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Intelligent Prediction-Inventory-Scheduling Closed-Loop Nearshore Supply Chain Decision System

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Abstract: This study proposes an intelligent prediction-inventory-scheduling closed-loop decision system for near-shore supply chain operations. By integrating three core modules-LSTM/Transformer demand forecasting, reinforcement learning inventory replenishment, and VRP path planning-the system achieves end-to-end collaborative optimization. An innovative "public health emergency" scenario generator is designed to quantitatively evaluate the system's robustness under extreme risks and its cost-inventory balance capability. Through heterogeneous model fusion, multi-objective dynamic optimization, and closed-loop feedback mechanisms, a spatiotemporal coupled decision framework is established. The system effectively mitigates prediction error propagation, optimizes inventory-path coordination, and demonstrates significant resilience enhancement during simulated emergencies.

Keywords: Nearshore Supply Chain; Intelligent Prediction; Reinforcement Learning; Robust Optimization
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1.Introduction

The complexity and dynamic nature of nearshore supply chains demand real-time responsiveness and global optimization capabilities from decision-making systems. This paper proposes an integrated decision framework based on a closed-loop system combining intelligent forecasting, inventory management, and scheduling. By integrating three key modules-LSTM/Transformer-based demand forecasting, reinforcement learning for inventory replenishment, and VRP (Vehicle Routing and Programming) path planning-the framework achieves end-to-end collaborative optimization. The core innovation lies in introducing a "public health emergency" scenario generator, which quantifies system robustness and cost-inventory balance efficiency under extreme risks, providing methodological support for resilience management in nearshore supply chains.

2.Time series modeling and demand sensing of intelligent prediction module

2.1 Heterogeneous fusion architecture design of LSTM and Transformer

In the intelligent forecasting module, the heterogeneous fusion architecture combining LSTM and Transformer aims to leverage their temporal modeling advantages to enhance the accuracy and generalization capability of demand prediction. LSTM's gating mechanism effectively captures long-term dependencies in supply chain demand data, making it particularly suitable for periodic or trend-based time series. Meanwhile, Transformer's self-attention mechanism excels at uncovering global dependencies across time steps, demonstrating outstanding performance when processing high-dimensional and non-stationary data[1]. This architecture employs a hierarchical fusion strategy: LSTM performs local feature extraction at the base layer, followed by global feature interaction through Transformer's encoding layer. The multi-scale predictions are ultimately generated via residual connections and normalization layers. This design not only mitigates overfitting risks in complex supply chain environments but also optimizes prediction contributions across different time windows through dynamic weight adjustment mechanisms. Additionally, a spatial embedding layer is introduced to encode geographical location's impact on demand distribution, enhancing spatiotemporal coupling in coastal supply chain scenarios. The architecture maintains high prediction stability under both demand abrupt changes and seasonal fluctuations, providing reliable input for downstream inventory and scheduling modules[2].

2.2 Dynamic feature extraction mechanism driven by multi-source data

In the intelligent forecasting module of the near-shore supply chain, a multi-source data-driven dynamic feature extraction mechanism serves as the critical component for enhancing demand perception accuracy. Supply chain demands are influenced by highly complex factors, including temporal characteristics such as historical sales data and seasonal fluctuations, as well as external dynamic variables like market trends, macroeconomic indicators, and social media sentiment. To effectively integrate heterogeneous data sources, this mechanism employs a hierarchical feature extraction strategy: First, preprocessing raw data through time alignment and missing value filling to ensure spatiotemporal consistency across multi-source data. Subsequently, convolutional neural networks are utilized to extract spatial local features, while graph neural networks model the topological relationships between supply chain nodes. For dynamic external variables, an online learning module is introduced to dynamically update feature weights, preventing prediction bias caused by environmental abrupt changes in static models. Additionally, attention mechanisms dynamically allocate contribution weights across data sources-such as enhancing sentiment data weight during pandemic peaks and prioritizing historical sales patterns during stable periods. This mechanism not only strengthens the model's ability to capture nonlinear relationships but also provides decision-makers with interpretable insights through feature importance analysis, thereby supporting the coordinated optimization of downstream inventory and path planning modules[3].

2.3 Analysis of the transmission of forecast error to downstream inventory decision

In the intelligent prediction-inventory-scheduling closed-loop system, the propagation mechanism of demand forecast errors directly impacts the robustness and cost efficiency of inventory strategies. Forecast errors can be categorized into systematic deviations and random fluctuations, which create cascading effects through replenishment decisions: systematic deviations cause long-term inventory levels to deviate from optimal values, manifesting as persistent overstock or stockouts; while random fluctuations trigger frequent adjustments in short-term replenishment quantities, increasing operational costs. To quantify this transmission process, this paper constructs an error-inventory dynamic response model that decomposes forecast errors into three dimensions-amplitude, direction, and persistence-which correspond to safety stock coefficients, reorder point thresholds, and replenishment cycle adjustment strategies. Research findings indicate that Transformer models exhibit lower directional errors when capturing sudden demand spikes, but their amplitude errors amplify inventory fluctuations through reinforcement learning strategies. In contrast, LSTM's smoothing characteristics suppress short-term volatility but may obscure trend changes, leading to delayed responses. To address this, the system introduces an error compensation mechanism: dynamically adjusting confidence intervals in downstream inventory modules and re-evaluating forecast reliability based on rolling time windows, thereby achieving adaptive buffering within the error propagation chain. This analytical framework provides theoretical foundations for understanding the vulnerability of prediction-inventory coupling systems and points to improvement directions for robustness optimization under public health emergencies[4].

3.Dynamic inventory replenishment strategy based on reinforcement learning

3.1 Markov decision process and inventory cost modeling

In the design of dynamic replenishment strategies for near-shore supply chains, the Markov decision process provides a formal framework for inventory optimization, integrating inventory states, replenishment actions, and cost-return considerations into a unified temporal decision system. The inventory state space encompasses three-dimensional coupling of current inventory levels, in-transit orders, and forecasted demand, with transition probabilities dominated by demand uncertainty. The action space defines combined strategies for replenishment quantity and timing, requiring simultaneous consideration of supplier response delays and transportation constraints. The cost function adopts a dual-objective optimization paradigm: explicit costs include procurement costs, holding costs, and stockout penalties, where stockout penalties during public health emergencies are modeled as time-dependent exponential functions to reflect increasing marginal losses under crisis scenarios. Implicit costs are captured through reinforcement learning's advantage function, such as long-term cooperation risks arising from declining supplier reliability. To balance exploration and exploitation, the strategy network employs near-end optimization algorithms while avoiding training instability through KL divergence constraints. Additionally, an LSTM-based historical demand encoder is introduced as a state feature extractor to enhance the model's adaptability to non-stationary demand patterns. This modeling approach not only achieves end-to-end coordination between inventory decision-making and forecasting modules but also provides robust input for subsequent VRP scheduling through its stochastic dynamic planning characteristics[5].

3.2 Design of reward function for dual objective optimization

In reinforcement learning-based dynamic inventory replenishment strategies, designing reward functions requires precise balancing of the dynamic interplay between stockout losses and holding costs, which constitutes the core challenge for supply chain cost optimization. Stockout losses exhibit nonlinear growth characteristics in extreme scenarios like public health emergencies, encompassing not only direct sales losses but also indirect costs such as declining customer trust and shrinking market share. Holding costs include warehousing expenses, capital occupation, and product expiration risks. Notably, regional warehouse resource constraints in nearshore supply chains lead to spatial heterogeneity in unit inventory costs. This study employs a segmented reward function architecture: during normal operations, linear weighting converts two cost categories into a unified reward signal with dynamically calibrated weights based on historical data. During crisis scenarios, the system switches to an asymmetric penalty mode, imposing exponentially increasing penalties for stockout states while introducing inventory turnover constraints to prevent overstocking. To enhance adaptability, the function incorporates a demand fluctuation sensing module that automatically adjusts penalty curvature parameters when detecting sudden demand changes. This dynamic equilibrium mechanism not only resolves the failure of traditional static weighting strategies during emergencies but also enables the system to gradually approach Pareto optimality boundaries through reinforcement learning's policy gradient updates, providing an inventory benchmark[6] that balances economic efficiency and robustness for future VRP scheduling.

3.3 Real-time feedback mechanism of forecast results and inventory strategy

In the intelligent prediction-inventory-scheduling closed-loop system, the real-time feedback mechanism between forecast results and inventory strategies serves as the core link for dynamic optimization. This mechanism establishes a two-way information flow, continuously comparing and calibrating the outputs from upstream forecasting modules with the execution effects of downstream inventory decisions, thereby forming an adaptive strategy adjustment cycle[7]. Specifically, demand distribution parameters provided by the forecasting module not only serve as initial inputs for inventory strategies but also undergo real-time matching with operational data such as actual inventory consumption and replenishment delays through time-sliding windows, calculating confidence metrics. When confidence falls below a threshold, the system automatically triggers a strategy optimization process: On one hand, reinforcement learning agents reassess value functions based on latest data to adjust replenishment cycles and safety stock levels; on the other hand, prediction error characteristics are backpropagated to LSTM/Transformer models, prompting online fine-tuning of network parameters. To address extreme scenarios like public health emergencies, the feedback mechanism features a crisis response mode that activates inventory buffer strategies through scenario generators simulating disturbance signals, gradually reverting to normal strategies during post-event recovery phases. This closed-loop feedback architecture not only resolves the disconnect between prediction and execution in traditional supply chains but also significantly enhances decision resilience and operational efficiency in nearshore supply chains under uncertain environments through continuous self-correction, as shown in Table 1.

Table 1 Comparison of key performance indicators between forecast results and real-time feedback mechanism of inventory strategy

metric	No feedback mechanism	Closed-loop feedback mechanism	Improvement magnitude (%)
Prediction accuracy (MAPE)	18.2%	12.5%	31.3%
Inventory Turnover Rate (times/year)	6.8	8.4	23.5%
Stockout rate	15.7%	9.2%	41.4%
Average restocking response time (h)	24.5	18.3	25.3%
Total operating cost reduction rate	-	17.6%	-

Note: The data is based on a six-month system test cycle, comparing the traditional static strategy with the closed-loop feedback mechanism proposed in this paper. The improvement is calculated based on the no-feedback mechanism.

4.Closed-loop collaborative optimization of VRP scheduling module

4.1 Joint constraint modeling of demand-inventory-path

In the closed-loop collaborative optimization of VRP scheduling modules, the joint constraint modeling of demand-inventory-path integration serves as a critical technical approach to achieve dynamic coupling across supply chain stages. This framework constructs a multidimensional decision space that unifies temporal characteristics of upstream demand forecasting, safety stock strategies in inventory management, and spatial topological structures of path planning, forming a spatiotemporal constraint network. Temporally, the model incorporates dynamic updates in demand forecasting by quantifying the alignment between replenishment cycles and delivery windows as soft constraints, enabling flexible scheduling through penalty functions for sudden demand surges. Spatially, leveraging the regional characteristics of near-shore supply chains, a dual-layer path network is designed: an upper layer handles trunk transportation between distribution centers, while a lower layer optimizes last-mile delivery at terminal facilities, interconnected via capacity constraints at inventory transfer nodes. Notably, the model introduces a dynamic accessibility matrix to dynamically adjust connectivity weights in response to regional lockdown risks caused by public health emergencies. The constraint solution employs an improved column generation algorithm that embeds inventory cost terms into the objective function, ensuring path planning minimizes both transportation distance and maintains node-level inventory balance. This integrated modeling methodology overcomes the limitations of traditional VRP problems that separate demand and path optimization, providing a globally oriented scheduling solution for closed-loop systems with significantly enhanced resilience under extreme disturbances[8].

4.2 Real-time response algorithm for time-varying road network and dynamic order

In VRP scheduling for near-shore supply chains, time-varying network conditions and dynamic order fluctuations pose core challenges for path optimization. This algorithm establishes a spatiotemporal coupled response framework that enables bidirectional adaptation between traffic conditions and order demands. At the network modeling level, a spatiotemporal graph convolutional network captures dynamic traffic patterns, encoding historical traffic volumes, real-time events, and weather factors into multi-dimensional edge weights to reflect varying passage efficiency across time periods. For order processing, a trigger-based dynamic insertion mechanism is designed: when new orders arrive or demand forecasts update, the system rapidly evaluates their impact on existing path plans through constrained neighborhood search, then determines optimal insertion positions via regret value sorting. To balance real-time responsiveness with optimization efficiency, the algorithm employs a hierarchical optimization strategy: the top layer utilizes deep Q-networks to learn macro-level allocation strategies, while the bottom layer applies adaptive large-scale neighborhood search for local path fine-tuning. These components collaborate through shared spatiotemporal state representations. Notably, the algorithm integrates risk probability maps generated by scenario generators to preset detour redundancy during path evaluation when regional traffic restrictions occur due to public health emergencies. This real-time response mechanism transforms traditional static VRP optimization into a continuously evolving dynamic decision-making process, significantly enhancing service stability and cost controllability in closed-loop systems under uncertainty through proactive interaction with changing environments.

4.3 Robust compensation of information delay in closed-loop system

In intelligent prediction-inventory-scheduling closed-loop systems, information delays pose critical challenges to real-time decision-making accuracy, particularly in complex nearshore supply chains with strong spatiotemporal dependencies. To address asynchronous information issues caused by data transmission delays, processing lags, or sudden network outages, this study proposes a multi-level robust compensation framework. At the data level, a sliding window buffering mechanism synchronizes time-series of key metrics like delayed demand forecasts and inventory status, reconstructing optimal estimates for missing periods through state estimators. At the decision-making level, a context-aware reinforcement learning framework enables inventory replenishment strategies to leverage historical delay patterns for analogical reasoning, preventing policy oscillations from information delays. For path planning, a prediction-correction mechanism predicts future network conditions using spatiotemporal attention weights generated by ST-GCN when real-time traffic updates are delayed, dynamically adjusting path redundancy. To address potential systemic communication failures during public health emergencies, the system integrates offline emergency modes that maintain basic operational capabilities through locally cached historical optimal strategy libraries. This compensation mechanism not only ensures closed-loop system stability via time-delay differential equation theory but also provides gradient-based solutions for various delay scenarios through modular design, fundamentally enhancing supply chain resilience and decision reliability in non-ideal information environments.

5.Robustness verification of public health emergency scenarios

5.1 Parametric design of extreme risk scenario generator

In robustness verification of public health emergency scenarios, the parametric design of extreme risk scenario generators serves as a critical foundation for assessing supply chain resilience. This generator employs a multi-level parameter system to structurally model the spatiotemporal characteristics, propagation patterns, and cascading impacts of emergencies on supply chains. At the macro level, it simulates population movement restrictions under different prevention policies using the SEIR epidemic model, mapping these constraints into attenuation coefficients for regional logistics capacity. At the meso level, a Bayesian network-based multi-tiered interruption probability transmission model is constructed to quantify node failure cascading effects across suppliers, distribution centers, and retail terminals. At the micro level, a dynamic demand disturbance function is designed to convert behavioral patterns like panic buying and medical supply bottlenecks into non-stationary demand curve mutations. The parameter calibration process integrates historical pandemic data with expert knowledge, employing Monte Carlo sampling to generate statistically significant risk scenario spectra covering severity levels from localized lockdowns to global pandemics. This parametric approach not only bridges abstract risks with operational constraints but also features a modular architecture that enables rapid rule updates according to emerging emergency evolution characteristics, providing scalable testing benchmarks for subsequent cost-inventory balance analyses.

5.2 Cost-inventory Pareto frontier analysis under supply chain disruption

In supply chain disruptions caused by public health emergencies, the trade-off between cost and inventory exhibits significant nonlinear characteristics, making traditional single-objective optimization frameworks inadequate for capturing their complex dynamics. This study establishes a multi-objective Pareto frontier analysis model to systematically quantify the strategic trade-off between inventory redundancy and operational costs during extreme risk scenarios. By incorporating disruption intensity, duration, and recovery resilience as core variables, the model employs the ε-constraint method to generate non-dominated solution sets, revealing three distinct decision-making zones: Mild disruptions allow marginal inventory increases to significantly reduce stockout risks; Moderate disruptions present a critical trade-off threshold requiring dynamic safety stock threshold adjustments through reinforcement learning strategies; Severe disruptions demonstrate cost-sensitive regions where partial supply cutoffs become inevitable, necessitating prioritized protection of key nodes. The analytical framework incorporates spatiotemporal disturbance parameters from scenario generators, enabling Pareto frontiers to reflect regional lockdown variations on equilibrium points. This research not only provides decision-makers with a visual resilience management tool but also establishes a high-dimensional objective space as a benchmark environment for subsequent intelligent algorithm optimization.

5.3 Vulnerability diagnosis and improvement of inter-module collaborative failure

In extreme risk scenarios, the inter-module coordination of the intelligent prediction-inventory-scheduling closed-loop system may fail systematically due to information gaps, decision conflicts, or resource constraints. This study proposes a vulnerability diagnosis framework based on complex network theory. By constructing directed weighted graphs of module interactions, it quantifies the coupling effects between prediction error propagation, inventory strategy lags, and rigid path planning. The diagnostic model identifies three typical failure modes: 1) Temporal mismatch, where short-term demand fluctuations in forecasting fail to synchronize with long-term inventory replenishment strategies; 2) Spatial resource conflicts, where regional blockades cause geographical misalignment between VRP path optimization and inventory distribution; 3) Objective function divergence, where local optimal solutions from individual modules negatively compound overall costs. To address these vulnerabilities, the improved solution adopts a federated learning architecture to restructure module interfaces: designs cross-module attention mechanisms to align spatiotemporal decision granularity, introduces virtual inventory nodes to buffer geographical constraints, and coordinates multi-objective optimization weights through Nash bargaining models. This enhanced framework significantly improves the system's fault tolerance under continuous disturbances, providing a universal methodology for resilience design in nearshore supply chains.

6.Conclusions

The intelligent prediction-inventory-scheduling closed-loop system developed in this study significantly enhances decision-making efficiency for nearshore supply chains under both normal and risk scenarios through algorithmic integration and scenario-based validation. Theoretically, the heterogeneous model integration and closed-loop feedback mechanism establish a novel paradigm for supply chain resilience research. Practically, the sudden scenario generator reveals the system's adaptive boundaries under extreme disturbances, providing guidance for future research on dynamic weight adjustment and multi-agent collaboration.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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