supply as a case study, the comprehensive optimal solution yielded an operational cost of 12.285 billion yuan and a customer satisfaction score of 0.72. The operational cost represents a 38.57% reduction from the baseline scenario, while customer satisfaction increased by 28.16%. Within the optimal solution, regional allocation shares for logistics providers 1, 2, and 3 were 56.32%, 26.88%, and 16.80%, respectively, with logistics demand for regions 1–4 concentrated on provider 1. In practical operations, enterprises can select decision schemes based on specific contexts and conditions. This model provides a rational approach for optimizing operational costs and enhancing customer satisfaction.

This study explores dynamic optimization in logistics and supply chain management, achieving certain results while acknowledging existing limitations. Real-world scenarios involve numerous uncertainties requiring more complex handling. Future work will comprehensively address multiple uncertainty factors to enhance supply chain resilience against such impacts.

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