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Construction and Practice of Supply Chain Optimization Decision System Driven by Artificial Intelligence

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Abstract: This article focuses on the supply chain optimization decision-making system driven by artificial intelligence (AI), aiming at coping with the complex challenges faced by enterprise supply chain management and improving its operational efficiency and competitiveness. Through the combination of theoretical research and case practice, this article first expounds the theoretical and technical basis of supply chain management, AI and decision-making system. On this basis, the system is constructed in detail, covering demand analysis, architecture design and key module design, in which the key module adopts demand forecasting method combining time series with neural network, inventory optimization strategy based on EOQ model and transportation scheduling scheme of genetic algorithm. The practice in large-scale electronic product manufacturing enterprises shows that after the system is implemented, the inventory turnover rate of enterprises increases by 37.14%, the shortage rate decreases by 62.20%, and the transportation cost decreases by 18.33%. The research shows that the AI-driven supply chain optimization decision-making system can effectively solve the supply chain management problems of enterprises, which is of great value to improve the operational efficiency of enterprises, but some models still need to be optimized when dealing with extreme market changes.

1. Introduction

At the moment of global economic integration and increasingly fierce market competition, supply chain management has become a key area for enterprises to gain competitive advantage [1]. The supply chain covers many links, from raw material procurement, manufacturing, product distribution and sales, etc. Any slight deviation in decision-making in any link may lead to "bullwhip effect", which will lead to increased costs and reduced efficiency [2]. Therefore, how to realize the efficient optimization decision of supply chain has become the focus of both academic and business circles.

In recent years, AI technology has developed rapidly. The AI method represented by machine learning (ML) and deep learning, with its powerful data processing and analysis capabilities, provides a new way for supply chain optimization [3-4]. AI can mine and analyze massive supply chain data, and reveal the hidden laws and patterns behind the data, thus helping enterprises to make more accurate and scientific decisions [5]. In this context, it is of great theoretical and practical significance to construct an AI-driven supply chain optimization decision system.

Theoretically, the research on the deep integration of AI and supply chain optimization decision system is still in the development stage, and many theories and methods need to be further improved and expanded [6]. The purpose of this study is to deeply analyze the internal logic and key technology of the combination of the two, and enrich the relevant theoretical system. In practice, enterprises are faced with practical challenges such as improving the response speed of supply chain, reducing costs and enhancing flexibility. The AI-driven supply chain optimization decision-making system is expected to provide innovative solutions for enterprises and enhance their supply chain management level and market competitiveness.

This article will focus on the AI-driven supply chain optimization decision-making system, focusing on the construction principle and practical application of the system.

2. Related theoretical and technical basis

Supply chain management aims to integrate suppliers, manufacturers, distributors and retailers, realize the efficient flow of products, information and funds, meet customer needs and maximize the overall value of the supply chain [7]. The theory covers procurement management, emphasizing the acquisition of raw materials with appropriate price, quality and delivery time; Production management, focusing on production planning, scheduling and resource allocation to ensure efficient production; Logistics management, responsible for the transportation, storage and distribution of products, and strive to balance the cost and service level [8]. By coordinating these links, supply chain management is committed to improving overall efficiency, reducing operating costs and enhancing the competitiveness of enterprises.

ML, as the core of AI, allows computers to learn patterns and laws from data through algorithms, and then make predictions and decisions [9]. Supervised learning uses labeled data to train models to predict unknown outputs, while unsupervised learning finds potential structures in unlabeled data. As a branch of ML, deep learning is based on deep neural network, which can automatically extract complex features from a large number of data, and has achieved remarkable results in the fields of image recognition and voice processing, providing a powerful tool for deep mining and analysis of supply chain data.

Decision system is a system that analyzes, evaluates and selects various feasible schemes based on specific objectives. In the field of supply chain, it helps decision makers to make key decisions such as purchasing, inventory and distribution with the help of data and models [10]. Common decision-making models include linear programming and integer programming, which are used for resource allocation and optimal scheduling. Analytic hierarchy process decomposes complex decision-making problems into multiple levels by constructing hierarchical structure model, which provides scientific basis for decision-making. These theories and models lay the foundation for building an AI-driven supply chain optimization decision-making system and help to realize more scientific and efficient supply chain decision-making.

3. Construction of AI-driven supply chain optimization decision system

3.1. System requirements analysis

Supply chain involves many participants with different needs. For suppliers, clear purchase order forecast is expected to arrange production and inventory reasonably. Manufacturers pay attention to the accurate formulation of production plans to avoid overcapacity or shortage. Retailers are eager for accurate demand forecasting to reduce the risk of shortage and backlog. From the functional requirements, the system needs to have accurate demand forecasting, scientific inventory optimization, efficient transportation scheduling and other functions. In terms of performance requirements, it is necessary to ensure the timeliness of data processing to cope with the rapidly changing market. At the same time, the accuracy of the system should be high to ensure the reliability of the decision.

3.2. System architecture design

This system adopts hierarchical architecture, which has clear hierarchical division and responsibility definition, and is conducive to the development, maintenance and expansion of the system.

The data layer is at the bottom of the architecture, just like the "data warehouse" of the system, which is responsible for collecting, storing and managing all kinds of supply chain data. These data come from a wide range of sources, including internal sales records, inventory ledgers, production reports, as well as external market data and supplier information. The data layer should not only complete the simple storage of data, but also preliminarily clean and preprocess the data, remove duplicate and erroneous data, unify the data format, and provide a high-quality data foundation for the upper model layer.

The model layer is the core "brain" of the system, bearing various AI algorithms and decision-making models. Aiming at demand forecasting, a forecasting model is constructed by using time series analysis and neural network. Inventory optimization is based on classical theories such as economic order quantity model and reorder point model, and combined with real-time demand forecast and cost data for dynamic optimization. The transportation scheduling module adopts intelligent algorithms such as genetic algorithm and ant colony algorithm to solve the vehicle routing problem and transportation resource allocation problem. The model layer generates valuable decision information through deep mining and analysis of the data provided by the data layer.

As an interactive interface between the system and users, the application layer transforms the decision information output by the model layer into intuitive, understandable and operable suggestions. It provides customized functional interfaces for all participants in the supply chain, for example, suppliers can view the forecast report of purchase orders, manufacturers can get detailed production plans, and retailers can get inventory management and replenishment reminders. The application layer should not only display information, but also have a good user experience, and the operation interface is concise and clear, which is convenient for users to understand and implement relevant decisions quickly.

3.3. Key module design

(1) Demand forecasting module

Demand forecasting is very important for supply chain decision-making. This module adopts the method of combining time series analysis with ML. First, the moving average method is used to preliminarily process the data, and the formula is:

$$[MA_t = \frac{\sum_{i=t-n+1}^{t} Y_i}{n}] \tag{1}$$

Where MA_t is the moving average of t period; Y_i is the actual value of i period; n is the number of items in the moving average.

Then, combined with neural network algorithm to predict the depth. Take the multi-layer perceptron as an example, its input layer receives the processed data and outputs the predicted value through the nonlinear transformation of the hidden layer. Let the weight matrix from the input layer to the hidden layer be W_1, the weight matrix from the hidden layer to the output layer be W_2, and the activation function be σ, then the calculation formula of the predicted value $\hat{Y}$ is:

$$\widehat{Y} = \sigma(W_2\sigma(W_1X + b_1) + b_2) \quad (2)$$

Where X is the input data and b_1 and b_2 are the offset items.

In order to verify the prediction effect, the prediction errors of different methods are compared, and the results are shown in Figure 1 below:

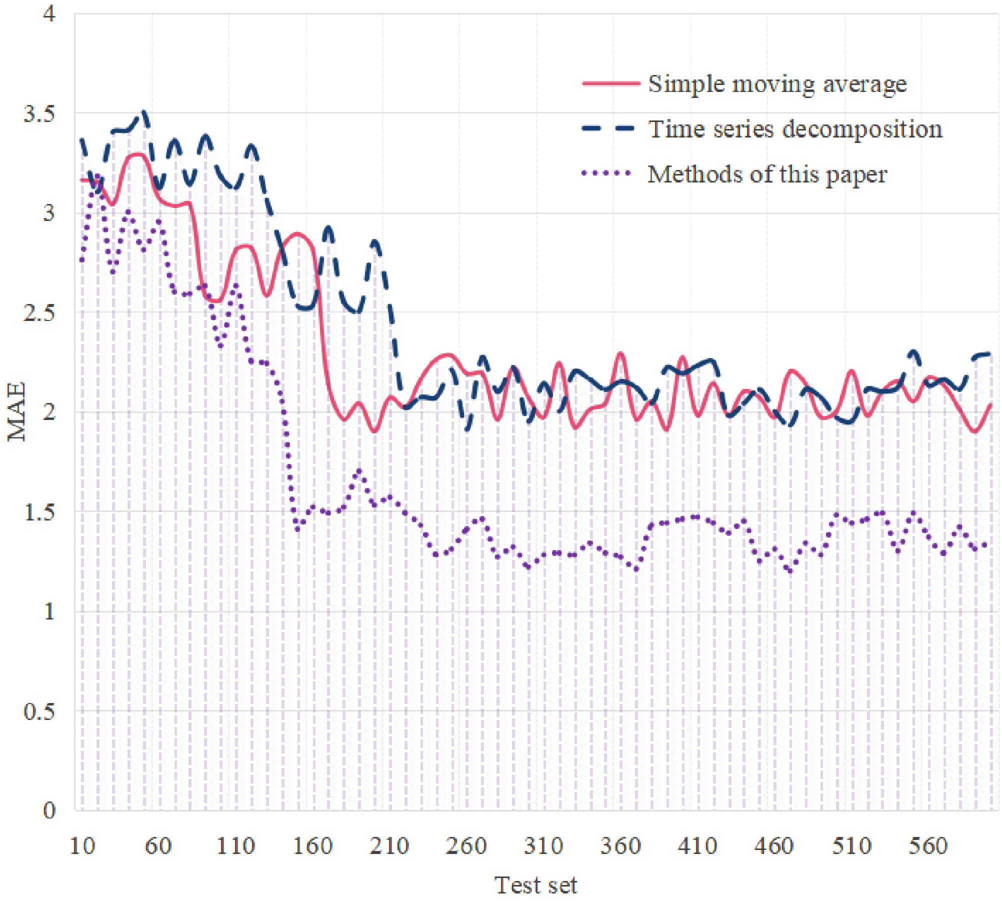

Figure 1 Comparison of prediction errors of different methods

It can be seen from Figure 1 that the combination method adopted in this article has advantages in prediction accuracy.

(2) Inventory optimization module

Inventory optimization aims at balancing inventory cost and shortage cost. Based on EOQ model and combined with real-time demand forecast, dynamic adjustment is made. The basic formula of EOQ is:

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (3)$$

Among them, D is the annual demand, S is the cost of each order, and H is the annual holding cost of unit goods.

Considering the uncertainty of demand, safety stock SS is introduced, and the calculation formula is:

$$SS = z\sigma_L \quad (4)$$

Where z is the safety factor and σ_L is the standard deviation of the demand in the lead time. Through these formulas and adjustment strategies, the optimal management of inventory can be realized and the total inventory cost can be reduced.

(3) Transportation dispatching module

The transportation scheduling module uses genetic algorithm to solve vehicle routing problem (VRP). By coding the vehicle path, taking transportation cost and time as fitness functions, the path is continuously iteratively optimized. For example, the fitness function F can be expressed as:

$$F = \alpha C + \beta T \tag{5}$$

Among them, C is the transportation cost, T is the transportation time, and α and β are the weight coefficients, which are adjusted according to the actual demand to meet different transportation objectives and realize efficient transportation scheduling.

4. Systematic practice and case analysis

This practice selects a large electronic product manufacturing enterprise as the object. The enterprise has a wide range of products, and its supply chain involves many suppliers, production bases and sales outlets around the world. It is typical to face the problems of large demand fluctuation, complex inventory management and high transportation cost. First of all, build a data collection platform within the enterprise to integrate the data of sales, inventory, transportation and other links. Then, the data is transmitted to the data layer of the system for preprocessing. Then, according to the actual business needs of the enterprise, the related models of demand forecasting, inventory optimization and transportation scheduling are configured and trained at the model level. After repeated debugging and optimization, the system is deployed to the application layer for the use of all departments of the enterprise, and corresponding training is provided.

In order to evaluate the effect of the system, key indicators such as inventory turnover rate, out-of-stock rate and transportation cost reduction rate are set, and the data before and after the implementation of the system are compared. The results are shown in the following Table 1:

Table 1: Comparison of Inventory-Related Indicators Before and After System Implementation

Indicator	Before System Implementation	After System Implementation	Change Rate
Inventory Turnover Rate (times/year)	3.5	4.8	+37.14%
Out-of-Stock Rate (%)	8.2	3.1	-62.20%

As can be seen from Table 1, after the implementation of the system, the inventory turnover rate is significantly improved, indicating that the efficiency of enterprise inventory management is improved and the occupation cost is reduced; The out-of-stock rate has dropped significantly, which helps to improve customer satisfaction.

In terms of transportation cost, the statistics of transportation cost and transportation mileage before and after the implementation of the system show the following results in Table 2:

Table 2: Comparison of Transportation-Related Indicators before and After System Implementation

Indicator	Before System Implementation	After System Implementation	Change Rate
Transportation Cost (10,000 yuan/year)	1200	980	-18.33%
Average Transportation Distance (km)	850	780	-8.24%

As can be seen from Table 2, the transportation cost is obviously reduced, and the average transportation mileage is also shortened. This is due to the fact that the transportation scheduling module uses genetic algorithm to optimize the vehicle path, which improves the transportation efficiency and reduces the unnecessary transportation mileage, thus reducing the transportation cost.

On the whole, the AI-driven supply chain optimization decision-making system has achieved good results in the practice of enterprises, effectively solved some key problems faced by enterprises in supply chain management, and improved the overall operational efficiency and competitiveness of enterprises.

5. Conclusions

This article deeply discusses the construction and practice of AI-driven supply chain optimization decision system. On the theoretical level, the related theories and technologies of supply chain management, AI and decision-making system are combed to lay a solid foundation for the system construction. Through the analysis of system requirements, the functional and performance requirements of all participants in the supply chain are clearly defined. The system architecture design adopts hierarchical mode, which makes data, model and application cooperate orderly. In the design of key modules, demand forecasting is combined with various methods to improve the accuracy, inventory optimization is based on classical model and dynamically adjusted, and transportation scheduling uses genetic algorithm to optimize the path.

The practice in a case enterprise shows that the system has achieved remarkable results. In inventory management, the inventory turnover rate is greatly increased, and the shortage rate is significantly reduced, which not only reduces the capital occupation, but also improves customer satisfaction. In terms of transportation cost, the transportation cost is reduced, the average transportation mileage is shortened, and the resource utilization is optimized. This fully proves the feasibility and effectiveness of the deep integration of AI and supply chain optimization decision system, and provides an innovative and practical solution for enterprise supply chain management.

However, practice also exposes the limitations of the system. In the face of extreme market changes, some models have poor adaptability. Future research can focus on improving the model's ability to cope with extreme situations and further improving the system robustness. At the same time, we will continue to pay attention to the development of new AI technologies and constantly update the optimization system to better adapt to the complex and ever-changing supply chain environment and create greater value for enterprises.

References

[1] Li Xiang, Wang Meiqi, Guo Chang. Research on the Decision Optimization of a Dual-channel Supply Chain Considering the Service Level of Physical Stores. Chinese Journal of Management, vol. 21, no. 8, pp. 1217-1226, 2024.

[2] Zhang Mingqiang, Gao Hua, Yuan Dongfeng, et al. Design and Implementation of an Artificial Intelligence Detection System for Appearance Quality with Cloud-edge Collaboration. Computer Integrated Manufacturing Systems, vol. 29, no. 10, pp. 3440-3449, 2023.

[3] Song Hua. Theoretical Exploration and Prospect of the Digital Supply Chain with Artificial Intelligence. China Business and Market, vol. 38, no. 1, pp. 44-54, 2024.

[4] Xin Daleng, Qiu Yue. Artificial Intelligence, Stability of the Industrial and Supply Chains, and the Export Resilience of Enterprises. Economic Theory and Business Management, vol. 45, no. 2, pp. 37-54, 2025.

[5] Wu Jun, Zhang Lei. Master-slave Interactive Optimization of Product Family Architecture Design and Supply Chain Delay Decision. Computer Integrated Manufacturing Systems, vol. 30, no. 10, pp. 3719-3729, 2024.

[6] Qian Wuyong, Zhang Haonan. Research on the Credit Risk Evaluation of Supply Chain Finance Based on the Adaboost-DPSO-SVM Model. Journal of Industrial Technological Economics, vol. 41, no. 3, pp. 72-79, 2022.

[7] Wang Hui, Wang Junjie, Wang Tengfei, et al. Optimal Decision of the Wind Power Supply Chain Based on CVaR under Uncertain Output. Journal of Electric Power Science and Technology, vol. 38, no. 4, pp. 134-142, 2023.

[8] Wang Jingjing, Xu Minli. Research on the Decision-making of a Closed-loop Supply Chain Considering Echelon Advantages under the Extended Producer Responsibility System. Journal of Industrial Engineering and Engineering Management, vol. 38, no. 4, pp. 222-238, 2024.

[9] Qiu Ruozhen, Wu Xu, Sun Yue, et al. A Robust Optimization and Coordination Model of the Supply Chain Considering Big Data Investment Decision under Uncertain Demand. Chinese Journal of Management Science, vol. 31, no. 1, pp. 128-141, 2023.
[10] Qiu Ruozhen, Chu Xiaojing, Sun Yue. A Robust Optimization-based Decision-making Model for a Dual-channel Supply Chain under Price and Delivery Time-sensitive Demand. Chinese Journal of Management Science, vol. 31, no. 9, pp. 114-126, 2023.