

Article

Demand Prediction-Based Lateral Transshipment Location–Allocation–Inventory Model for Two-Echelon Multi-Product Supply Chain

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Abstract

Manufacturing firms increasingly face challenges in inventory allocation due to rising logistics costs, regional demand heterogeneity, and demand fluctuations. To address these issues, this study proposes a demand prediction-based multi-product lateral transshipment location–allocation–inventory (LAI) model for a two-echelon supply chain under a vendor-managed inventory environment. An integrated framework combining an improved grey demand prediction model with the success history-based adaptive differential evolution algorithm (IGDP-SHADE) is developed. The IGDP model is employed to forecast product demand under small-sample and highly volatile conditions, while the SHADE algorithm optimizes facility location, inventory allocation, replenishment, and lateral transshipment decisions with the objective of minimizing total system costs. A case study based on the excavator supply chain of Sany Heavy Industry is conducted to evaluate the proposed approach. The results demonstrate that the IGDP model achieves a mean absolute percentage error (MAPE) of 13.86% and a root mean squared logarithmic error (RMSLE) of 0.1806, outperforming benchmark models including ARIMA and Holt–Winters in forecasting seasonal small-sample demand data. Compared with Gurobi, the proposed IGDP-SHADE algorithm obtains the same optimal solution while reducing computational time by 17.47%. Sensitivity results indicate that introducing the lateral transshipment mechanism reduces total system costs by 2.97% compared with the scenario without transshipment. Furthermore, the optimal number of centralized storage points is identified as six, enabling an effective balance between transportation, inventory holding, and transshipment costs.

Keywords: two-echelon multi-product supply chain; grey demand prediction; lateral transshipment; location–allocation–inventory



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1. Introduction

To capture market share, companies continuously introduce new products or upgrade existing ones to meet increasingly differentiated customer demands, which has shortened product lifecycles and intensified market demand fluctuations [1]. Along with this trend, fluctuations in market demand have become increasingly pronounced. Because of the extended production cycles typical of heavy industrial goods, downstream enterprises

often struggle to respond to dynamically changing market demand through stable long-term supply systems. The risk of shortage may result in lost orders, leading many firms to stockpile inventory in advance as a risk mitigation strategy [2].

However, large-scale stockpiling inevitably increases inventory and transportation costs. Moreover, excessive inventory held by downstream companies can obscure actual market demand, making it difficult for upstream suppliers to assess true market conditions accurately. This, in turn, raises manufacturing costs for producers and increases transportation and inventory expenses across supply chain stages, triggering a chain reaction of demand-side inefficiencies [3,4]. Vendor-managed inventory (VMI), as a core model for integrating resources across the supply chain, has been implemented in various fields such as manufacturing and retail [5,6]. By allowing suppliers to take the lead in inventory decisions, VMI helps lower the overall inventory costs and mitigates the bullwhip effect within the supply chain.

Another factor contributing to high logistics costs in manufacturing is the extensive geographical span of the supply chain network. Production bases are often located in industrial cluster zones, where distributors are scattered across different regions. This necessitates large-scale, long-distance cross-regional transportation from production sites to end consumers, increasing cargo turnover time and intermediate circulation links, thereby raising logistics and warehousing expenses. This situation also increases the risk of inventory buildup. Simultaneously, the current market demands high responsiveness to product needs. If manufacturing companies cannot quickly meet the replenishment demands of downstream customers, it will directly affect downstream operations [7]. Therefore, an effective allocation strategy is key to reducing transportation and warehousing costs while maintaining service levels [8]. By implementing lateral transshipment strategies, products can be rapidly redistributed among regional peer nodes to satisfy market demand. Owing to its flexibility and rapid response capability, lateral transshipment has been widely adopted in emergency logistics and humanitarian supply chains to address demand surges and supply disruptions under uncertain environments [9,10]. In contrast, the role of lateral transshipment in coordinating inventories across geographically dispersed downstream nodes for high-value industrial products has received less attention. When combined with vertical allocation and integrated with the VMI model, suppliers can monitor inventory levels at downstream nodes in real time, forecast replenishment needs, and conduct timely transfers. This approach can reduce the frequency and cost of long-distance transportation, optimize inventory distribution, and enhance overall market responsiveness.

In traditional supply chain management, decentralized decision-making regarding facility location and inventory control helps reduce logistics costs but does not achieve global optimization [11]. In the manufacturing industry, the location–allocation–inventory problem (LAIP) employs integrated decision-making to enable dynamic coordination among supply chain network layouts, resource allocation, and inventory levels. It also facilitates the holistic optimization of costs across the entire chain, including facility construction, distribution, inventory holding, and stockouts [12]. However, conventional optimization approaches typically rely on constructing new facilities to maintain supply chain functions, which can hinder flexible adjustments amid significant fluctuations in market demand, leading to redundant infrastructure and substantially increased costs. Based on a review of the existing literature, although LAIP is a classical inventory optimization problem [13], limited attention has been devoted to selecting specific existing network nodes to directly undertake lateral transshipment functions and integrating this mechanism into the LAIP.

In a two-echelon supply chain LAIP decisions, demand uncertainty directly affects inventory allocation and replenishment planning. Demand forecasting provides quantitative support for inventory control and facility-related decisions by transforming uncertain

market demand into estimable planning information [14–18]. In practice, regional demand fluctuations may continuously alter inventory imbalance patterns among downstream nodes. Under such conditions, fixed transshipment structures may lead to inefficient inventory redistribution and increased logistics costs. Therefore, incorporating forecast-driven demand information into inventory allocation and transshipment decisions is important for improving supply chain adaptability under dynamic demand conditions [19].

Among various demand forecasting approaches, time-series methods such as ARIMA, Holt–Winters exponential smoothing, and machine learning models have been widely adopted for demand prediction tasks [20–22]. However, the forecasting performance of these methods often depends on the availability of sufficient historical observations, particularly when modeling complex seasonal patterns and nonlinear demand dynamics. Machine learning and deep learning approaches generally require large-scale datasets to achieve stable predictive performance [23]. The excavator industry exhibits typical small-sample and information-poor characteristics. Due to the relatively niche market size, frequent product updates, long-term and complete demand records are often unavailable. In this study, only annual demand-related data from 2021 to 2025 were collected, resulting in a limited number of observations with potential data incompleteness. Under such circumstances, grey prediction models provide a suitable alternative because they can generate reliable forecasting results from small samples and partially known information systems [24,25].

To provide a clearer overview of the existing research streams and to identify the research gaps in this paper, Table 1 summarizes representative studies in grey demand prediction, lateral transshipment, and LAIP.

Table 1. Research gaps in grey demand prediction, lateral transshipment, and LAIP literature.

	Grey Demand Prediction	Lateral Transshipment	LAIP
Representative studies	Nguyen et al. (2025) [24], Tang et al. (2025) [25]	Noham et al. (2026) [9], Wang et al. (2024) [10]	Yang et al. (2026) [13]
Main focus	Develop grey forecasting models for small-sample and information-poor demand prediction problems.	Inventory balancing and rapid response through lateral transshipment, primarily in emergency logistics.	Integrated optimization of facility location, inventory allocation, and transportation decisions.
Limitations	Mainly focuses on single-region demand prediction, with limited attention to seasonal patterns and residual information in regionally heterogeneous demand series.	Mainly focus on emergency scenarios, with limited attention to inventory coordination among geographically dispersed downstream nodes for high-value industrial products.	Mainly focus on new facility construction, with limited attention to the selection of existing network nodes and the integration of lateral transshipment mechanisms into LAIP models.
This paper	Develops an IGDP model integrating seasonal decomposition and residual correction for multi-region demand forecasting.	Introduces lateral transshipment into a VMI-based manufacturing supply chain and dynamically selects centralized transshipment nodes.	Develops a forecast-based LAIP framework incorporating lateral transshipment.

The objective of this study is to develop a prediction-based optimization framework to address the cost management problems in multi-product supply chains. The main contributions of this paper are as follows:

- This study develops a forecast-driven integrated optimization framework that jointly considers demand prediction, centralized transshipment node selection, inventory allocation, and lateral transshipment decisions in a multi-product two-echelon supply chain.
- Unlike conventional studies relying on static demand assumptions, this study incorporates demand forecasting into inventory allocation and transshipment decision-making processes, thereby enhancing the adaptability of the supply chain network under demand fluctuations.
- The paper develops a hybrid forecasting framework combining seasonal decomposition and grey prediction to capture seasonal demand variations under limited regional sales data conditions.
- To efficiently solve the resulting combinatorial optimization problem, an IGDP-SHADE solution framework integrating the proposed forecasting method with the SHADE metaheuristic algorithm is developed and analyzed through a case study.

To support the above research, the structure of this paper is arranged as follows: Section 2 reviews the relevant literature. Section 3 defines the research problem and presents the model assumptions and mathematical formulation. Section 4 introduces the IGDP-SHADE solution framework for the proposed optimization problem. Section 5 presents the case study and sensitivity analysis results, followed by a discussion. Section 6 draws the conclusions.

2. Literature Review

To highlight the uniqueness of this paper compared with other existing research, a review of the literature will be conducted across four key areas: (1) demand prediction; (2) VMI; (3) LIP and LAIP; (4) a replenishment method that considers lateral transshipment.

2.1. Demand Prediction

In practical supply chain environments, regional sales data is often limited and characterized by significant fluctuations and seasonal variations, particularly in multi-product manufacturing systems. While recent frontiers in demand forecasting extensively utilize deep learning and machine learning models [14,16,22], these approaches generally require large-scale historical datasets to maintain accuracy. Some scholars have developed improved ARIMA time series prediction models and applied them to prediction scenarios with limited data, achieving good forecasting performance by adapting to dynamically changing data patterns [26]. Under such conditions, grey prediction models have attracted increasing attention because of their capability to handle small-sample and incomplete information problems.

Existing studies have extended grey prediction methods to various complex forecasting scenarios. For example, Tang et al. [25] employed multiple grey models to simulate and forecast global launch vehicle success rates, enabling the identification of key reliability constraints under uncertain conditions. Zhang et al. [27] proposed a fractional-order discrete grey Gompertz model to study population aging, offering better support for non-linear growth analysis. Tang et al. [28] introduced a self-adaptive nonlinear grey Bernoulli model for industrial power demand prediction. Jin et al. [29] and Jiang [30] conducted forecasting studies on energy demand scenarios by improving grey prediction models. Nguyen et al. [24] combined a dynamic efficiency evaluation method with the GM(1,1) model to evaluate and forecast the performance of logistics enterprises in Vietnam for logistics enterprise performance forecasting under limited data conditions. Wang et al. [31] introduced a seasonal cycle GM(1,1) model incorporating seasonal indices and disturbance

factors for railway passenger volume forecasting under fluctuating conditions, even in the presence of external shocks.

These studies demonstrate that mathematical transformations or the introduction of seasonal and disturbance factors can improve the forecasting accuracy for small-sample data or datasets containing seasonal characteristics. These methodologies provide a theoretical foundation for the prediction approach in this paper, which targets the characteristic information scarcity of the excavator industry. In addition, forecasting has gradually been incorporated into supply chain optimization and inventory management problems. Early studies, such as Li et al. [32] integrated the GM(1,1) model with a metaheuristic optimization framework to address inventory optimization problems under fluctuating demand conditions, highlighting the role of forecasting information in supply chain decision-making processes. However, existing literature rarely embeds forecast-driven demand into comprehensive LAIP frameworks considering lateral transshipment.

Therefore, building upon the theoretical value of the aforementioned grey forecasting frontiers, this paper utilizes the proposed IGDP model not merely as a predictive tool, but as a critical data-driven input to guide inventory allocation and transshipment node selection in the subsequent optimization stages.

2.2. VMI

Under the VMI framework, suppliers leverage real-time sales data and inventory visibility from their customers to implement dynamic replenishment strategies, enabling them to maintain optimal stock levels. VMI research primarily encompasses three streams.

The first involves the design of supply chain coordination contracts to harmonize the incentives and goals of the supply chain members in a VMI setting, leading to win-win outcomes [33,34].

The second stream of research on VMI focuses on establishing mathematical models to determine the optimal decision variables in VMI systems, aiming to optimize the supply chain network structure by minimizing total costs or maximizing system benefits. For instance, Zhang et al. [35] investigated the collaborative optimization of front-end supply logistics and VMI warehouse inventory–transportation systems, establishing a joint inventory–transportation optimization model and decision-making framework based on milk-run and distribution–consolidation to achieve integrated optimization of inbound logistics, inventory, and transportation under the VMI mode. Mohammadi et al. [36] developed a bi-objective nonlinear integer programming model for a four-level perishable product supply chain under VMI to minimize total cost and delivery time.

The third stream involves research on VMI control and strategy optimization. Examples include constructing a VMI model for two-echelon supply chains to optimize product replenishment quantities [37], and further optimizing replenishment cycle lengths [38] to minimize the total cost of the supply chain system.

2.3. LIP and LAIP

Joint LIP optimization involves collaborative decision-making across the strategic, tactical, and operational levels of the supply chain [39]. This field involves two core issues: first, the location and allocation problem, and second, the inventory management problem [40].

Regarding model solution methods for LIP: Guo et al. [41] constructed a mixed-integer nonlinear programming model for closed-loop supply chains with a secondary market and designed an improved differential evolution algorithm for its solution. Liu [42] established a data-driven two-stage sparse distributionally robust risk optimization model and proposed a distribution–separation hybrid particle swarm optimization algorithm to obtain the optimal location allocation scheme and maximum expected return under

the worst-case scenario. In order to handle the LIP under stochastic supply disruptions, unknown demand, and replenishment lead times, Liu et al. [43] designed a tailored hybrid genetic algorithm embedded with a direct search method.

For LAIP, Tirkolaee et al. [44] developed a mixed-integer linear programming model for a supply chain network consisting of production plants, central warehouses, and retailers. They solved it using an improved simplified linear particle swarm optimization algorithm. Sahraei et al. [45] constructed a bi-level programming model considering budget constraints and demand uncertainty to jointly optimize the location, allocation, and inventory of relief material warehouses, verifying that the genetic algorithm exhibits superior performance in solving this problem.

These studies demonstrate the necessity of employing metaheuristic algorithms to solve LIP or LAIP. However, recent research has also successfully adopted exact algorithms; for instance, Yang et al. [13] formulated a two-stage stochastic mixed-integer linear programming model for offshore wind-to-hydrogen systems and solved it using a novel Benders decomposition-based exact algorithm. Consequently, this paper designs a heuristic algorithm while simultaneously utilizing the Gurobi optimizer to obtain exact solutions for algorithm performance comparison. Despite these methodological advancements, limited research has focused on LAIP decision-making based on demand forecasting. Therefore, this paper extends the classical LAIP by introducing forecasting inputs and lateral transshipment mechanisms, and develops the IGDP-SHADE framework.

2.4. Lateral Transshipment

Compared with scenarios where lateral transshipment is not allowed, integrated transshipment considering lateral transshipment yields better economic benefits than single vertical transshipment. Lateral transshipment can enhance the overall profit of the supply chain system by balancing inventory and reducing stockouts [46]. Wang et al. [10] developed a three-stage stochastic programming model for multi-period disaster rescue, demonstrating that integrating lateral transshipments can significantly enhance the resilience and demand satisfaction rate of the logistics network under uncertain disaster scenarios. Anvari et al. [47] prioritized demand points by integrating the multi-criteria decision-making method, and empirical analysis showed that in medium-scale earthquake scenarios, lateral transshipment can reduce the average transportation distance of relief materials compared with direct transportation. Keshavarz-Ghorbani [48] addressed the multi-warehouse and multi-product inventory management problem by constructing a mixed binary nonlinear programming model, integrating preventive lateral transshipment strategies with continuous and periodic review policies to minimize the total system cost while satisfying warehouse capacity and service level constraints. By comparing full pooling and partial pooling lateral transshipment strategies, it was found that the partial pooling strategy with optimized thresholds outperforms other strategies in reducing total costs and improving service levels [49]. Li et al. [50] proposed an integrated optimization model for inter-regional lateral transshipment of relief supplies in post-disaster allocation problems to coordinate transportation and deprivation costs.

Some scholars have also integrated location and inventory decisions by considering the existence of lateral transshipment in the supply chain. Ahmadi et al. [51] built a supply chain network consisting of factories, distribution centers, and customers, considering lateral transshipment between distribution centers. Under fuzzy demand and capacity constraints, they simultaneously optimized distribution center location and inventory allocation to achieve a trade-off between maximizing profit and improving service levels. Considering emergency lateral transshipment, the locations of reserve facilities for disaster relief materials and material allocation were optimized, allowing reserve facilities to transfer

various relief materials from facilities with redundant inventory to those with insufficient inventory according to actual needs after disasters to respond to uncertain demand [52].

These studies demonstrate the effectiveness of lateral transshipment in mitigating stockouts and reducing system costs. Therefore, this paper introduces the lateral transshipment mechanism into a two-echelon supply chain under the VMI mode.

2.5. Research Distinction

Existing studies on product demand forecasting have developed a relatively comprehensive methodological framework, providing valuable theoretical support and methodological references for this study. Grey forecasting models demonstrate good applicability in demand predictions characterized by small samples and incomplete information. Current research primarily focuses on structural improvements, parameter optimization, and forecasting accuracy enhancement of grey models, with various modeling mechanisms introduced to improve their capability to capture complex demand patterns. However, most existing studies emphasize the predictive performance of forecasting models themselves, while limited attention has been devoted to how forecasting results can further support collaborative supply chain optimization. In particular, the integration of demand forecasting with inventory allocation and node coordination decisions remains underexplored.

LAIPs generally aim to minimize total operational costs, including facility establishment, inventory holding, and transportation costs, by jointly optimizing facility location, allocation, and inventory management decisions. In most existing studies, the facilities under consideration are newly established entities. Once facility locations and service areas are determined, they are difficult to adjust dynamically in response to demand fluctuations and changes in node capabilities. In practical supply chain operations, this may result in redundant infrastructure investments and substantially increased costs. An alternative approach is to select certain existing supply chain nodes to undertake service functions and replenish inventories for peer nodes, thereby optimizing existing network resources rather than reconstructing the network structure. Compared with facility expansion strategies, this approach offers greater operational flexibility, avoids additional construction costs, and enables enterprises to dynamically adjust service nodes and coverage areas according to market demand. Nevertheless, existing LAIP studies have paid limited attention to the integration and dynamic coordination of existing network resources, particularly regarding the dynamic adjustment of service nodes under fluctuating demand conditions.

Although some studies have investigated inventory centralization through the selection of core service nodes to reduce overall inventory levels, these studies mainly focus on distributed inventory systems, where inventory decisions are typically made independently by individual nodes. Limited attention has been devoted to VMI environments, in which suppliers centrally coordinate inventory decisions and thereby enable integrated location and inventory optimization. Under the VMI framework, suppliers can formulate replenishment and inventory allocation strategies based on real-time sales and inventory information from downstream nodes, facilitating efficient coordination between inventory management and demand information. Such centralized inventory control mechanisms not only help mitigate the bullwhip effect but also improve inventory utilization efficiency. Therefore, how to dynamically select core service nodes based on demand forecasting results and further achieve the collaborative optimization of location, inventory, and demand management under the VMI framework remains an important research issue.

Based on the aforementioned research status, this paper develops a prediction-based LAIP framework under the VMI setting by leveraging the advantages of grey forecasting models in small-sample environments. On the one hand, the proposed grey forecasting approach enhances demand prediction effectiveness under limited data conditions. On

the other hand, the framework jointly optimizes core service node selection and inventory allocation based on existing supply chain network resources, thereby reducing inventory holding and transportation costs while improving the responsiveness and operational efficiency of supply chains under demand fluctuations.

3. Model Development

3.1. Problem Description

Consider a product $K = \{1, 2, \dots, k\}$ production and sales system consisting of one factory F and multiple agents $N = \{1, 2, \dots, n\}$, as shown in Figure 1. At the beginning of each period $t \in T$, the factory F allocates products q_{ik} to the agents, replenishes the inventory of all agents $N = \{1, 2, \dots, n\}$, selects an appropriate agent as the centralized inventory storage point, and allocates a centralized storage quantity for subsequent lateral transshipment. Agents $N = \{1, 2, \dots, n\}$ reevaluate their product inventory based on actual sales performance. When an agent $j \in N$ faces a product $k \in K$ inventory shortage, it needs to submit a product transshipment request to the factory. The factory F then decides whether to transship the required product $k \in K$ quantity a_{ijk} from the centralized storage point through lateral transshipment or to conduct emergency vertical transshipment b_{jk} directly from the factory. In this production and sales system, the problems to be solved are: how the factory should implement product allocation based on the sales performance of agents, and how to conduct product transshipment when stockouts occur.

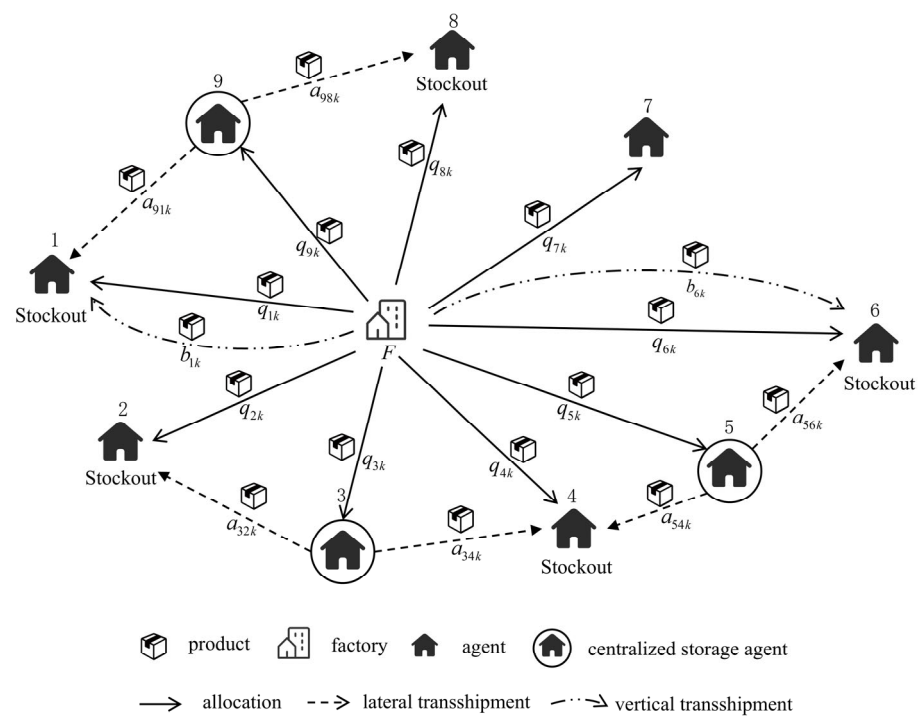


Figure 1. Schematic diagram of production and sales system. (The numbers 1–9 represent the agent nodes.).

Inventory allocation and transfer rules:

- Product allocation: Based on the forecast demand volume of each region, combined with total production capacity and the capacity constraints of each agent, the factory conducts initial product allocation to each agent;
- Selection of centralized storage agents: Considering the distance from the factory to each agent and the demand distribution of each region, multiple agents are selected

- as “centralized storage points” that will hold additional inventory for subsequent lateral transshipment;
- (c) Market demand fulfillment: Agents receive replenishment from the factory at the beginning of each month and use their existing inventory to meet customer demand;
 - (d) Lateral transshipment: Lateral transshipment is triggered when an agent’s inventory level drops to a level that cannot satisfy demand;
 - (e) Emergency transportation: Emergency transportation is triggered when lateral transshipment fails to fully meet an agent’s transshipment request.

3.2. Model Formulation

3.2.1. IGDP Model

When the demand time series exhibits periodic or seasonal fluctuations, directly applying the GM(1,1) model to the original series causes these fluctuations to be superimposed and fixed into the accumulated sequence during the one-time accumulating generation process. This leads to the accumulated sequence no longer satisfying the exponential growth law, thereby generating bias. To provide demand estimation inputs for the subsequent LAI optimization model, this section develops a forecasting framework combining seasonal decomposition and grey prediction. The primary process involves performing seasonal decomposition on the original series to obtain a seasonally adjusted series, utilizing GM(1,1) to forecast the trend term of this seasonally adjusted series, and subsequently correcting the residuals via ARMA.

The original demand series is processed using a classical multiplicative decomposition approach to separate long-term trend information from seasonal fluctuations and irregular disturbances. Considering that the magnitude of seasonal variation changes proportionally with the overall demand level, the multiplicative decomposition framework is adopted to extract the underlying trend-dominant demand sequence. After removing the seasonal effect, the resulting deseasonalized series is used as the input for the subsequent grey prediction procedure, thereby reducing the interference of periodic fluctuations on demand forecasting accuracy.

Let Y_t denote the observed demand value at period t . The centered moving average method is employed to extract the smooth trend term T_t from the series containing seasonal noise, where the seasonal period of the original series is denoted as L . When L is an even number, directly using a moving average of length L results in a center point offset; in this case, a two-step moving average structure is constructed for phase correction, with its mathematical expression being:

$$CMA_t = \frac{1}{2L} \left(Y_{t-L/2} + 2 \sum_{i=-(L/2)+1}^{(L/2)-1} Y_{t+i} + Y_{t+L/2} \right) \quad (1)$$

After obtaining the trend estimate $\hat{T}_t \approx CMA_t$, the initial seasonal features are extracted by calculating the relative ratio between the observed values and the trend values; the original seasonal ratio R_t at time t is Y_t/CMA_t .

To eliminate the interference of the random fluctuation term I_t , observations with the same seasonal phase within the sample period are averaged. Let $j(j = 1, 2, \dots, 12)$ denote the seasonal index within a cycle, yielding the initial seasonal component $\bar{S}_j$. To satisfy the theoretical constraint in multiplicative decomposition that the product of seasonal components within a complete cycle equals 1, normalization is performed on $\bar{S}_j$ to obtain the final seasonal index S_j .

The standardized seasonal index S_j is utilized to seasonally adjust the original series Y_t , thereby eliminating the interference of periodic fluctuations on the sales trend. The mathematical expression for the resulting trend component series T_t is given as

$$T_t = Y_t / S_{\varphi(t)} \quad (2)$$

where $\varphi(t)$ maps the linear time index t to its corresponding seasonal index j .

The extracted trend T_t is then used to construct a univariate GM(1,1) model, undergoing the 1-AGO transformation. The whitening equation is defined in Equation (3).

$$\frac{dT^{(1)}}{dt} + aT^{(1)} = b \quad (3)$$

where a is the development coefficient, and b is the grey action quantity.

The parameters $\hat{\mathbf{a}} = [a, b]^T$ are estimated via least squares using the data matrix constructed from the immediate mean generation sequence.

Solving the differential equation yields the time response function for $T^{(1)}$, which is restored to the original dimension via Inverse-AGO.

$$\hat{T}_t^{(0)} = \hat{T}_t^{(1)} - \hat{T}_{t-1}^{(1)}, \quad t = 2, 3, \dots, n + m \quad (4)$$

where m is the number of forecasting steps.

After the GM(1,1) trend fitting is concluded, although the model has captured the primary growth path, if the fitting residuals still contain unextracted autocorrelation features and random fluctuations, stationary modeling is performed on the residual series.

Let the true value of the extracted series at time t be $T_t^{(0)}$, and the fitted value from the GM(1,1) model be $\hat{T}_t^{(0)}$; the residual series ε_t is defined as $\varepsilon_t = T_t^{(0)} - \hat{T}_t^{(0)}$. Assuming ε_t meets stationarity requirements after testing, the grid search autoregressive moving average model (ARMA) is employed to correct the errors.

$$\varepsilon_t = c + \sum_{i=1}^p \phi_i \varepsilon_{t-i} + \sum_{j=1}^q \theta_j \eta_{t-j} + \eta_t \quad (5)$$

where p and q are the autoregressive order and the moving average order, respectively; ϕ_i and θ_j are the model coefficients to be estimated; and η_t is the stochastic disturbance term.

Then, based on the principle of system superposition, the deterministic trend component $\hat{T}_t^{(0)}$ output by the GM(1,1) model is additively synthesized with the random residual correction term $\hat{\varepsilon}_t$ output by the ARMA model. The corrected trend series $\hat{T}_t$ at time t is defined as:

$$\hat{T}_t = \hat{T}_t^{(0)} + \hat{\varepsilon}_t \quad (6)$$

Finally, the standardized seasonal index $S_{\varphi(t)}$ is re-mapped to the trend series $\hat{T}_t$ to restore the periodic fluctuation characteristics of the original series. At this point, the predicted value $\hat{Y}_t$ at time t can be expressed as:

$$\hat{Y}_t = \hat{T}_t \times S_{\varphi(t)} = (\hat{T}_t^{(0)} + \hat{\varepsilon}_t) \times S_{\varphi(t)} \quad (7)$$

3.2.2. LAI Model

We make the following assumptions: (1) The product demands of various agents are mutually independent; (2) the factory has limited supply capacity but can meet market demand; (3) at the period $t = 0$, before the factory allocates products to each agent, the

inventory level of each agent is zero; (4) transportation costs, inventory holding costs, and shortage costs all have a linear relationship with the quantity of products.

The definitions of symbols involved in the constructed model are shown in Table 2.

Table 2. Symbol description.

Set and Indices	
N	Set of agents, $N = 1, 2, \dots, i, \dots, j, \dots, n$
K	Set of products, $K = 1, 2, \dots, k$
T	Set of periods, $T = 1, 2, \dots, t$
Parameters	
i	Agent i where $i = 1, 2, \dots, n$
j	Agent j where $j = 1, 2, \dots, n$
ε_{ik}^t	Service level of product k at agent i in period t
sc_k	Unit shortage cost of product k
hc_k	Unit inventory holding cost of product k
tc_k	Unit lateral transshipment cost of product k
ec_k	Unit transportation cost of product k
oc_k	Unit replenishment cost from the factory to agent i
l_i	Distance from the factory to agent i
l_{ij}	Distance from agent i to agent j
d_{ik}^t	Market demand for product k at agent i in period t
Cap_k^t	Supply capacity of the factory for product k in period t
Q_{ik}	Inventory capacity of product k at agent i
Decision Variables	
q_{ik}^t	Quantity of product k allocated by the factory to agent i in period t
x_{ijk}^t	$x_{ijk}^t \in \{0, 1\}$, $x_{ijk}^t = 1$ means product k is transshipped from agent i to agent j in period t otherwise $x_{ijk}^t = 0$
y_i^t	$y_i^t \in \{0, 1\}$, $y_i^t = 1$ means agent i is selected as the central transshipment origin in period t otherwise $y_i^t = 0$
a_{ijk}^t	Quantity of product k transshipped from agent i to agent j in period t
b_{jk}^t	Quantity of emergency replenishment of product k from the factory to agent j in period t
s_{ik}^t	Shortage quantity of product k at agent i in period t
N_{ik}^t	Ending inventory of product k at agent i in period t

The model is constructed as follows:

The objective is to minimize the total system cost, including transportation costs from factories to agents, lateral transshipment costs, emergency replenishment costs, shortage costs, and inventory holding costs, as shown in Equation (8).

$$\min F = \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} q_{ik}^t ec_k l_i + \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} \sum_{t \in T} a_{ijk}^t tc_k l_{ij} + \sum_{j \in N} \sum_{k \in K} \sum_{t \in T} b_{jk}^t ec_k l_j + \sum_{j \in N} \sum_{k \in K} \sum_{t \in T} sc_k s_{ik}^t + \frac{1}{2} \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} hc_k (N_{ik}^{t-1} + N_{ik}^t) \quad (8)$$

To ensure that only agents selected as centralized transshipment outbound points can perform lateral transshipments for other agents (i.e., have lateral transshipment quantities). Here, M denotes a sufficiently large positive number, as shown in Constraint (9) to (11).

$$x_{ijk}^t \leq y_i^t, \forall i \in N, j \in N, k \in K, t \in T \quad (9)$$

$$a_{ijk}^t \leq M \cdot x_{ijk}^t, \forall i \in N, j \in N, k \in K, t \in T \quad (10)$$

$$a_{ijk}^t \leq M \cdot y_i^t, \forall i \in N, j \in N, k \in K, t \in T \quad (11)$$

To satisfy the required service level, the quantity of product k at agent i that meets market demand in period t cannot be lower than the present service level, as expressed in Constraint (12).

$$\frac{d_{ik}^t - s_{ik}^t}{d_{ik}^t} \geq \varepsilon_{ik}^t, \forall i \in N, j \in N, k \in K, t \in T \quad (12)$$

To guarantee that product allocation and replenishment quantities do not exceed the factory's available supply capacity, Constraint (13) is established.

$$\sum_{i \in N} q_{ik}^t + \sum_{j \in N/i} b_{jk}^t \leq Cap_k^t, \forall k \in K, t \in T \quad (13)$$

The inventory level of product k at agent i during period t cannot exceed the corresponding storage capacity, as shown in Constraint (14).

$$q_{ik}^t + N_{ik}^{t-1} \leq Q_{ik}, \forall i \in N, k \in K, t \in T \quad (14)$$

Products received through lateral transshipment are prohibited from being redistributed to other agents in order to prevent arbitrage opportunities and unnecessary repeated transfers, as specified in Constraint (15).

$$x_{ijk}^t + \sum_{i \in N/j} x_{jik}^t \leq 1, \forall i, j \in N, k \in K, t \in T \quad (15)$$

The number of selected centralized storage points is restricted to the predefined value R , as shown in Constraint (16).

$$\sum_{i \in N} y_i^t \leq R, \forall i \in N, k \in K, t \in T \quad (16)$$

Inventory flow conservation is maintained across consecutive periods through the inventory balance relationship described in Constraint (17).

$$N_{ik}^{t-1} + q_{ik}^t + b_{ik}^t + \sum_{j \in N/i} a_{jik}^t = d_{ik}^t + \sum_{j \in N/i} a_{ijk}^t + N_{ik}^t - s_{ik}^t \quad (17)$$

Constraint (18) to (19) define the binary decision variables, which indicate whether lateral transshipment is conducted between agents and whether an agent is selected as a centralized transshipment point, respectively.

$$x_{ijk}^t \in \{0, 1\}, \forall i \in N, j \in N, k \in K, t \in T \quad (18)$$

$$y_i^t \in \{0, 1\}, \forall i \in N, k \in K, t \in T \quad (19)$$

Constraint (20) specifies the non-negativity requirements for variables.

$$sc_k, hc_k, tc_k, ec_k, l_i, l_{ij}, a_{ijk}^t, b_{jk}^t, s_{ik}^t, N_{ik}^t \geq 0, \forall i \in N, j \in N, k \in K, t \in T \quad (20)$$

4. Solution Approach

This paper proposes the IGDP-SHADE algorithm to solve the LAIP for multi-type products in a two-echelon supply chain, as illustrated in Figure 2. The proposed algorithm adaptively adjusts the mutation factor and crossover probability during the search process, following the recent trend toward adaptive mechanisms in metaheuristic optimization [53], while preserving successful parameter settings. By integrating demand prediction with

optimization, the algorithm minimizes the total system cost while balancing service levels and inventory distributions among agents.

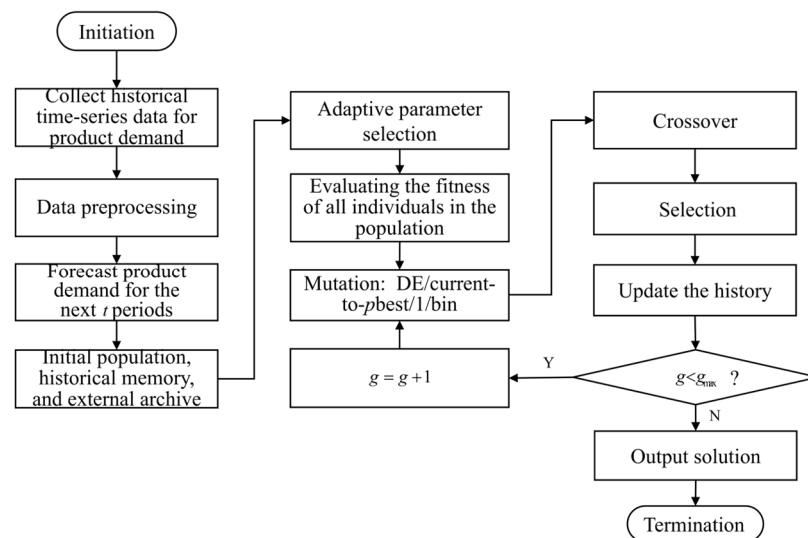


Figure 2. IGDP-SHADE algorithm flow.

4.1. Encoding and Decoding

In this paper, we adopt the real-number encoding method, which consists of two parts: the first part is the probability that each agent is selected as a centralized storage point in each period and the second part is the inventory allocation quantity of each product for each agent in each period. As shown in Equation (21), each individual in the population corresponds to a real-number vector $X_m = (x_1, x_2, \dots, x_D)$ with length D (where $D = T \times N + T \times N \times K$, T denotes the number of periods, N denotes the number of agents, and K denotes the number of product types). Here, $m = 1, 2, \dots, NP$, and NP is the population size.

$$x = [h_1, h_2, \dots, h_{T \times N}, q_1, q_2, \dots, q_{T \times N \times K}] \quad (21)$$

where $h = [x_1, x_2, \dots, x_{T \times N}]$ represents the probability of being selected as a centralized storage point. $q = [x_{T \times N + 1}, x_{T \times N + 2}, \dots, x_D]$ represents the inventory allocation quantity of each product for each agent in each period.

As illustrated in Figure 3, each chromosome consists of two concatenated segments of real-valued sequences, with a total length of D . This encoding scheme integrates the probability scores associated with centralized storage node selection decisions and the corresponding inventory allocation quantities into a unified real-valued vector.

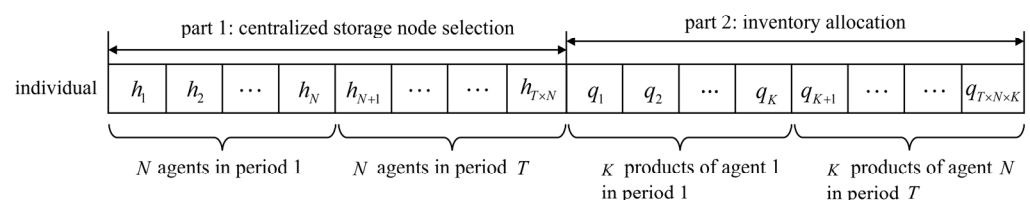


Figure 3. Illustration of the individual encoding structure.

The encoding–decoding mapping for centralized storage point selection decisions in the first segment is illustrated in Figure 4. Specifically, the first $T \times N$ real-valued elements of a chromosome are extracted and reshaped into a two-dimensional matrix defined by periods T and agent nodes N .

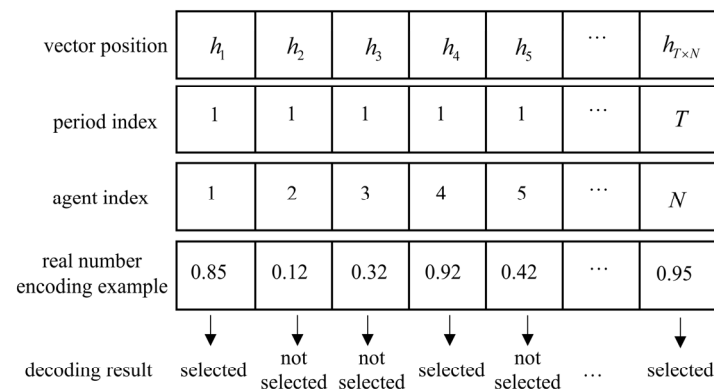


Figure 4. Encoding mapping for centralized storage point selection decisions.

When decoding the continuous real-valued encoding into discrete binary location selection decisions, a sorting and thresholding strategy is adopted to ensure that the selection scheme for centralized storage points satisfies the cardinality constraint. For each independent period t , the real-valued encoding variables $h_{t,n}$ corresponding to all N agents are extracted. To ensure that the number of centralized storage points does not exceed the predefined upper limit R , these N real-valued variables are sorted in descending order and then converted into binary selection states. A value of 1 indicates that the corresponding agent is selected as a centralized storage point, whereas a value of 0 indicates that the agent is not selected.

The decoding process for the inventory allocation decisions in the second segment is illustrated in Figure 5. This segment contains $T \times N \times K$ real-valued encoding variables, which are sequentially reshaped into a three-dimensional matrix defined by periods, agents, and product types during the decoding process. Since the allocated quantities of products must be non-negative integers, a rounding operation is performed to convert the real-valued variables into integer values, thereby determining the quantity of each product allocated to each agent in a specific period.

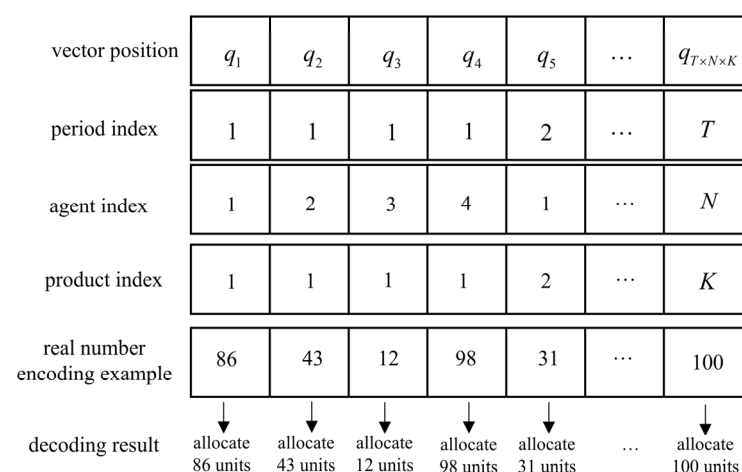


Figure 5. Mapping from encoded variables to inventory allocation decisions.

4.2. IGDP-SHADE Algorithm

The procedure of the proposed algorithm is outlined in the following steps.

1: Generate an initial population containing a certain number of individuals, where each individual represents a feasible solution; initialize the historical memory archive for recording successful parameters and the external archive for storing eliminated individuals, while setting hyperparameters such as population size, pbest ratio, and archive capacity;

2: Calculate the fitness of each individual (Line 2) in the initial population according to Equation (8);

3: Perform mutation (Line 8) and crossover (Line 9) operations, generating trial vectors while handling any boundary constraint violations (Line 10);

4: Calculate the fitness of the generated trial vector (Line 11). Apply greedy selection to retain the individual with better fitness between the trial vector and the original individual, move eliminated individuals to the external archive (Lines 12–15, 17–19), and update the global optimal solution and its fitness if the trial vector achieves a better fitness value (Line 16).

5: Collect the F and CR values that successfully generated better solutions in this iteration and update the historical memory (Lines 21–22). If the iteration termination condition is met, output the result; otherwise, return to Step 3 for the next iteration.

As shown in Algorithm 1, the pseudocode outlines the specific steps of the proposed method.

Algorithm 1: IGDP-SHADE

Input: population size: NP ; problem parameters: period T , agent N , product type K ; dimension: $D = T \times N + T \times N \times K$; maximum generations: $g_{\max}$; memory size: H ; archive size: A ; bounds: lower bound L , upper bound U

Output: optimal solution vector x_{best} and $f(x_{best})$

1: Initialize population $P_0 = (x_{1,0}, \dots, x_{NP,0})$ randomly within $[L, U]$; set memory contents $M_{CR,j}$, $M_{F,j} = 0.5$ for all $j = 1 \dots H$; set archive $A = \emptyset$; set memory index $idx = 1$;

2: Evaluate P_0 and set x_{best} to the best individual;

3: for $g = 1$ to $g_{\max}$ do

4: $S_{CR} = \emptyset$, $S_F = \emptyset$;

5: for $i = 1$ to NP do

6: Select r_i randomly from $\{1, \dots, H\}$;

7: $CR_{i,G} = randn_i(M_{CR,r_i}, 0.1)$, $F_{i,G} = randc_i(M_{F,r_i}, 0.1)$;

8: Generate mutant $v_{i,G}$ by current-to-pbest/1/bin;

9: Generate trial vector $u_{i,G}$ by binomial crossover with $CR_{i,G}$;

10: Boundary constraint handling: repair $u_{i,G}$ if out of $[L, U]$;

11: Calculate fitness $f(u_{i,G})$;

12: if $f(u_{i,G}) \leq f(x_{i,G})$ then

13: $x_{i,G+1} = u_{i,G}$;

14: $A = A \cup \{x_{i,G}\}$;

15: $CR_{i,G} \rightarrow S_{CR}$, $F_{i,G} \rightarrow S_F$;

16: if $f(u_{i,G}) < f(x_{best})$ then update $x_{best} = u_{i,G}$;

17: else

18: $x_{i,G+1} = x_{i,G}$;

19: end if

20: end for

21: if $S_{CR} \neq \emptyset$ and $S_F \neq \emptyset$ then

22: update $M_{CR,idx}$, $M_{F,idx}$ based on S_{CR} , S_F ;

23: $idx = idx + 1$; if $idx > H$ then $idx = 1$;

24: end if

25: Prune A if $|A| > H$;

26: end for

5. Computational Experiments and Discussion

5.1. Case Design

This paper takes the excavator product supply chain of Sany Heavy Machinery Co., Ltd. as the research background, with Kunshan City, Jiangsu Province, as the excavator production base. Three types of excavators are considered: small (<18.5 t), medium (18.5 t–28.5 t), and large (≥ 28.5 t). The unit storage costs for small, medium, and large excavators are set at 200, 300, and 400 yuan, respectively. The regular transportation costs for these three types are 15, 25, and 40 CNY/Kilometre per unit, respectively. The unit cost of lateral transfer is 1.2 times the regular transportation cost, while the emergency transfer cost is 1.5 times the regular transportation cost. The unit shortage costs are set at 1000, 10,000, and 100,000 CNY for small, medium, and large excavators, respectively. To reflect the varying operational conditions across the 31 provincial nodes, the target service levels are heterogeneously configured, ranging from approximately 0.85 to 0.995. Similarly, the maximum storage capacities for the three product types at each regional agent are mapped to an established matrix, with individual node capacities randomly initialized between 20 and 300 units. The factory's production capacity for each period is presented in Table 3.

Table 3. Factory production capacity (Units).

	Period 1	Period 2	Period 3
Small excavator capacity	3600	2150	3850
Medium excavator capacity	650	300	490
Large excavator capacity	400	250	390

Since the historical monthly sales data of Sany Heavy Machinery's excavators cannot be accurately obtained, and Sany Heavy Machinery's core agents have nationwide coverage, this paper adopts the monthly excavator sales data (mainly sourced from the China Construction Machinery Association) of major excavator manufacturers across 31 major provinces and municipalities directly under the Central Government in China from 2021 to 2025 to predict the national market demand from January to March 2026.

Given the presence of missing values in the dataset, this study employs the following two statistical imputation strategies to ensure data completeness:

a. Reverse extrapolation based on year-over-year growth. For cases where monthly sales data for a specific region in a given year are available but the corresponding data for the previous year are missing, the historical data is reconstructed using the known year-over-year trends. The calculation formula is:

$$\hat{y}_{i,m,t-1} = \frac{y_{i,m,t}}{1 + r_{i,m,t}} \quad (22)$$

where $\hat{y}_{i,m,t-1}$ represents the estimated sales volume for region i in month m of the previous year $t - 1$, $y_{i,m,t}$ is the known sales volume for the current year, and $r_{i,m,t}$ denotes the corresponding year-over-year growth rate.

b. Proportional estimation based on population distribution. The monthly sales proportion of the aggregate sample is treated as the general distribution probability of market demand for that period, which is then used to decompose the annual sales of a specific region:

$$\hat{y}_{i,m,t} = Y_{i,t} \times \frac{S_{total,m,t}}{S_{total,year,t}} \quad (23)$$

where the ratio term $S_{total,m,t}/S_{total,year,t}$ represents the monthly market share distribution derived from the aggregate data.

Subsequently, combined with Sany Heavy Machinery's market share, the corresponding market demand is predicted. It is assumed that there is one agent in each province/municipality, the number of centralized storage points is no more than 8, and the latitude and longitude of each region are obtained to calculate the distances between various locations.

5.2. Simulation Results

Common metrics used to evaluate forecasting performance include the RMSLE and the MAPE. The calculation formulas for these two performance indicators are defined as follows.

$$RMSLE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\log(y_i) - \log(\hat{y}_i))^2} \quad (24)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (25)$$

where n denotes the number of forecasting samples, y_i represents the actual value at the i -th time point, and $\hat{y}_i$ denotes the predicted value at the i -th time point.

The dataset was divided into a training set (January 2021–September 2025) and a testing set (October 2025–December 2025). The optimal order for the ARMA model was selected based on the minimum prediction error criterion, whereas the parameters for the Holt–Winters model were determined by minimizing the Akaike Information Criterion. The prediction error results of the IGDP model, in comparison with those of the traditional ARIMA and Holt–Winters models, are shown in Table 4.

As shown in Table 4, the IGDP model achieves lower RMSLE and MAPE values compared to both the ARIMA and Holt–Winters models, indicating its superior predictive performance. To further illustrate this, the fitting and forecasting results for Chongqing are visualized in Figure 6.

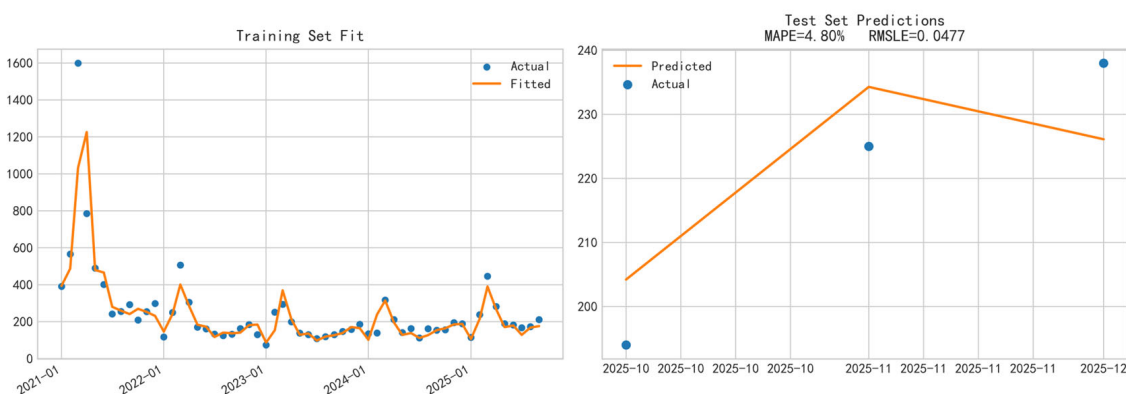


Figure 6. Fitting and prediction results on training and test sets.

Next, we applied trend extrapolation to determine the market share composition, resulting in a ratio of approximately 81.5%: 11.03%: 7.47% for small, medium, and large excavators, and Sany's market share in the excavator market is about 28.72%. The predicted regional demand for excavators obtained through the improved grey prediction model is converted into the corresponding detailed demand forecast for each model of Sany's excavators.

We use Python 3.11 as the development environment. The parameter settings of the proposed IGDP-SHADE algorithm were primarily determined according to the recommendations provided in the original SHADE framework proposed by Tanabe and Fukunaga [54]. The population size was set to 50 based on the scale of the optimization problem considered in this paper. The algorithm parameter settings are shown in Table 5.

The model is solved over 100 iterations, yielding a total system cost of 159,328,510.06. The convergence curve of the algorithm is shown in Figure 7.

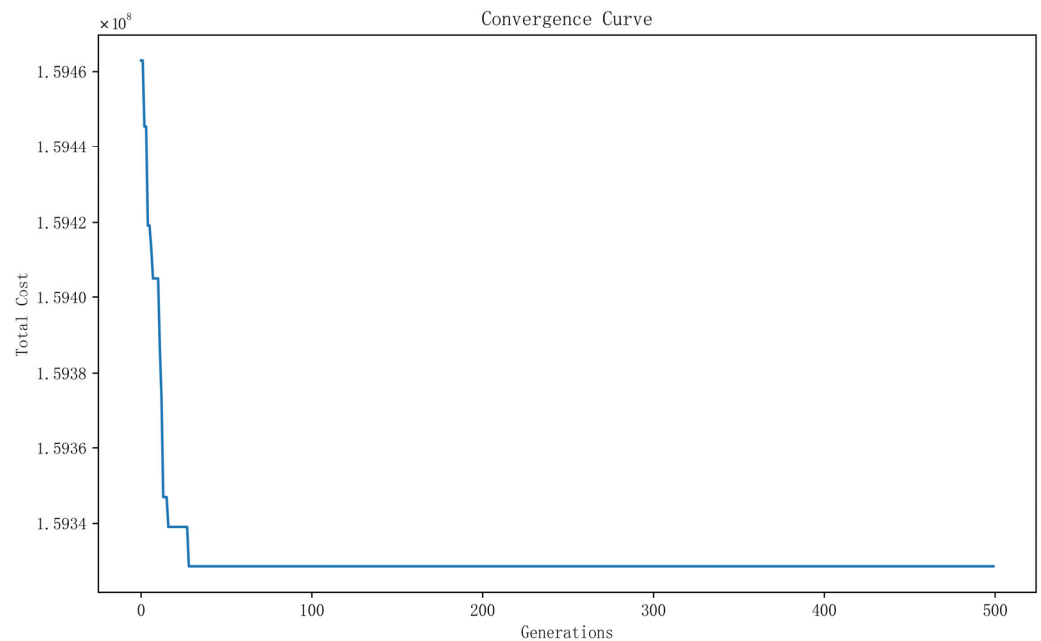
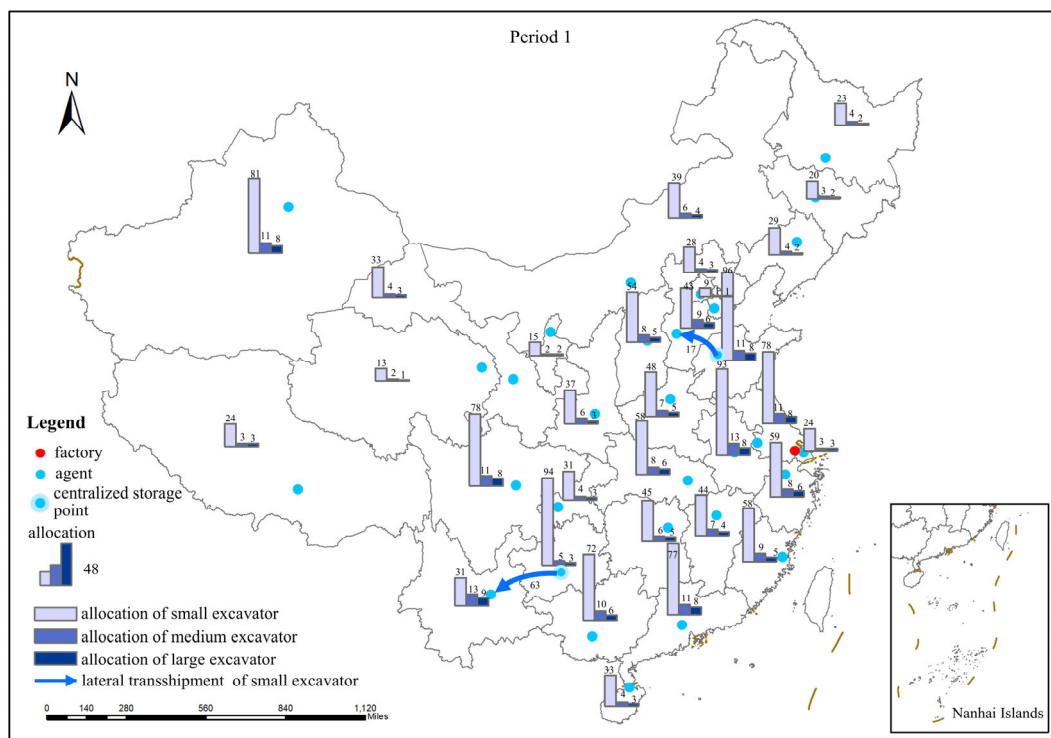


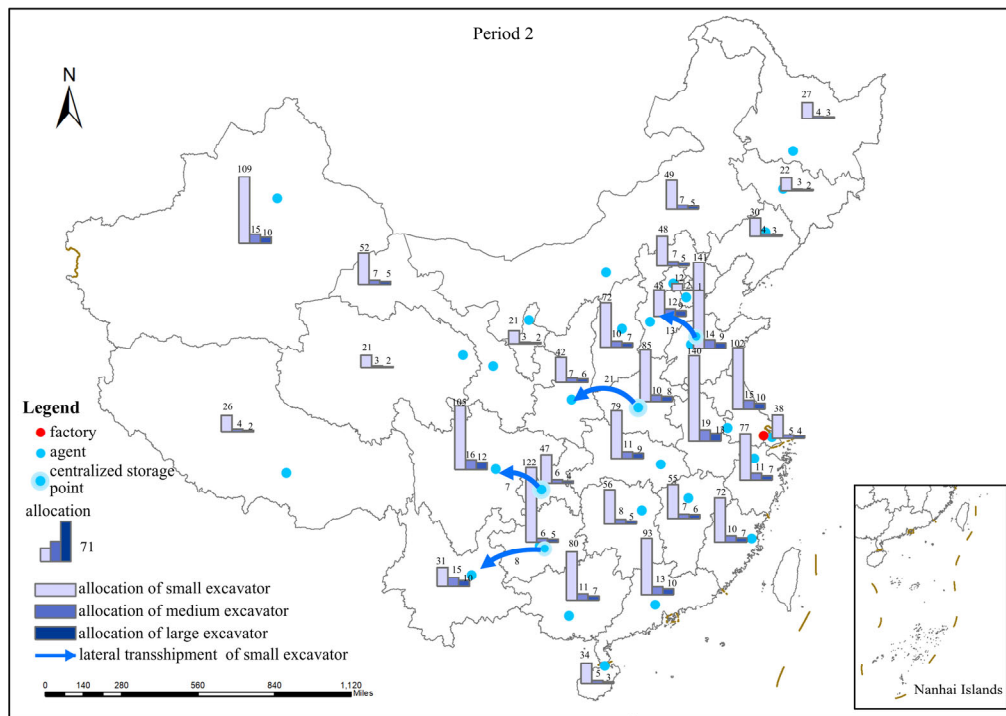
Figure 7. IGDP-SHADE algorithm convergence curve.

By solving the model using the IGDP-SHADE algorithm, we obtain the results for product allocation, lateral transshipment, emergency transshipment, and the selection of centralized storage points in each period, as shown in Figure 8.

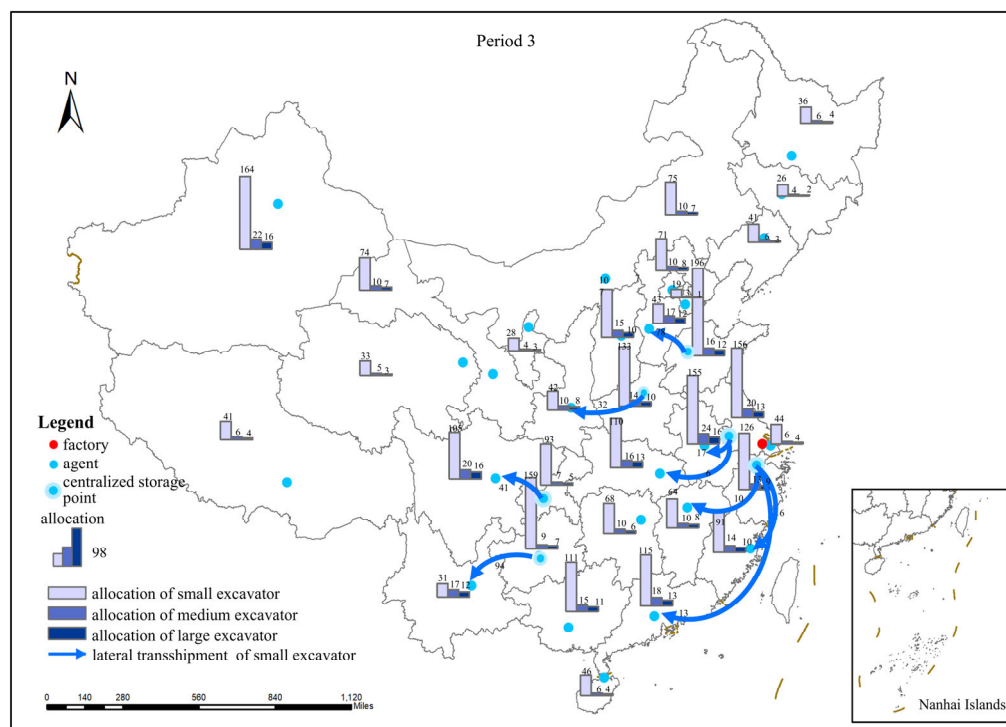


(a)

Figure 8. Cont.



(b)



(c)

Figure 8. Results of the model solved by the IGDP-SHADE algorithm. (a) Results for period 1; (b) results for period 2; (c) results for period 3. This figure is created based on the standard map (map review number: GS (2024) 0650) downloaded from the Standard Map Service Website of the National Administration of Surveying, Mapping and Geoinformation. The base map remains unmodified.

In this paper, the Gurobi exact solver is applied to solve the constructed LAIP optimization model, yielding a total system cost of 159,328,510.06. The detailed comparative results of the algorithms are presented in Table 6.

Table 4. Performance comparison of three prediction models.

	RMSLE	MAPE
IGDP	0.1806	13.86%
ARIMA	0.2369	23.94%
Holt–Winters	0.2682	22.64%

Table 5. IGDP-SHADE algorithm parameter settings.

Parameter Name	Symbol	Value
Population size	NP	50
Maximum number of iterations	$g_{\max}$	500
Historical memory size	H	10
External archive size	$ A $	50
pbest proportion	p	0.11
Initial crossover probability	M_{CR}	0.5
Initial scaling factor	M_F	0.5

Table 6. Comparison of algorithms.

Solution Method	CPU Time (s)	Objective Function Value (CNY)
IGDP-SHADE	1.89	159,328,510.06
Gurobi	2.29	159,328,510.06
Gaps	17.47%	0

The results show that the solution obtained by IGDP-SHADE is consistent with that of Gurobi, while achieving an approximately 17.47% reduction in CPU computation time compared with Gurobi. This indicates that IGDP-SHADE is able to achieve solutions of comparable quality to Gurobi while simultaneously exhibiting higher computational efficiency.

5.3. Sensitivity Analysis

5.3.1. Demand Fluctuation

To evaluate the system's robustness against demand uncertainty, we introduce a continuous perturbation parameter $\delta \in [-10\%, +10\%]$ to scale the baseline demand, such that the adjusted demand is $d_{ik}^{t'} = d_{ik}^t(1 + \delta)$. Figure 9 illustrates the variations in the total objective cost and individual cost components under this parameter shift. As δ increases, the demand fulfillment constraints become more difficult to satisfy. Because the unit cost of emergency transshipment is significantly higher than those of regular transport and lateral transshipment, the algorithm's global search process naturally guides the solution vectors to converge towards prioritizing regular transport and lateral transshipment to minimize the total cost. When $\delta > 0$, local inventory capacities become relatively constrained, leading to the more frequent generation of solutions relying on lateral transshipments to balance regional supply–demand mismatches. Throughout the interval $\delta \in [-10\%, +10\%]$, the algorithm consistently optimizes the emergency transshipment and inventory holding variables to approach their zero lower bounds. This proves that the proposed LAI model can absorb these demand fluctuations through dynamic routing, thereby avoiding high costs.

5.3.2. Comparison of Lateral Transshipment Strategies

To verify the strategic effectiveness of the centralized storage point and lateral transshipment mechanism in coping with regional demand fluctuations and cost control, this paper sets up a comparative experiment on transshipment strategies. Based on the completed and solved full model that includes lateral transshipment, the control model without

lateral transshipment is solved. In the baseline model without lateral transshipment, regional agents operate independently; when facing a shortage under regular transportation, the system can only rely on emergency transshipment from the factory to meet demand or bear the corresponding shortage costs. By comparing and analyzing the data differences in various decision variables and cost components between these two scenarios, the specific impact of introducing the lateral transshipment mechanism on optimizing the overall inventory allocation structure and total system cost is evaluated.

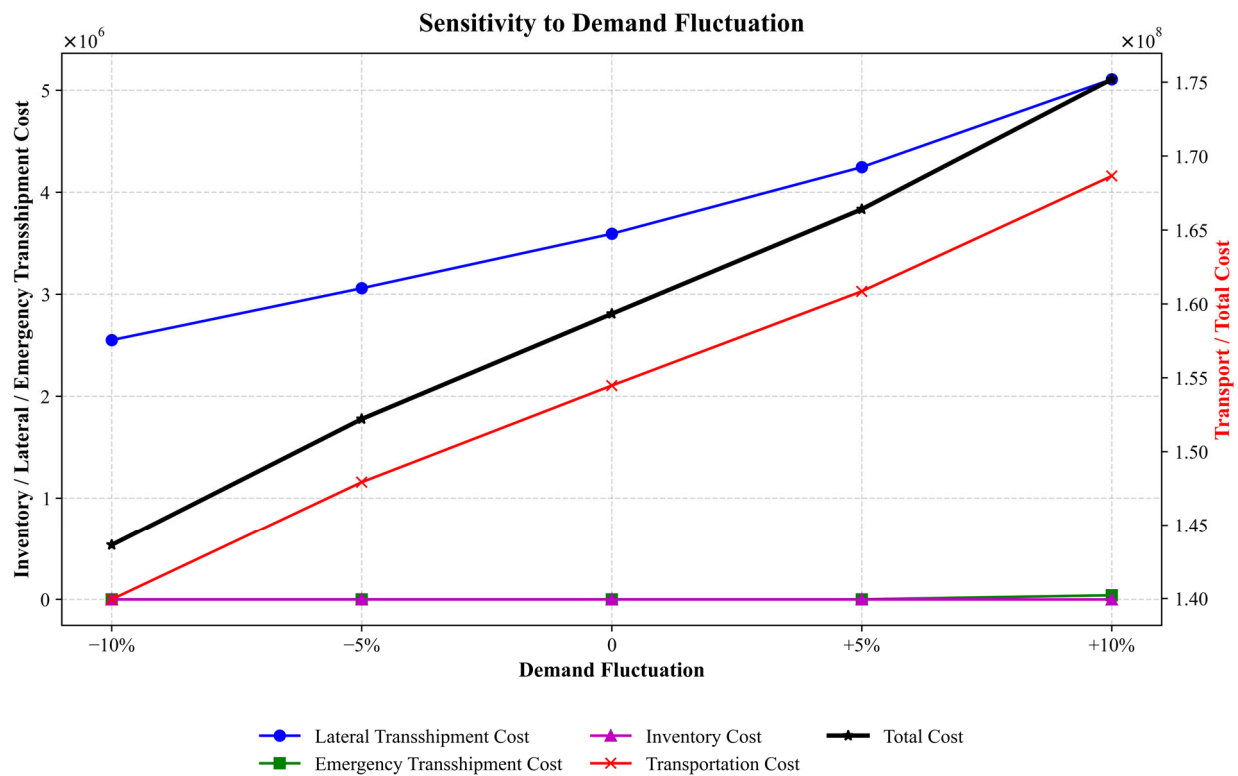


Figure 9. Sensitivity analysis of demand prediction.

Table 7 presents a comparison of various costs within the system with and without the lateral transshipment mechanism. It can be observed that under the mode without lateral transshipment, due to the system's inability to perform inter-regional resource collaborative replenishment, a high emergency transshipment cost of 16.797 million yuan was incurred. After introducing the lateral transshipment mechanism, the total system cost decreased from 164.21 million yuan to 159.33 million yuan, a reduction of approximately 2.97%, and the emergency transshipment cost dropped to 0 yuan. Although a lateral transshipment expense of 3.593 million yuan was incurred and the regular transportation cost also rose from 146.16 million yuan to 154.47 million yuan, representing an increase of 5.69%, the combined increase of the two is lower than the emergency transshipment cost under the mode without lateral transshipment. This indicates that lateral transshipment achieves an effective reduction in cost at a lower logistics price. The shortage costs under both modes are 126,200 yuan, indicating that under the same parameter settings and constraints, the lateral transshipment strategy achieves superior resource transshipment through structural optimization while ensuring the same level of service guarantee. The inventory costs under both groups of models are 0, indicating that under the current transshipment logic, the system tends to balance the relationship between logistics costs and service levels through lower-cost inter-regional adjustments.

Table 7. Cost Breakdown Without Lateral Transshipment (Yuan).

Indicators	Without Lateral Transshipment	With Lateral Transshipment	Changes
Total cost	164,214,575.70	159,328,510.06	Decreased by 2.97%
Transportation cost	146,155,248.54	154,473,459.84	Increased by 5.69%
Lateral transshipment cost	-	3,593,050.22	-
Emergency transshipment cost	16,797,327.16	0	Decreased
Shortage cost	1,262,000.00	1,262,000.00	No change
Inventory cost	0	0	No change
Whether emergency transshipment occurred	Yes	No	-

5.3.3. Shortage Cost and Lateral Transshipment Cost

Increasing the unit shortage cost multiplier from 1 to 30 times the baseline value yields changes in lateral transshipment costs, emergency transshipment costs, inventory costs, regular transportation costs, and total costs, as illustrated in Figure 10. Regarding the overall trend, the total system cost exhibits a monotonically increasing curve with a gradually leveling growth rate, with its absolute value rising from approximately 159 million to 168 million. This indicates that despite a 30-fold sharp increase in the shortage cost, the overall escalation of the total cost is effectively controlled at about 5.6%, demonstrating the system's capacity for cost regulation. Observing the numerical changes of each cost reveals that the regular transportation cost accounts for the majority of the cost proportion, rising steadily from 154 million to 161 million in a nearly linear growth. When the shortage cost multiplier increases from 1 to 10, the lateral transshipment cost remains at its initial baseline of approximately 3.6 million. This shows that within a 10-fold increase in the shortage cost, the system can completely hedge against the shortage risk simply by increasing the regular factory shipments. However, when the multiplier exceeds 10, the lateral transshipment cost curve begins to climb upward, reaching approximately 5.2 million when the multiplier is 30. This implies that after the shortage cost multiplier exceeds 10, relying solely on regular transportation to satisfy all residual demands loses its marginal economic advantage, and the system must more frequently activate lateral transshipments as a supplement. Throughout this entire parameter space, the emergency transportation cost and inventory cost are consistently suppressed near the zero lower bound. This demonstrates that when facing prohibitive shortage costs, the system prefers to utilize a proactive transport network for cost control, rather than relying on reactive emergency replenishment or massive inventory stockpiling.

To evaluate the substitution effect of transshipment strategies within the collaborative network, this study incrementally increases the lateral transshipment cost multiplier from 1.0 to 1.5 with a step size of 0.1, and the cost evolution trends are illustrated in Figure 11. From a global perspective, despite a 50% increase in the multiplier, the total system cost exhibits strong robustness, increasing only marginally from approximately 159 million to 161 million, with an overall growth rate of less than 2%. In the interval where the multiplier rises from 1.0 to 1.3, the lateral transshipment cost increases proportionally with the multiplier to a peak of around 4.5 million, while the emergency transportation cost consistently remains at 0. This indicates that within this numerical range, the global economic viability of lateral transshipment remains superior to emergency transport. However, when the multiplier reaches the critical threshold of 1.4, a mutation occurs in the system's cost structure: the emergency transportation cost suddenly jumps from 0 to approximately 0.65 million, and concurrently, the lateral transshipment cost not only stops growing but experiences a numerical drop, decreasing to about 4.4 million. This result reflects the

variable substitution effect; namely, when the lateral transshipment price at local nodes inflates beyond the critical value of emergency transport costs, the system curtails a substantial amount of uneconomical lateral flows and switches to emergency transport to meet the rigid service level constraints. Furthermore, throughout the entire sensitivity cycle, the inventory cost remains strictly at 0, further verifying that the system primarily relies on the mutual substitution between different transportation strategies to achieve a strict minimization of the global cost when dealing with lateral transshipment cost fluctuations.

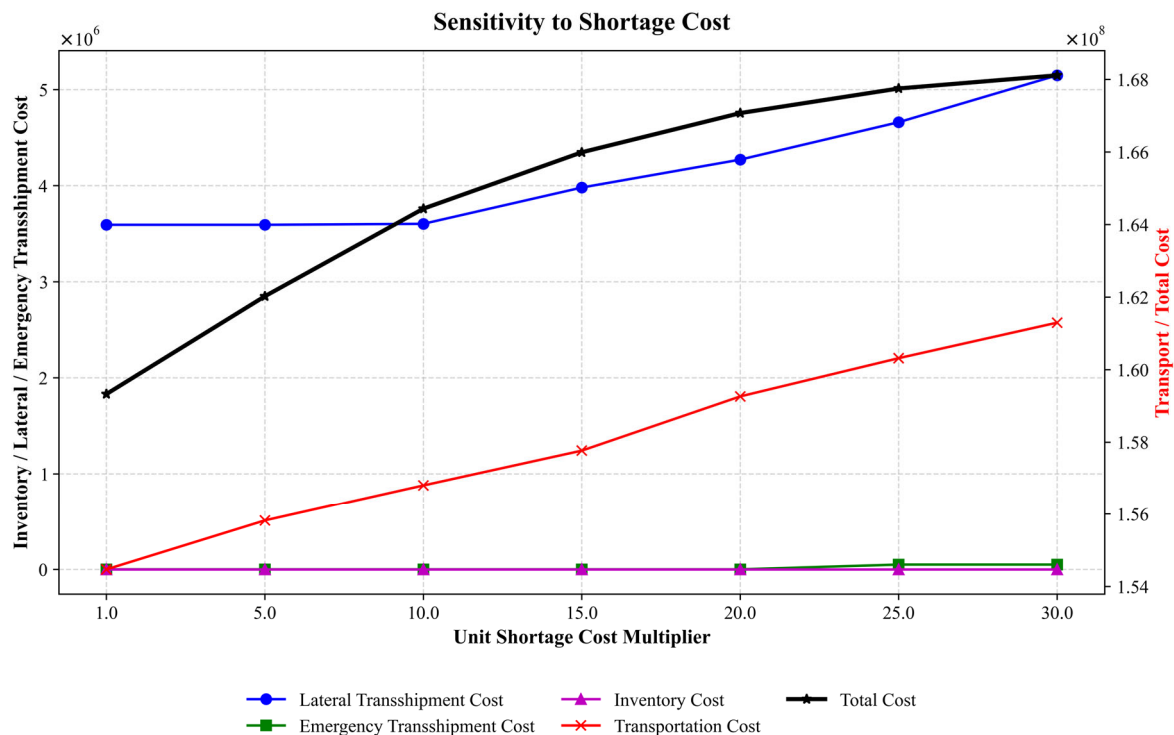


Figure 10. Sensitivity analysis of shortage cost.

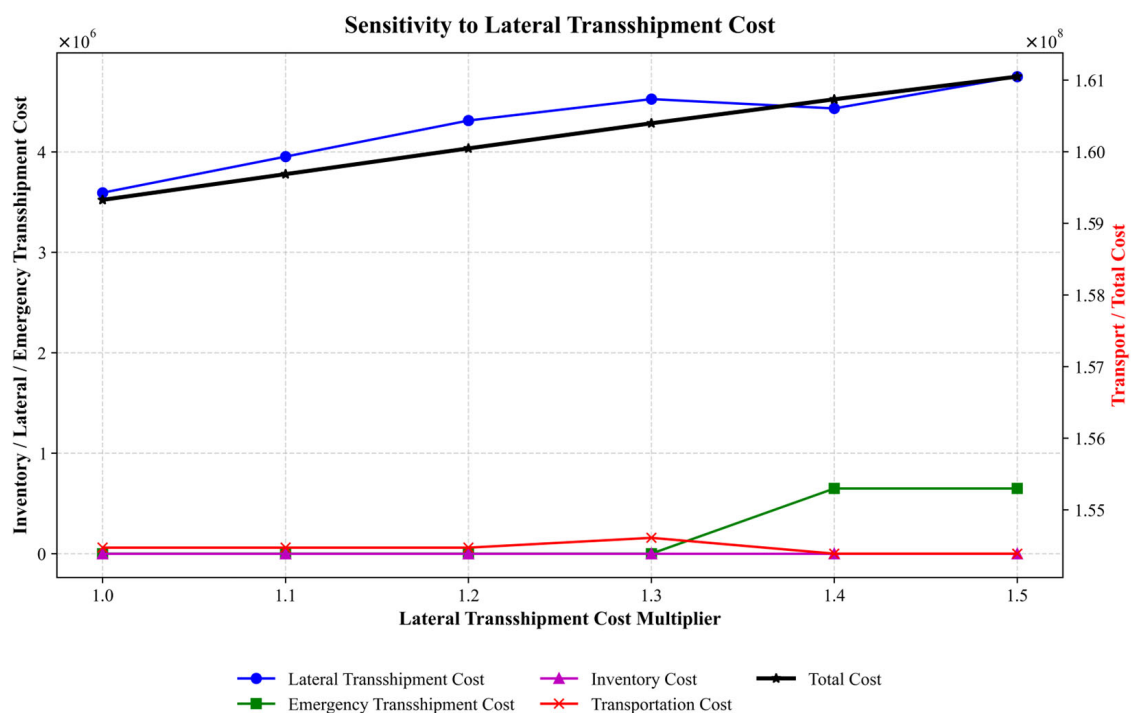


Figure 11. Sensitivity analysis of lateral transport cost.

5.3.4. Central Storage Points Limit

To evaluate the impact of location decisions on the supply chain, we conducted a sensitivity analysis on the maximum allowable number of central storage points, denoted as R . Figure 12 illustrates the variations in distinct cost components as R incrementally increases from 2 to 14. When $R = 2$ or 4, lateral transshipments and emergency shipments are required to fulfill the demand in order to satisfy the service level constraints. Since the unit cost parameters satisfy $ec_k < tc_k < oc_k$, activating these transshipment mechanisms incurs significantly higher costs. However, when R reaches 6, the marginal benefit of allowing an additional location approaches zero. This mathematically demonstrates that the system intrinsically requires approximately 6 central storage points, which can balance the spatial distribution without triggering redundant facility allocation.

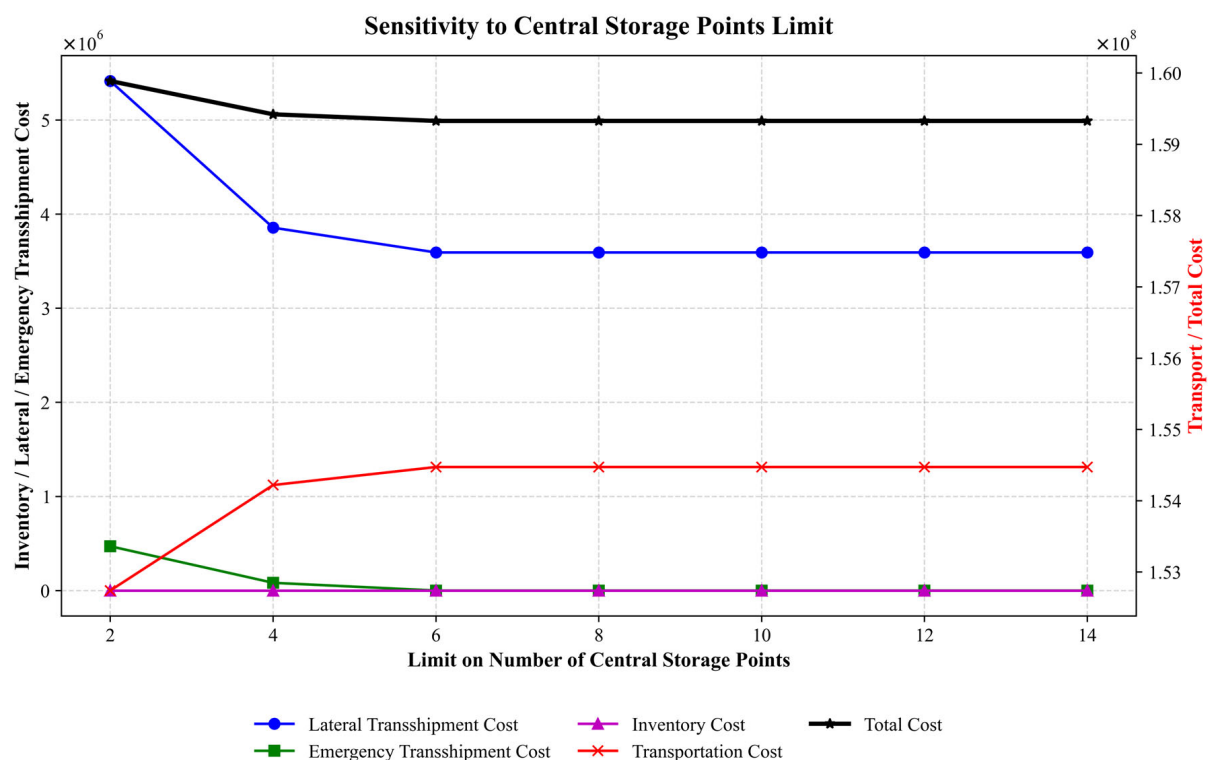


Figure 12. Sensitivity analysis of central storage points limit.

5.4. Discussion and Management Implications

5.4.1. Discussion

To evaluate the effectiveness of the proposed IGDP model, recent studies on demand forecasting were compared, as shown in Table 8. In this paper, the proposed IGDP model achieved a MAPE of 13.86% and an RMSLE of 0.1806, outperforming benchmark models including ARIMA and Holt–Winters in the excavator demand forecasting scenario. In comparison, due to the essential differences in the types and scales of datasets used in various studies, a direct cross-domain numerical comparison of MAPE is not entirely rigorous. However, referring to the general patterns in existing literature, it can be found that the IGDP model proposed in this study demonstrates both rationality and reliability. First, according to classical statistical evaluation criteria, a forecasting model with a MAPE value between 10% and 20% is considered to have reasonable forecasting accuracy. In comparison with the results reported by Thongkunwong et al. [55], the 13.86% achieved by the IGDP model in this study clearly falls within this confidence interval, representing a fully acceptable and accurate forecasting result. Second, according to the studies by Chen et al. [56] and Sutthichaimethee et al. [57], the forecasting performance of GM-

ARIMA hybrid models is superior to that of traditional standalone ARIMA or classical grey models, a pattern that is equally consistent with the experimental results in this paper. Furthermore, in the studies by Sutthichaimethee et al. [57] and Jin et al. [29], when dealing with small-sample data characterized by non-linearity and incomplete information, grey hybrid models exhibit excellent forecasting effectiveness. In certain scenarios, their forecasting precision can even surpass that of complex machine learning models such as BP neural networks, ANNs, or SVR, which also illustrates the unique advantages of grey forecasting in sample-scarce systems. Comparing our findings with these recent literatures corroborates the rationality of the research results and the reliability of the proposed method in this paper.

Table 8. Performance comparison between the proposed IGDP model and typical models reported in the recent literature.

Reference	Application Field	MAPE	Comparative Conclusion
Chen et al. (2023) [56]	Forecasting global average temperature	S-GM-ARIMA (0.48%) < GM(1,1) (0.53%) < ARIMA (0.57%) < Ridge Regression (0.60%) < Lasso Regression (0.61%)	GM-ARIMA outperforms single traditional statistical models.
Fang et al. (2024) [58]	Quantity prediction of urban C&D waste	GM-ARIMA (8.5%) < GM (12.11%) < ARIMA (14.26)	
Thongkunwong et al. (2025) [55]	Predicting the number of breast cancer patients	FDGM (15.25%) < FGM (15.49%) < DGM (17.41%) < GM (17.78%)	A MAPE between 10% and 20% is acceptable.
Sutthichaimethee et al. (2025) [57]	Forecasting agricultural waste and greenhouse gas emissions	Path-GMM-Nearest-Neighbor (1.09%) < GM-ARIMA (3.99%) < Fuzzy (7.25%) < BP (7.99%) < ANN (9.89%) < Regression (19.05%)	GM-ARIMA outperforms single traditional statistical models.
Jin et al. (2025) [29]	Forecasting quarterly solar energy generation	SDPGM(1,N) (2.21%) < BP (12.01%) < SVR (14.86%) < GMC(1,N) (20.93%) < DGM (1,N) (26.65%) < GM(1,N) (27.60%) < SARIMAX (36.31%)	Grey models outperform machine learning models under certain conditions of limited information.
This paper	Forecasting the demand of excavators in China	IGDP (13.86%) < Holt Winters (22.64%) < ARIMA (23.94%)	GM-ARIMA outperforms single traditional statistical models.

To validate the effectiveness and practical relevance of the proposed LAI model with lateral transshipment, recent studies published between 2024 and 2026 were reviewed and compared in terms of research focus, and major findings. As shown in Table 9, the selected studies mainly focus on location-inventory-routing problems, location-allocation optimization, and inventory-routing problems. Although lateral transshipment has been widely investigated in recent studies, limited attention has been paid to incorporating it into LAIP.

In addition, the proposed LAI model integrates demand forecasting results into inventory allocation decisions and evaluates the impacts of multiple factors, including demand fluctuations, shortage costs, and lateral transshipment costs.

The comparative analysis reveals that the findings of the proposed model are generally consistent with those reported in recent literature. Specifically, lateral transshipment effectively mitigates demand imbalances and reduces total system costs, while demand uncertainty and shortage costs remain critical drivers of network performance. Furthermore, the proposed model demonstrates robustness under demand variations and provides additional managerial insights regarding the coordination between demand forecasting and inventory allocation.

Table 9. Comparison of computational results between the proposed LAI model and typical models reported in the recent literature.

Reference	Research Focus	Parameters Tested	Transshipment Types Considered	Core Sensitivity Conclusion Consistent with this Paper
Wang et al. (2024) [59]	Location–inventory–routing with lateral transshipment	Comparison of models with and without lateral transshipment	Lateral transshipment between warehouses	Lateral transshipment strategy effectively reduces total cost
Yang et al. (2024) [60]	Location–allocation with lateral transshipment		Lateral transshipment between emergency warehouses	
Man et al. (2025) [61]	Inventory-routing problem with lateral transshipment	Demand forecast $\pm 10\%$ fluctuation	Reactive lateral transshipment only	Demand deviation linearly raises total cost, regular transport dominates cost growth; lateral transshipment avoids frequent emergency dispatch under moderate uncertainty
Mohammadpour Larimi et al. (2025) [62]	LIP with lateral transshipment	Shortage cost	Lateral transshipment between distribution centers	Shortage cost causes the most significant variations in objective functions
Yang et al. (2026) [13]	LAIP	Demand distribution; unit transport/storage cost ($\pm 40\%$)	-	Demand distribution unevenness drives total cost up; system exhibits strong robustness to $\pm 40\%$ cost perturbations.
This paper	LAIP with lateral transshipment	a. Comparison of models with and without lateral transshipment; b. Demand forecast $\pm 10\%$ fluctuation c. Shortage cost; d. Lateral transshipment cost; e. Central storage points limit	Lateral transshipment between agents	-

5.4.2. Management Implications

Drawing on the sensitivity analysis results regarding demand fluctuations, comparison of lateral transshipment strategies, shortage costs, lateral transshipment costs, and central storage points limit, this study offers practical managerial insights for enterprises engaged in cross-regional collaborative inventory and transshipment decisions.

1. Strengthen demand-driven inventory coordination capabilities. The demand sensitivity analysis demonstrates that increasing demand primarily leads to higher regular transportation and lateral transshipment costs, while emergency transshipment and inventory holding costs remain close to zero. This finding suggests that the proposed framework can effectively absorb demand fluctuations through dynamic routing and inventory reallocation rather than relying on costly reactive measures. For decision-makers, this implies that forecasting errors can propagate throughout the supply chain and amplify operational costs. Therefore, enterprises should enhance forecasting accuracy by integrating multi-source demand data, implementing rolling forecasting

mechanisms, and conducting scenario-based planning. More importantly, demand forecasts should be directly incorporated into inventory allocation and transshipment decisions to enable proactive resource coordination across regions.

2. Establish regional inventory-sharing networks through lateral transshipment. The comparative analysis indicates that introducing lateral transshipment reduces total system costs by 2.97% while completely eliminating emergency transshipment costs. Although regular transportation and lateral transshipment expenses increase, these additional costs are significantly lower than the emergency replenishment costs incurred under a decentralized strategy. This finding highlights that lateral transshipment should not be regarded merely as an emergency response mechanism but rather as a strategic tool for regional inventory coordination. Enterprises operating in construction machinery supply chains, which are characterized by high-value products, wide service coverage, and heterogeneous demand patterns, should establish inventory-sharing networks among regional distributors. Such networks can facilitate resource pooling and improve responsiveness without increasing overall service costs.
3. Identify economic thresholds for transshipment decisions. The sensitivity analysis reveals that the effectiveness of lateral transshipment depends strongly on cost thresholds. When the lateral transshipment cost multiplier remains below 1.4, the system consistently favors inter-regional coordination over emergency replenishment. However, once this threshold is exceeded, emergency transportation becomes economically preferable for certain demand scenarios. Similarly, when shortage costs increase beyond ten times the baseline value, the system begins to activate lateral transshipment more frequently to mitigate shortage risks. These findings suggest that managers should continuously monitor the relative costs of transportation alternatives and establish cost-trigger mechanisms for dynamic decision-making. Investments in information sharing, transportation coordination, and process optimization can help maintain the economic advantage of lateral transshipment within collaborative supply chain networks.
4. Optimize network configuration through a limited number of centralized storage points. The sensitivity analysis on centralized storage point limits indicates that the marginal benefits of adding new facilities diminish significantly once the number of centralized storage points reaches six. Beyond this threshold, additional facilities generate limited cost savings while increasing network complexity and coordination requirements. Therefore, enterprises should avoid excessive facility deployment and instead focus on strategically selecting a limited number of regional hubs based on geographic accessibility, storage capacity, and demand coverage. For the studied case, configuring six centralized storage points provides an effective balance among transportation efficiency, transshipment flexibility, and network operating costs.

6. Conclusions

This paper aimed to minimize total supply chain costs and optimize the LAIP decisions within a two-echelon system under conditions of demand fluctuation and regional dispersion. To achieve these objectives, an integrated framework was proposed. First, an ARMA-GM(1,1) model is employed to forecast demand under small-sample conditions. Subsequently, the SHADE algorithm is utilized to collaboratively optimize the location, allocation, and transshipment decisions. Taking the excavator transshipment scenario of Sany Heavy Machinery as a case study, the proposed model and algorithm are validated. The main conclusions are as follows:

- (a) Under conditions of limited data where the demand time series exhibits both trend variations and seasonal perturbations, the proposed IGDP forecasting model achieves

the lowest RMSLE and MAPE compared to classical time series forecasting models such as ARIMA and Holt–Winters, recording 0.1806 and 13.86%, respectively.

- (b) The case study results demonstrate that the proposed IGDP-SHADE successfully achieves the objective of minimizing total supply chain costs while improving network coordination efficiency. The IGDP-SHADE algorithm obtains the same optimal objective value as the Gurobi exact solver while reducing CPU time by 17.47%, demonstrating both solution quality and computational efficiency.
- (c) The sensitivity analysis results demonstrate that introducing the lateral transshipment mechanism reduces total system costs by 2.97% compared with the scenario without transshipment, while the optimal number of centralized storage points is identified as six. Furthermore, the proposed framework maintains stable performance under varying demand levels and cost parameters by dynamically adjusting transportation and transshipment strategies. These findings confirm the robustness of the proposed framework and highlight the importance of cost-threshold-based decision-making in regional inventory coordination.

Despite these contributions, this paper has the following limitations:

- (a) When forecasting product demand, constrained by the scale of the available empirical data, the model does not fully account for the impact of multidimensional external factors such as macroeconomic conditions and market volatility. Forcibly introducing high-dimensional features under current data constraints would easily lead to model overfitting. Future research could attempt to introduce advanced algorithms such as transfer learning or few-shot learning to achieve multi-factor-driven demand forecasting while circumventing the risk of overfitting.
- (b) The optimization phase of this study primarily utilizes deterministic point forecasts as inputs. Future research could directly incorporate prediction errors into the decision-making model—for instance, by constructing interval forecasts or scenario trees and employing robust optimization or distributionally robust optimization. This would enable the inventory and transshipment strategies to maintain more stable cost and service performance under demand deviations, thereby mitigating the amplification effect of forecasting errors within the supply chain network.

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