Industrial Engineering and Innovation Management (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/ieim.2025.080109
ISSN 2522-6924 Vol. 8 Num. 1

Information Technology of Intelligent Manufacturing Supply Chain Management Based on Machine Learning

Jie Li

Zhejiang Hailiang Co., Ltd., Zhuji, Zhejiang, 311800, China

Keywords: Machine Learning; Intelligent Manufacturing; Supply chain management; Demand forecast; Logistics optimization

Abstract: Aiming at the problems existing in traditional supply chain management, such as inaccurate demand forecast, low efficiency of inventory management and frequent adjustment of production plan, this study proposes an intelligent manufacturing supply chain management system solution based on ML (Machine Learning) technology and DNN (Deep Neural Network). In terms of methods, this article first carries out detailed data processing and feature engineering, and extracts key features from sales, production, inventory, suppliers and logistics. Then, the demand forecasting model based on LSTM (Long Short-Term Memory), inventory classification and supplier evaluation model based on DNN and logistics path optimization model based on CNN (Convolutional Neural Network) are constructed. The effectiveness and practicability of the system are verified by experiments. The results show that the system significantly improves the accuracy of demand forecasting, optimizes inventory management and production planning, and improves supplier management and logistics efficiency. Specifically, the accuracy of demand forecasting has increased by more than 19%, inventory turnover rate has increased by 31.5%, production efficiency has increased by 21%, supplier performance score has increased by 10.5%, and logistics transportation time has been shortened by 15%. These improvements have reduced the operating costs of enterprises and improved their market competitiveness and customer satisfaction.

1. Introduction

In today's increasingly fierce global competition, intelligent manufacturing, as a key force to promote industrial transformation and upgrading, is gradually changing the face of traditional manufacturing [1]. At present, the manufacturing industry is moving towards a highly automated, intelligent and networked direction [2]. As the core of manufacturing industry, the efficiency and flexibility of supply chain management are directly related to the market competitiveness of enterprises [3]. However, in the face of complex and changeable market demand, uncertain supply environment and increasing personalized customization demand, the traditional supply chain management model has been difficult to meet the requirements of intelligent manufacturing [4].

ML, with its powerful data processing ability and pattern recognition ability, provides a new opportunity to solve the above problems [5]. By digging deep into the potential laws in the supply chain data, ML can realize accurate prediction of market demand, dynamic adjustment of production plan and collaborative optimization of all links in the supply chain. This can significantly improve the intelligent level and response speed of supply chain management [6].

In recent years, the research in the field of intelligent manufacturing and supply chain management has made remarkable progress [7]. In terms of intelligent manufacturing, scholars have conducted in-depth research on the architecture, key technologies and application scenarios of intelligent manufacturing system, which has promoted the rapid development of intelligent manufacturing technology [8]. In supply chain management, with the application of big data, cloud computing and other technologies, the level of information and intelligence of supply chain management has been continuously improved, and a number of new methods of supply chain management based on data analysis have emerged [9]. Furthermore, the application of ML in supply chain management has gradually attracted attention. Researchers use ML algorithm to mine and analyze the supply chain data, and realize the accurate prediction and optimization of all links in the supply chain [10]. However, at present, there is relatively little research on the specific application of DNN model in intelligent manufacturing supply chain management, and the related theory and method system are not perfect.

The purpose of this study is to explore the possibility and effectiveness of applying DNN model to intelligent manufacturing supply chain management. By constructing an intelligent manufacturing supply chain management system based on ML, it provides strong support for the intelligent transformation of manufacturing industry, which has important theoretical significance and practical value.

2. Intelligent manufacturing and ML foundation

2.1. Overview of intelligent manufacturing

Intelligent manufacturing is to use modern information technologies such as Internet of Things and big data to comprehensively perceive, analyze, make decisions, execute and serve the manufacturing process, so as to realize the efficient, flexible, green and sustainable operation of the manufacturing system. Its core lies in the automation, digitalization, networking and intelligence of manufacturing process through intelligent means [11]. Its characteristics include intelligent allocation of manufacturing resources, intelligent control of production process, intelligent products and services and intelligent supply chain management.

Intelligent manufacturing system usually consists of intelligent equipment, intelligent factory, intelligent service, intelligent supply chain and intelligent management. Among them, intelligent equipment is the foundation of manufacturing process, intelligent factory realizes the automation and digitalization of production process, intelligent service provides personalized products and services, intelligent supply chain realizes the efficient coordination of all links in the supply chain, and intelligent management is responsible for the optimization and decision-making of the whole manufacturing system.

2.2. ML foundation

ML is a process that enables computer systems to automatically learn from data and improve their performance through algorithms and statistical models. It involves data preprocessing, feature extraction, model selection, training and evaluation [12]. ML can be divided into supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. Supervised learning is training on labeled data, while unsupervised learning is discovering potential structures or patterns on unlabeled data. Semi-supervised learning combines the characteristics of the first two, and reinforcement learning is to learn the best strategy by interacting with the environment.

DNN is an important model in ML. It is composed of multi-layer neurons and can automatically learn the hierarchical feature representation of data. Through optimization techniques such as back propagation algorithm and gradient descent, DNN can realize efficient training and prediction on large-scale data sets. In intelligent manufacturing supply chain management, DNN can be used in demand forecasting, inventory management, production planning and other links.

3. Realization of intelligent manufacturing supply chain management system based on DNN

3.1. Data processing and feature engineering

When building an intelligent manufacturing supply chain management system based on DNN, data processing and feature engineering are crucial steps. The system needs to comprehensively collect supply chain related data from various sources. Including sales records, production plans, inventory levels, supplier information and logistics data. These data are distributed in relational database, NoSQL database, file system and real-time data stream. Aiming at the problems of missing, abnormality and repetition in the collected data, this article carries out systematic cleaning and pretreatment. This includes filling in gaps, removing anomalies, removing duplicates, type conversion and data normalization to ensure the consistency and reliability of data quality. On this basis, according to the actual demand of supply chain management, this article carries out feature engineering and extracts meaningful features such as time series trend, seasonal factors and correlation indicators from the original data. Finally, we use feature selection algorithm to screen out the most critical features for model prediction, aiming at reducing model complexity and improving operation efficiency and prediction accuracy.

3.2. DNN model construction and training

When dealing with data science problems related to supply chain, the choice of model is very important. It directly determines the effectiveness and accuracy of the solution. Firstly, the general direction of the model is determined according to the specific task type. When choosing a model, we must fully consider the task type and data characteristics to ensure that the selected model can maximize its effectiveness.

(1) LSTM

As a key link in supply chain management, demand forecasting is directly related to inventory control, production planning and market response speed. In the face of time series data, it is difficult for traditional forecasting methods to capture long-term dependencies and complex patterns in the data. As a special type of circulating neural network, LSTM was born to solve this problem. By introducing three control structures: input gate, forget gate and output gate, LSTM effectively solves the problems of gradient disappearance and gradient explosion of RNN in long-term dependent learning. The purpose of forget gate is to decide what information to discard from the internal memory cell state:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

Where f_t is the output of forget gate, σ is sigmoid function, and both W_f and b_f are model parameters.

In the demand forecasting scenario, LSTM can learn the long-term dependence in time series by using multi-dimensional information such as historical sales data, seasonal factors and market trends, and accurately predict future demand. In the commodity demand forecast of e-commerce platform, LSTM can capture the holiday effect, the influence of promotion activities on sales volume, and the trend of sales volume change during the product life cycle, providing scientific basis for inventory management and procurement strategy.

(2) DNN

Inventory classification is another important link in supply chain management. It helps enterprises to manage inventory resources more efficiently and optimize inventory structure. DNN can automatically extract high-level features from data through multi-layer nonlinear transformation, which is very important for classification tasks. In the inventory classification scenario, DNN can learn multi-dimensional information such as the sales model, seasonal characteristics and price sensitivity of goods, and turn this information into effective classification basis. In the inventory classification of clothing industry, DNN can accurately classify goods into different seasons and style categories according to the characteristics of clothing styles, colors and materials, which provides strong support for inventory management and sales strategies.

(3) CNN

Logistics path optimization involves the optimization of multiple nodes, multiple paths and various constraints. Although the traditional optimization method can solve the problem to a certain extent, it is difficult to find the optimal solution in a reasonable time when facing the large-scale and high-dimensional logistics network. CNN is a deep learning model that has achieved great success in the fields of image processing and pattern recognition. It provides a new idea for logistics path optimization.

CNN can efficiently extract the feature information in the spatial structure through convolution layer, pooling layer and other structures. In the scene of logistics route optimization, we can regard logistics network as a special "image", in which nodes represent cities or warehouses and edges represent transportation routes. By extracting the features of these "images" through CNN, we can learn the spatial structure and transportation mode in the logistics network and provide strong support for path optimization. In the distribution path planning, CNN can consider many factors, such as road congestion, transportation cost, delivery time window and so on, to plan the optimal driving route for distribution vehicles and improve logistics efficiency and customer satisfaction.

After the model construction is completed, the next step is to enter the training stage. In order to ensure that the model can fully learn the characteristics and laws in the data, this article divides the processed data set into training set, verification set and test set. During the training process, the parameters of the model will be iteratively updated on the training set through optimization techniques such as backpropagation algorithm and gradient descent or stochastic gradient descent, so as to minimize the loss function. The formula is as follows:

$$w^{(l)} := w^{(l)} - \alpha \frac{\partial L}{\partial w^{(l)}} \tag{2}$$

$$b^{(l)} := b^{(l)} - \alpha \frac{\partial L}{\partial b^{(l)}} \tag{3}$$

Where: $w^{(l)}$ is the updated formula of l layer weight. $b^{(l)}$ is the updated formula of l layer bias. α is the learning rate. It controls the step size of parameter update.

This article also monitors the performance of the model on the verification set and adjusts the model parameters in time to avoid over-fitting. In order to improve the generalization ability of the model, this article adopts strategies such as early stop and learning rate attenuation to optimize the training process. Through these measures, we can ensure that the model can fully learn the data characteristics and maintain good generalization performance during the training process.

3.3. Development and implementation of system function modules

The intelligent manufacturing supply chain management system based on DNN should include multiple functional modules to meet the comprehensive needs of supply chain management (see Figure 1).

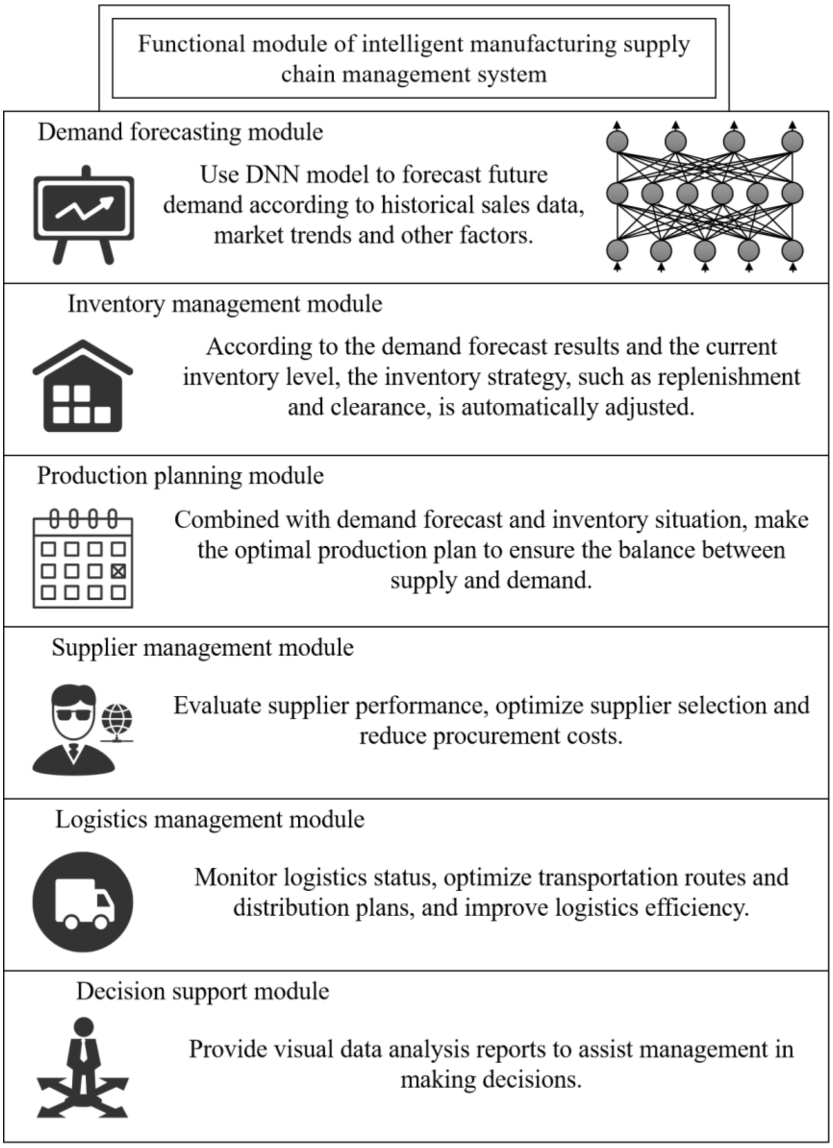

Figure 1 Functional module of intelligent manufacturing supply chain management system

In the stage of system realization, this article adopts micro-service architecture to build an intelligent manufacturing supply chain management system based on DNN. This architecture allows us to divide the system into several independent functional modules, and each module can be independently developed, deployed and expanded. According to the specific requirements of each module, this article chooses Java as the main programming language, and combines with mature technology stack such as Spring Boot to develop the system. Through clearly defined interfaces and protocols, we realize the data interaction and interface call between modules, and ensure the cooperative work of the whole system.

After the system development is completed, we enter the comprehensive testing stage. In order to ensure the correctness and stability of the system function, this article designs a detailed test plan, and carries out unit test, integration test and system test in turn. We use simulated data and actual data to test the system comprehensively to verify the performance of the system in the actual scene and ensure that the system can meet the actual needs of enterprises. The results are shown in Table 1:

Table 1 Overview of System Testing Results

Test Type	Test Content	Test Data	Test Result
Unit Testing	Verify the correctness of internal logic of each module	Simulated Data	Passed
		Actual Data	Passed
Integration Testing	Verify the interaction and collaboration functions between modules	Simulated Data	Passed
		Actual Data	Passed
System Testing	Functional Testing: Verify the completeness of system functions	Simulated Data	Passed
		Actual Data	Passed
	Performance Testing: Measure system response time, throughput	Simulated Data	As Expected
		Actual Data	As Expected
	Security Testing: Check system security	Simulated Attack Data	Passed

By simulating the actual operation scenario, we measure the response time and resource utilization of the system (see Figure 2 for details).

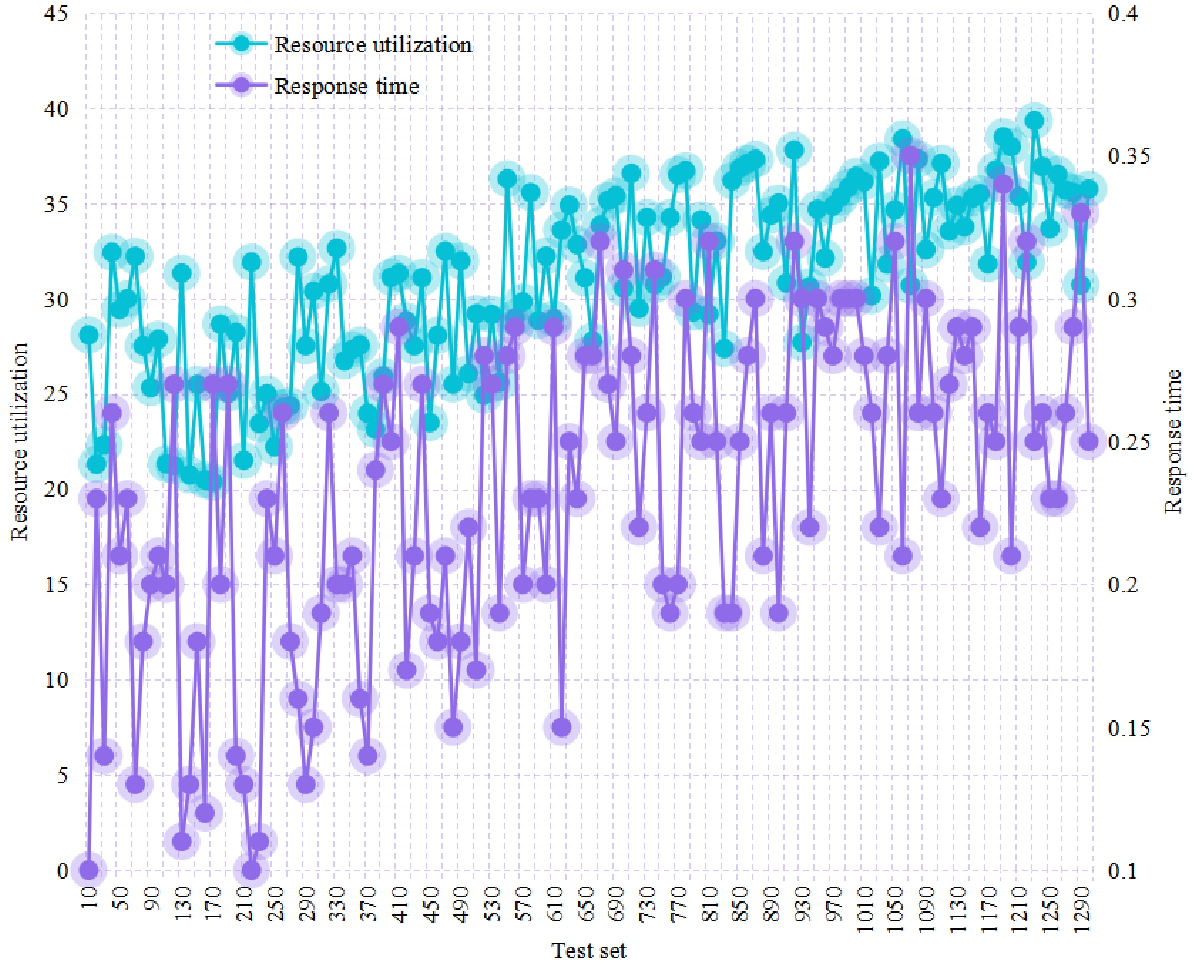

Figure 2 System response time and resource utilization

The above results show that the intelligent manufacturing supply chain management system based on DNN has gone through a comprehensive testing stage after its development. The function of the system is correct and stable, and the performance meets the expectations. The system can process the data in the actual scene, meet the actual needs of enterprises, and provide strong support for the efficient management of intelligent manufacturing supply chain. Therefore, this article believes that the system is reliable and effective, and offers a systematic approach to application deployment in the actual environment.

4. Case analysis and application effect evaluation

4.1. Case background and system application

In order to verify the effectiveness and practicability of intelligent manufacturing supply chain management system based on DNN, this article chooses a large manufacturing enterprise as the research object. The enterprise mainly produces electronic equipment and has a complex supply chain system, including multiple production bases, extensive supplier network and global sales channels. In recent years, with the intensification of market competition and the diversification of consumer demand, enterprises are facing problems such as inefficient supply chain management, overstocked inventory and frequent adjustment of production plans.

In order to improve this situation, enterprises decided to introduce an intelligent manufacturing supply chain management system based on DNN. In terms of data, we collected the sales data, production planning data, inventory data, supplier data and logistics data of the enterprise in the past three years. These data cover the main links of the supply chain and provide rich samples for the training and testing of the system. The implementation process of system application includes data preparation, model training, system deployment and personnel training.

4.2. Application effect analysis

After the application of the system, this article makes a comprehensive analysis of the supply chain management effect of enterprises. The specific results are shown in Table 2:

Table 2 Analysis of Enterprise Supply Chain Management Effects

Management Aspect	Improvement Measures	Pre-Improvement Situation	Post-Improvement Situation
Demand Forecasting Accuracy	Applying LSTM Model for Forecasting	Baseline Forecasting Accuracy	Forecasting Accuracy Increased by over 19%
Inventory Management	Using DNN Model to Automatically Adjust Inventory Strategy	Baseline Inventory Turnover Rate	Inventory Turnover Rate Increased by 31.5%
		Baseline Inventory Cost	Inventory Cost Reduced by 15%
Production Plan Flexibility	System Automatically Adjusts Production Plans Based on Real-Time Demand	Baseline Production Plan Adjustment Time	Production Plan Adjustment Time Reduced by 36%
		Baseline Production Efficiency	Production Efficiency Increased by 21%
Supplier Management	Utilizing DNN Model to Evaluate and Optimize Suppliers	Baseline Supplier Performance Score	Supplier Performance Score Increased by 10.5%
		Baseline Procurement Cost	Procurement Cost Reduced by 5%
Logistics Efficiency	Applying CNN Model to Optimize Logistics Routes	Baseline Logistics Transportation Time	Logistics Transportation Time Reduced by 15%
		Baseline Transportation Cost	Transportation Cost Reduced by 9%

Table 2 shows in detail the improvement effect of each management link after the application of DNN-based intelligent manufacturing supply chain management system. By comparing the specific values before and after the improvement, we can clearly see that the system has achieved remarkable results in improving the accuracy of demand forecasting, optimizing inventory management, enhancing the flexibility of production planning, improving supplier management and improving logistics efficiency. These improvements have significantly improved the operational efficiency of enterprises, reduced costs and enhanced the market competitiveness of enterprises.

5. Conclusions

This study successfully applied DNN to intelligent manufacturing supply chain management system. Through detailed theoretical analysis, technical framework design, system implementation and case analysis, this article verifies the effectiveness and practicability of the intelligent manufacturing supply chain management system based on ML. The specific research results and contributions are as follows:

Theoretical innovation: This article deeply discusses the integration path of intelligent manufacturing and ML, and puts forward the theoretical framework of intelligent manufacturing supply chain management system based on DNN. This provides a new perspective and thinking for the research in related fields.

Technical breakthrough: In the process of system realization, this article develops a solution based on DNN model for the key problems in supply chain management, and realizes technical breakthrough and innovation.

The intelligent manufacturing supply chain management system based on ML can improve the efficiency and accuracy of supply chain management, and reduce the operating costs and risks of enterprises. It can help enterprises to better grasp market demand, optimize resource allocation, improve production efficiency and product quality, and enhance their market competitiveness and sustainable development ability. Therefore, the system has important application value and practical significance. Future research can further explore and optimize the system, and make greater contributions to promoting the development of intelligent manufacturing and improving the level of supply chain management.

References

[1] Huang M, Yi P, Shi T, et al. A modal interval based method for dynamic decision model considering uncertain quality of used products in remanufacturing[J]. Journal of Intelligent Manufacturing, 2018, 29(4):925-935.

[2] Alavidoost M H, Tarimoradi M, Zarandi M H F. Bi-objective mixed-integer nonlinear programming for multi-commodity tri-echelon supply chain networks[J]. Journal of Intelligent Manufacturing, 2018, 29(4):809-826.

[3] Jinliang C, Guoli L, Yu W. Enhance or impair: how does downstream complexity influence supply chain resilience with reconciling effects of intelligent manufacturing?[J]. Journal of Manufacturing Technology Management, 2023, 34(8):1356-1376.

[4] Gupta V, Jayant A, Singh K, et al. Implementation of Low Carbon Supply Chain Management Practices (LCSCMP) in Indian Manufacturing Industries using ISM-DEMATEL[J]. Journal of Advanced Manufacturing Systems, 2024, 23(04):985-1006.

[5] Abdullahi H O, Mohamud I H. The Impact of ICT on Supply Chain Management Efficiency and Effectiveness: A Literature Review[J]. Journal Europeen des Systemes Automatises, 2023, 56(2):309-315.

[6] Ji Z, Peigen L, Yanhong Z, et al. Toward New-Generation Intelligent Manufacturing[J]. Engineering, 2018, 4(4):11-20.

[7] Lu S, Liu S, Zhu Y, et al. A drl-based decentralized computation offloading method: An example of an intelligent manufacturing scenario[J]. IEEE Transactions on Industrial Informatics, 2022, 19(9): 9631-9641.

[8] Wang S, Meng J, Xie H S X. Reference training system for intelligent manufacturing talent education: platform construction and curriculum development[J]. Journal of Intelligent Manufacturing, 2023, 34(3):1125-1164.

[9] Wang Q, Chen H, Qiao L, et al. Path planning for UAV/UGV collaborative systems in intelligent manufacturing[J].

IET Intelligent Transport Systems, 2020, 14(11): 1475-1483.
[10] Cong Y, Tian D, Feng Y, et al. Speedup 3-D texture-less object recognition against self-occlusion for intelligent manufacturing[J]. IEEE transactions on cybernetics, 2018, 49(11): 3887-3897.
[11] Wang Z H, Li Y T, Wu Y C. Design of intelligent manufacturing IoT sensing system for polymer process monitoring[J]. The International Journal of Advanced Manufacturing Technology, 2023, 129(7): 2933-2947.
[12] Manjula R, Chauhan N. A secure and trusted consensus protocol for blockchain-enabled supply chain management system[J]. Peer-to-Peer Networking and Applications, 2024, 17(6):3815-3840.