

Prediction and Optimization of Commodity Stagnation Risk for Cross-Border Multi-Overseas-Warehouse

Feiran Yang

*School of Mathematical Sciences, Hebei Normal University, Shijiazhuang, China
yangfeiran0730@163.com*

Abstract. Aiming at the problems of inaccurate prediction of commodity stagnation risk, unbalanced inventory allocation, and high inventory holding cost and severe stagnation loss in the collaborative operation of multiple cross-border overseas warehouses, this paper constructs a multi-dimensional feature indicator system covering inventory attributes, supply chain operations, market sales, and overseas warehouse heterogeneity. With data optimization conducted via the 3σ criterion, Pearson correlation analysis and recursive feature elimination, a hybrid LightGBM model integrated with an attention mechanism is established. This study defines stagnation labels based on inventory turnover days in the next 30 days to accurately identify core risk factors. Taking accuracy, F1-score and other metrics as evaluation criteria, this paper compares the proposed model with multiple traditional machine learning models. On the basis of the predicted continuous stagnation risk scores, a multi-objective inventory optimization model is constructed to minimize inventory holding cost as well as stagnation and stockout losses. Combined with practical operational constraints, the improved NSGA-II algorithm is adopted for model solution to realize risk-oriented inventory allocation.

Keywords: Cross-border overseas warehouse, stagnation risk prediction, LightGBM-attention mechanism, multi-objective inventory optimization, improved NSGA-II

1. Introduction

With the rapid development of global cross-border e-commerce, multi-overseas warehouse operations have been widely adopted to shorten delivery cycles and enhance local customer experience. Cross-border enterprises deploy independent warehouses worldwide and replenish inventory via bulk sea transportation for local order fulfillment. However, long replenishment cycles of 14–28 days, fluctuating market demand, diverse regional consumption preferences, and high warehousing and abandonment costs have caused serious slow-moving inventory issues in multi-warehouse systems [1].

Over 62% of sellers face uneven stock across warehouses; the same items may sit unsold in one but be out of stock in another, industry surveys show. For clothing, home goods and seasonal items, up to 35% of inventory becomes slow-moving, causing an average loss over 180,000 US dollars per warehouse each year. Old methods forecast per warehouse by historical sales only, ignoring location, shipping time, promotions, product life cycles, and local demand; thus risky items are often missed,

and separate ordering creates more stuck stock and tied capital. Digital operations create much data from various sources, yet data isolation and insufficient use of data features still hold back inventory risk management; so, a risk prediction framework with multiple dimensions and a collaborative inventory optimization model are needed, to warn of multi-warehouse stagnation early and move stock flexibly.

Current studies mainly concentrate on single-warehouse scenarios using only time-series sales data, neglecting spatial correlations among multiple warehouses and lacking systematic multi-dimensional feature frameworks [2]. In addition, existing research separates risk prediction from inventory optimization without integrated two-stage solutions. To address these gaps, this paper establishes a five-dimensional feature system covering warehouse, product, market, logistics and operational attributes, and develops an integrated framework combining multi-warehouse stagnation risk prediction and multi-objective stochastic inventory optimization. This study complements existing inventory risk management theories for multi-overseas warehouse networks.

Practical work across several warehouses can be supported by the two-stage method people put forward; first, it forecasts the likelihood that each product type will become unsold at different storage sites, so that high-risk items are spotted ahead of time; second, under limits set for stagnation risk, it adjusts order amounts, when to move stock between locations, and the safe buffer levels to hold; the method helps cut down costs from storing, discarding, and returning slow-selling goods while keeping the out-of-stock rate steady; it also makes stock turn over faster and money use more efficient, giving guidance built on data for the careful handling of stock across many storage places.

In recent years, various researchers have conducted the following research:

First, XGBoost is adopted for demand forecasting and a two-stage inventory allocation model is established to optimize basic inventory and dynamic replenishment for overseas warehouses [3]. However, the model only utilizes single-dimensional sales features without multi-dimensional operational indicators, failing to distinguish slow-moving risk differences across warehouses [4].

Second, Zhang built a slow-moving early warning model with multi-dimensional indicators for single overseas warehouses, integrating product, promotion and logistics features to boost prediction accuracy. The research is limited to single-warehouse settings and ignores cross-warehouse inventory transfer and linked spatial demand, incapable of resolving structural slow-moving stock imbalances among multiple warehouses [5].

Third, Xu & Zhao designed a hybrid inventory control model integrating machine learning and operational research to address multi-location inventory allocation. The model does not take slow-moving risks as core constraints and only uses average demand as inputs, unable to quantify the impact of slow-moving losses on inventory decisions [6].

In summary, existing literature has three major limitations: insufficient mining of multi-dimensional operational features under multi-warehouse scenarios, disconnection between slow-moving risk prediction and inventory optimization without closed-loop linkage, and lack of collaborative optimization strategies targeting cross-warehouse inventory imbalance and differentiated slow-moving risks. These gaps lay the innovative foundation for this research.

2. Methodology

2.1. Multi-dimensional operational feature system of cross-border overseas warehouses

In this study, a set of indicators is built from several angles for the situation of many overseas warehouses, and it shows the whole-life status of cross-border goods, covering four main sides: the

side of inventory features, the side of how the supply chain works, the side of market sales, and the side of differences among overseas warehouses in different regions.

First, the inventory side shows the inside stock condition, like how much stock is on hand, the number of days to turn over the stock, the cost to hold inventory, the shelf life of each batch, and the time between reorders;

Second, the supply chain side catches the limits that come from both upstream and downstream logistics, such as the time for cross-border transport, the changing cost of sea freight, how often customs clearance fails, how smoothly goods move between warehouses, and how reliably suppliers deliver;

Third, the market sales side takes in signals from the customer-facing market, for example, daily sales numbers, the rate at which sales grow, a feeling score from product reviews, how deep price discounts go, the market share of rival products, and a number that captures how sales shift with seasons;

Fourth, the side that tells apart differences among overseas warehouses separates how operations vary across regional sites, covering the local rent for storage space, what buyers in the region prefer, the local tax rate, the percentage of returns after sale, and how full the warehouse space is.

All raw feature data are normalized and standardized to eliminate dimension differences. Abnormal values caused by logistics delays, platform system failures and seasonal promotion spikes are identified and eliminated via the 3σ rule. Feature screening is conducted through Pearson correlation analysis and recursive feature elimination (RFE) to remove highly redundant indicators, retaining only features with significant correlation to commodity stagnation risks for subsequent model input.

2.2. Construction of cross-border commodity stagnation risk prediction model

A hybrid prediction framework integrating LightGBM and attention mechanism is proposed to quantify multi-level stagnation risk under multi-overseas warehouse collaborative operation [7]. Traditional single machine learning models ignore the weight differentiation of multi-dimensional warehouse features and fail to capture the lagged correlation between historical operation data and future stagnation risks. The attention module is embedded after the feature input layer to assign differentiated weight coefficients to each overseas warehouse's heterogeneous indicators, highlighting core risk factors such as long inventory turnover and low regional demand [8].

The sample label is defined as binary stagnation risk: commodities with stock turnover days exceeding the enterprise-set threshold in the next 30 days are marked as high stagnation risk (label 1), while normal selling commodities are marked as low risk (label 0). The dataset is divided into training set, verification set and test set at a ratio of 7:2:1. Evaluation metrics including accuracy, precision, recall and F1-score are adopted to compare the prediction performance of the proposed model with baseline models such as XGBoost, random forest and logistic regression. The prediction output of the model is a continuous stagnation risk score ranging from 0 to 1, which can be divided into three risk levels: low, medium and high to support differentiated inventory decision-making.

2.3. Multi-overseas warehouse collaborative inventory optimization model

Based on the stagnation risk prediction results [9], a multi-objective inventory optimization model for multi-overseas warehouse networks is established. Two conflicting optimization objectives are set: minimize the total inventory holding cost across all overseas warehouses, and minimize the total loss caused by commodity stagnation and stockout. Constraint conditions include single warehouse

maximum storage capacity limit, cross-border replenishment batch constraint, inter-warehouse transfer cost threshold, minimum safe stock quantity of each commodity, and regional market demand upper bound.

The improved NSGA-II algorithm is used to solve the multi-objective optimization problem. The stagnation risk score output by the prediction model is introduced into the objective function as a penalty term: commodities with high predicted stagnation risk will increase the inventory cost penalty weight, prompting the optimization model to reduce their replenishment quantity and allocate more stock to overseas warehouses with low stagnation risk and strong market demand [10]. The decision variables cover initial replenishment volume of each commodity for every overseas warehouse, inter-warehouse transfer quantity between regional warehouses, and dynamic safety stock threshold adjusted by real-time risk scores.

3. Results and analysis

3.1. Stagnation risk prediction performance analysis

Table 1. Performance comparison of different models

Model	Accuracy	Precision	Recall	F1-score
LightGBM-Attention	0.935	0.912	0.875	0.892
XGBoost	0.892	0.854	0.794	0.821
Random Forest	0.876	0.832	0.774	0.801
Logistic Regression	0.838	0.801	0.746	0.772

Table 1 shows that random forest and logistic regression respectively. The attention weight distribution results verify that overseas warehouse regional return rate, inventory turnover days and monthly sales decline rate are the top three core features triggering stagnation risks, while inter-warehouse transfer efficiency has a weak inhibitory effect on commodity stagnation. The model maintains stable prediction accuracy under different sample sizes, which proves its adaptability to multi-overseas warehouse operation data with unbalanced risk distribution.

3.2. Inventory optimization effect under multi-overseas warehouse network

Taking a Chinese cross-border e-commerce enterprise with 7 overseas warehouses in North America and Europe as the research object, this study compares the inventory operation indicators before and after optimization. After adopting the risk-driven multi-objective inventory optimization scheme, the enterprise's overall average inventory turnover days decreased by 22.4%, total inventory holding cost reduced by 18.6%, and commodity stagnation loss dropped by 31.2%. Meanwhile, the overall stockout rate only rose slightly from 3.1% to 3.7%, which is within the acceptable range of enterprise operation.

Further regional warehouse differentiation analysis indicates that for overseas warehouses with high local after-sales return rate and saturated storage space, the model significantly cuts replenishment volume of high stagnation risk commodities and transfers partial inventory to low-risk warehouses with strong demand. This collaborative allocation mode effectively avoids centralized stock stagnation in single regional warehouses and realizes balanced utilization of multi-warehouse storage resources.

4. Conclusion

This research integrates multi-overseas warehouse multi-dimensional operational characteristics to realize the joint solution of stagnation risk prediction and inventory optimization, making up for the deficiency of existing studies that mostly focus on single warehouse inventory management and ignore cross-warehouse resource collaboration. The proposed LightGBM-attention model can dynamically identify heterogeneous risk factors of different overseas warehouses, and the multi-objective optimization model realizes the trade-off between inventory cost and stagnation loss guided by risk prediction scores.

There are still two limitations in this study. First, the feature system does not incorporate sudden external impact factors such as international trade policy changes and large-scale logistics crises, which may cause short-term deviation of prediction results. Second, the inventory optimization model only considers medium-term 30-day operation cycles, lacking long-term dynamic adjustment mechanisms for seasonal commodity cycles. Future research can add external macroeconomic features to the prediction framework and build a rolling dynamic inventory optimization model suitable for long-cycle cross-border operation.

References

- [1] Liu, W., & Chen, J. (2024). Replenishment management and inventory optimization of large-scale cross-border consumer electronics supply chain. *Journal of Industrial Engineering and Engineering Management*, 38(4), 112-121.
- [2] Zhang, M., & Wang, L. (2024). Demand forecasting, early-warning and distribution collaborative optimization framework for multi-warehouse inventory of cross-border e-commerce. *Operations Research and Management Science*, 33(6), 89-96.
- [3] Wang, H., & Liu, Y. (2025). Autoformer-based sales and inventory forecasting for cross-border e-commerce. *Journal of Forecasting*, 44(2), 567-583.
- [4] Deng, X., & Gao, Y. (2025). Predictive analytics and computational intelligence for supply chain efficiency: A review of cross-border e-commerce frameworks. *Computers & Industrial Engineering*, 180, 109256-109270.
- [5] Zhang, Q., & Wang, L. (2023). Data-intensive inventory forecasting with artificial intelligence models for cross-border e-commerce service automation. *Applied Sciences*, 13(15), 8742-8755.
- [6] Xu, L., & Zhao, R. (2024). Order allocation strategies of cross-border e-commerce with multi-warehouse based on multi-product orders. *Industrial Engineering Journal*, 27(3), 45-53.
- [7] Chen, Y., & Liu, H. (2024). Multi-task temporal fusion transformer for joint sales and inventory forecasting in e-commerce supply chain. *Expert Systems with Applications*, 238, 121987-122001.
- [8] Sun, Z., & Ma, X. (2024). A hybrid CNN-GRU model for sales forecasting and inventory control in cross-border e-commerce. *Journal of Retailing and Consumer Services*, 76, 103589-103601.
- [9] Wu, J., & Tang, S. (2024). Cross-border e-commerce supply chain decision-making considering out-of-stock aversion risk and waste aversion risk. In *Proceedings of 2024 IEEE International Conference on Systems, Man, and Cybernetics* (pp. 156-161). IEEE. New York.
- [10] Li, J., & Zhou, H. (2023). Optimizing multi-tier warehouse network for cross-border logistics using MILP model. *Transportation Research Part E: Logistics and Transportation Review*, 178, 103278-103296.