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Computer-Aided Design AND APPLICATIONS

Reinforcement Learning-Driven Fashion Design and Supply Chain Collaborative Management

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Abstract. Aiming at the shortcomings of traditional supply chain management methods in coping with market demand changes and optimizing inventory strategies, this study proposes a computer-aided supply chain collaborative management model based on RL (Reinforcement Learning). The model combines computer-aided technology to simulate the interaction between design and supply chain, learn and optimize collaborative strategies, and achieve the goal of improving market response speed, reducing operating costs, and improving overall business performance. This study initially devised a comprehensive framework encompassing a rational state space, action space, and reward function to capture the core components and decision-making dynamics of supply chain collaborative management. Following this, an appropriate RL algorithm was chosen for model training, with its efficacy and progressiveness confirmed through empirical research. The experimental outcomes revealed that, in comparison to alternative methods, the RL-based model demonstrated notable advantages in terms of demand forecasting accuracy, inventory turnover rate, and response speed. Consequently, it can be inferred that RL holds substantial promise for application in garment design and supply chain collaborative management.

Keywords: Reinforcement Learning; Collaborative Management of Supply Chain; Fashion Design
DOI: https://doi.org/10.14733/cadaps.2025.S7.228-242

1 INTRODUCTION

With the introduction of market-oriented reforms and the opening of the Chinese economy to the global market, China's clothing industry has rapidly developed and become the world's largest clothing producer and exporter. With the rapid development of e-commerce, more convenient and efficient shopping options and lower prices have been provided, forcing more physical stores to increase their marketing efforts to attract customers [1]. However, despite the rapid development and continuous growth of China's clothing industry, it still faces many challenges, including rising labour costs, intensified competition from other countries, and reduced profit margins due to changes in clothing sales models. The cost of raw materials and labour is constantly increasing. On the other hand, with the growing demand for clothing diversity and fast-paced, the development trend of the clothing industry is gradually moving towards "diversification and short cycles" [2]. The industry employs millions of people and generates billions of dollars in economic activity annually. The supply chain is a crucial link in the clothing production process and one of the key steps to ensure clothing quality. In the clothing manufacturing process, the supply chain takes a long time and largely determines clothing quality and production efficiency. Enterprises urgently need to improve human resource utilization efficiency, and accelerate clothing order scheduling and production speed without significant changes to existing production methods [3]. Optimizing service quality and innovating marketing strategies to combat competitive pressure have greatly reduced the profitability of the clothing manufacturing industry. Clothing orders have also shifted from long cycles, large quantities, and single varieties to short cycles, small batches, and multiple varieties, as well as a decrease in clothing unit prices. This unfavourable trend has put forward higher requirements for the transformation and upgrading of the clothing manufacturing industry. This may lead to delayed delivery of orders, reduced profitability, and a negative impact on the company's industry reputation and future development. Therefore, the reasonable arrangement of assembly line workstations in the clothing supply chain and real-time dynamic scheduling of the clothing supply chain is crucial for clothing enterprises to achieve higher economic benefits. At present, the software products related to the clothing manufacturing industry are not perfect, with single functions and poor universality, requiring secondary customized development, which is difficult to meet the production needs of most clothing enterprises [4]. With the rapid development of information technology, more and more clothing companies are seeking more efficient clothing supply chain assembly line layout and scheduling systems to meet their production and development needs. With the introduction of strategies such as Industry 4.0 and Made in China 2025, intelligent manufacturing is receiving increasing attention from both academia and industry. The long duration of supply chain assembly line arrangement and scheduling, or the unreasonable arrangement and scheduling plan of supply chain assembly line workstations, will have a significant adverse impact on the efficiency of clothing production.

The system can automatically adjust the shape parameters based on user input of body type data, style preferences, and material requirements, achieving efficient and accurate personalized customization design [5]. Continuously optimizing various aspects of clothing design while strengthening seamless collaboration between design and supply chain. Reinforcement learning, as a machine learning method that learns optimal strategies through trial and error, can simulate the learning process of humans in complex decision-making environments. This deficiency directly leads to a high dependence on the personal skills and experience of plate makers in the conversion process from design to production, which not only limits the improvement of design efficiency but also makes it difficult to meet the growing demand for personalized customization [6]. Through reinforcement learning, the system can learn and solidify the best practices, professional knowledge, and expert experience in clothing pattern design, reducing reliance on manual pattern makers. Reinforcement learning algorithms can analyze large amounts of historical design data, identify inefficient processes in the design process, and gradually improve through iterative optimization. However, its limitations are becoming increasingly prominent, especially in integrating the deep principles, professional knowledge, historical design experience, and expert wisdom of fashion design, which seems inadequate. In order to overcome these challenges and respond to the urgent market demand for fast response, highly personalized, and intelligent production, reinforcement learning (RL) technology has been introduced and applied to the collaborative management of clothing design and supply chain, injecting new vitality into clothing CAD systems. This can not only significantly improve design efficiency, but also ensure stable improvement in design quality through data-driven decision support [7]. Through directed graphs, the various components of clothing design and their logical relationships can be clearly represented, such as pattern structure, stitching sequence, material selection, etc. At present, most of the research on the optimization problem of clothing sewing assembly line workstation layout belongs to the single objective clothing sewing assembly line workstation layout optimization problem, and there is insufficient research on the multi-objective clothing sewing assembly line workstation layout optimization problem [8]. This article conducts practical research and analysis on this type of problem and establishes corresponding mathematical models. The time required for orchestration is much shorter than that required for manual orchestration, and the target balance rate and total equipment loss of orchestration results are better than those of manual orchestration results. A deep reinforcement learning-based dynamic scheduling method for the clothing sewing process to minimize the maximum completion cycle is proposed to address the problem of poor real-time response capability [9]. Finally, the algorithm's effectiveness was validated through enterprise production examples, and the results showed that the algorithm can effectively solve this type of problem. And adjust the encoding, crossover, mutation and other operations of the NSGA-I algorithm based on the characteristics of this type of problem [10]. By establishing a scheduling optimization model and transforming it into a sequential decision-making problem based on Markov decision processes, state features, candidate action sets, reward functions, exploration and utilization strategies are defined. Modelling and solving real-time dynamic scheduling problems for the clothing sewing process based on deep reinforcement learning, aiming at the poor adaptive performance of dynamic events faced by static scheduling methods in the clothing production scheduling process. Through the verification of the production process of jeans sewing in enterprises, the method proposed by the research institute is slightly inferior in achieving scheduling goals compared to genetic algorithms [11]. However, it greatly improves decision-making efficiency and can achieve real-time response to the problem of dynamic order arrival, ensuring the efficiency and continuity of the scheduling plan. And combined with the DDON algorithm to train a deep neural network for describing state-action values, in order to select the most suitable scheduling rules. Divide all functional requirements of the system into multiple functional modules for implementation, using Python as the development language and MSOL as the database management system to design the database. In order to better assist enterprises in production and management, we collected and analyzed the production needs of a certain order-based service enterprise in Henan, and determined the system's functional requirements and development technology. After practical application testing, the system can be used normally and meet the production needs of the enterprise for clothing sewing assembly line arrangement and scheduling [12].

The paper presents the following innovations: firstly, the establishment of an RL-based collaborative framework for fashion design and supply chain; secondly, the comprehensive consideration of market demand, design innovation, production costs, and other factors in model construction, accompanied by the detailed design of state space, action space, and reward function; and lastly, empirical validation of the model's validity and practicality, providing theoretical direction and practical insights for clothing enterprises. Structured into seven sections, this paper delves into the application of RL in fashion design and supply chain collaborative management. Section one introduces the research background, significance, objectives, and problem definition, and outlines the paper's structure. Section two reviews existing research gaps and proposes innovations. Sections three to five conduct a deep analysis of the problem, construct the model and explore application examples. Section six presents empirical research to verify the model's effectiveness. Finally, section seven summarizes the research findings and suggests future directions.

2 RELATED WORK

As an advanced machine learning method, deep learning has been widely applied in the field of supply chain management in recent years. Liu et al. [13] utilized deep learning to optimize key supply chain links such as inventory management, demand forecasting, and logistics scheduling and achieved significant results. Creating a 3D mesh model that highly replicates the actual product shape is crucial for achieving accurate simulation. Reinforcement learning can continuously learn and optimize decision-making strategies through interaction with the environment, demonstrating enormous potential in collaborative management of clothing design and supply chain. Meng et al. [14] combined computer-aided simulators with reinforcement learning techniques to explore their potential applications in reinforcement learning-driven clothing design and supply chain collaborative management. By analyzing historical production data, market demand changes, and customer feedback, reinforcement learning algorithms can dynamically adjust production details such as weaving parameters and stitching paths to achieve more efficient and accurate production. Given the unique weaving characteristics of double needle bed knitted tubular fabrics, a planar mesh model was first constructed based on its unfolded form as the basis for subsequent 3D simulations. On this basis, we utilize the powerful capabilities of matrix operations and coordinate mapping techniques to accurately locate and determine the joint position in the 3D mesh model, ensuring the accuracy and reliability of the simulation results. In order to depict the spatial geometry of the stitches more finely, Rolf et al. [15] innovatively introduced an eight-point model, which can capture the key geometric features of the stitches through effective transformations of the planar mesh model and generate realistic stitch simulation effects. Clothing is processed and produced through a sewing assembly line consisting of several workstations. Equipment loss occurs during the processing of each device and is measured by the equipment loss coefficient. The number of production processes for clothing is fixed and cannot be separated. Each process is only operated at one workstation, and only one process can be processed at a time. A single garment sewing assembly line has a certain number of workstations, which allocate various types of equipment to corresponding workstations. Due to the characteristics of the clothing sewing process, Wang and Sung [16] analyzed the constraints of a single sewing assembly line. The sewing process of a garment is completed entirely in one sewing assembly line. With the rapid development of economic globalization and the market, consumers' personalized needs are increasing, and clothing companies are facing increasingly fierce competition. However, at present, the information transmission process between nodes in the supply chain of clothing enterprises is characterized by a lack of information sharing, slow supply chain efficiency, and an inability to achieve rapid response. Based on the current research status of clothing supply chain management, the application trend of RFID technology, and the current situation of RFID technology in clothing supply chain management, this paper summarizes and analyzes the research status and proposes the necessity of this study. Wu et al. [17] quantitatively analyzed the application of RFID technology and Non-RFID technology in the supply chain management of clothing enterprises through system dynamics methods.

At the same time, RFID technology is gradually being applied to supply chain management in the clothing industry. RFID technology can not only achieve information sharing, rapid response, and improve information accuracy in the supply chain but also save a certain degree of labour costs to optimize the supply chain of clothing enterprises. Based on the typical clothing supply chain structure, establish a system dynamics simulation model for RFID technology and non-RFID technology and conduct a comparative analysis. Yan et al. [18] constructed a simulation model based on deep learning technology and its application in the supply chain management of clothing enterprises. At the same time, a comparative analysis was conducted on the simulation results of RFID technology and Non-Deep Learning technology based on the implementation results in data of BS clothing enterprise projects. The proposal of deep learning technology can weaken the bullwhip effect in clothing enterprise supply chain management and improve the rapid response capability of the supply chain by achieving information sharing and improving supply chain efficiency. Establish a simulation model of deep learning in BS supply chain management for clothing enterprises. The competition among clothing enterprises has transformed into competition among clothing supply chain management. Therefore, Yaghin et al. [19] analyzed the need for close cooperation, information sharing, and improved supply chain efficiency among the supply chain nodes of clothing enterprises to achieve rapid response to market demand. In addition, it also introduces an innovative hybrid solving strategy that significantly improves the efficiency and accuracy of the solving process through convection processing and deblurring techniques, providing strong technical support for practical applications. Reinforcement learning, with its powerful self-learning and optimization capabilities, can continuously learn from actual operational data, dynamically adjust supply chain strategies to adapt to market changes, and achieve seamless integration between design and production. A core manufacturer and multiple distribution centres not only focus on traditional cost and efficiency optimization but also innovatively incorporate social sustainability standards into their considerations. In order to address the common fuzzy random uncertainty in the supply chain, Zheng and Jiang [20] designed a mixed integer nonlinear programming model with opportunity constraints. In fashion design, reinforcement learning can help designers predict fashion trends, and optimize fabric selection and pattern design while considering the feasibility and cost-effectiveness of the supply chain. In supply chain management, reinforcement learning can monitor inventory levels, production progress, and logistics status in real-time, intelligently schedule resources, and ensure efficient collaboration and stable operation of the supply chain.

While RL applications in supply chain management have shown some success, research in fashion design and collaborative supply chain management remains limited. Existing studies often concentrate on a single supply chain segment or specific business context, neglecting a comprehensive analysis of the entire fashion design and collaborative supply chain management system. This paper aims to address these issues in depth.

3 FASHION DESIGN AND SUPPLY CHAIN COLLABORATIVE MANAGEMENT ANALYSIS

3.1 Fashion Design Process and Its Relationship With The Supply Chain

Fashion design is a complex and creative process, which involves many links and factors. Generally speaking, the fashion design process includes inspiration, design conception, sketch drawing, sample garment making, fitting adjustment and other steps. In this process, designers need to consider market demand, fashion trends, material selection, cost control and other factors.

Fashion design and supply chain are closely intertwined. The supply chain must align with design requirements for material preparation, production scheduling, and inventory management. Conversely, design must consider supply chain constraints to ensure feasibility and productivity. Thus, collaborative management between fashion design and supply chain is crucial for the overall clothing business. Figure 1 illustrates the collaborative management architecture of the supply chain.

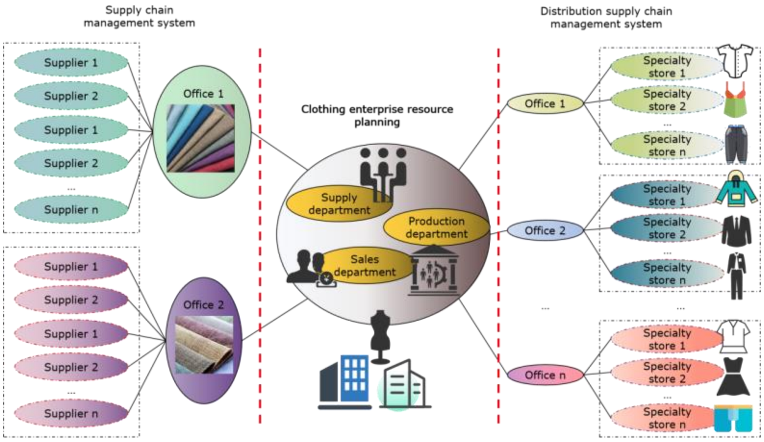

Figure 1: Architecture diagram of supply chain collaborative management.

The collaborative management of the supply chain in the clothing industry faces many challenges. First, the uncertainty of market demand makes it difficult for the supply chain to accurately predict and respond. The diversification and rapid changes in consumer demand have brought great pressure to supply chain management. Second, inventory control is another important challenge. Too much inventory will lead to capital occupation and waste, while too little inventory may lead to shortages and loss of sales opportunities.

4 COLLABORATIVE MANAGEMENT MODEL OF SUPPLY CHAIN BASED ON RL

4.1 Model Building Ideas and Objectives

The core idea of constructing a collaborative management model of the supply chain based on RL is to regard the management decision-making of the supply chain as a sequential decision-making process. Specifically, all the links in the supply chain (such as demand forecasting, production planning, inventory management, logistics distribution, etc.) are regarded as different states in the state space, and the decisions or actions that supply chain managers may take in these links are regarded as the action space. Through the RL algorithm, the model can learn an optimal strategy, which can choose the optimal action in a given state to achieve the long-term goals of supply chain management, such as reducing costs, improving response speed, and optimizing inventory.

4.2 Design of State Space, Action Space, and Reward Function

In the design of state space, it is necessary to comprehensively consider various key factors in the supply chain, such as market demand, inventory level, production capacity, logistics status, etc., and quantify these factors into specific States in the state space.

Assume that the state s is a vector, which contains the key factors in the supply chain:

$$s = \left[s_1, s_2, s_3, \ldots, s_n\right] \tag{1}$$

Among them, s_i can represent the quantitative value of factors such as market demand, inventory level, production capacity, and logistics status.

Action space covers all decisions or actions that supply chain managers may take, such as adjusting production plans, changing inventory strategies, optimizing logistics distribution routes, etc.

Action a is a collection of decisions or actions that supply chain managers may take:

$$a \in A = \left[a_1, a_2, a_3, \ldots, a_m\right] \tag{2}$$

Among them: a can be to adjust production plans, change inventory strategy, optimize logistics distribution routes, etc.

The reward function is the key link in the RL model, and it needs to be designed according to the specific objectives of supply chain management. For example, cost reduction can be set as a positive reward, while out-of-stock or excess inventory can be set as a negative reward.

The reward function $R(s,a)$ is used to evaluate the quality of taking action a in the state s, which can be set according to the goal of supply chain management:

$$R(s,a) = R_{\cos t}(s,a) + R_{stock}(s,a) + R_{service}(s,a) \tag{3}$$

Among them: $R_{\cos t}(s,a)$ is a reward related to cost; $R_{stock}(s,a)$ is a reward related to inventory level; $R_{service}(s,a)$ is a reward related to service level.

4.3 Selection of RL Algorithm and Model Training Strategy

When choosing the RL algorithm, it is necessary to consider the specific characteristics and complexity of supply chain collaborative management. Collaborative management of the supply chain often involves many state variables and decision variables, which makes the state space and action space quite huge. In order to deal with this challenge effectively, this paper chooses the Actor-Critic algorithm (as shown in Figure 2), which combines the methods of strategic gradient and value function estimation and can not only deal with the problem of continuous action space but also learn effectively in high-dimensional state space.

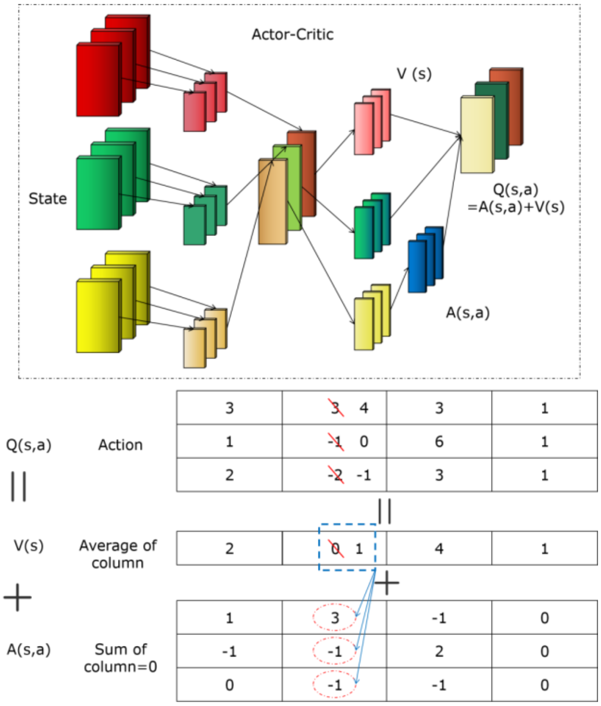

Figure 2: Actor-critic algorithm flow chart.

The Actor-Critic algorithm's core idea is to represent and learn the Actor and Critic components separately. The Actor selects actions based on the current state, while the Critic estimates the value following an action, aiding in updating the Actor's strategy. This separation allows the algorithm to concurrently learn the optimal strategy and the corresponding state value function, enhancing learning efficiency and stability. In this paper, we apply the Actor-Critic algorithm to a supply chain collaborative management model. Specifically, we input various supply chain states (e.g., market demand, inventory levels, production capacity) and output corresponding collaborative management actions (e.g., adjusting production plans, optimizing inventory strategies) through the actor-network. The Critic network estimates the long-term value of these actions, updating and optimizing the Actor network's strategy.

A. Actor part (policy function update):

The goal of the strategy function $\pi_\theta(a|s)$ is to maximize the expected return. The strategy parameter θ is updated by the following gradient rise:

$$\nabla_\theta J(\theta) \approx \sum_t \nabla_\theta \log\pi_\theta(a_t|s_t)\, Q_\omega(s_t,a_t) \tag{4}$$

Where $J(\theta)$ is the performance function of the strategy and $Q_\omega(s_t,a_t)$ is the value of taking action a_t in state s_t ?

B. Critic part (value function update):

The value function $Q_\omega(s,a)$ is used to evaluate the value of the action a taken in the state s, and is updated in the following ways:

$$\delta = r_t + \gamma Q_\omega(s_{t+1},a_{t+1}) - Q_\omega(s_t,a_t) \tag{5}$$

$$\omega \leftarrow \omega + \alpha\delta\nabla_{\omega} Q_{\omega}(s_t, a_t) \tag{6}$$

Where r_t is the reward received at time step t, γ is the discount factor, and a is the learning rate.

C. Joint update:

At each time step, both the Actor and Critic components are updated. The Actor adjusts its strategy based on the value estimate from the Critic, while the Critic updates its value function based on the observed return and the value of the subsequent state. In practical applications, to handle continuous action spaces, neural networks are often used to approximate the strategy function $\pi_\theta(a|s)$ and the value function $Q_\omega(s,a)$. The update steps using neural network approximation are as follows:

Actor-network update:

$$\nabla_\theta J(\theta) \approx \sum_t \nabla_\theta \log\pi_\theta(a_t|s_t) A(s_t, a_t) \tag{7}$$

Among them, $A(s_t, a_t)$ is the dominance function, which can be expressed as $A(s_t, a_t) = Q_\omega(s_t, a_t) - V(s_t)$, and $V(s_t)$ is the state value function.

Critic network update:

$$\delta = r_t + \gamma V(s_{t+1}) - V(s_t) \tag{8}$$

$$\omega \leftarrow \omega + \alpha\delta\nabla_\omega V(s_t) \tag{9}$$

By applying the Actor-Critic algorithm, we can effectively address the challenges of high-dimensional state space and continuous action space in supply chain collaborative management.

In the model training strategy, the combination of off-line training and on-line training is adopted. Off-line training can use historical data to pre-train the model so that it has a certain initial strategy; Online training can make the model interact with the environment continuously in the actual operation process and further optimize the strategy.

5 RL-DRIVEN FASHION DESIGN AND SUPPLY CHAIN COORDINATION STRATEGY

In the collaboration of fashion design and supply chain, the optimization objectives mainly include improving design innovation and market response speed, reducing inventory cost and production costs, and improving overall business performance. Through the application of RL, the close cooperation between design and supply chain can be realized, so as to better meet market demand, improve product quality and reduce operating costs.

RL learns an optimal collaborative strategy by simulating the interaction between design and supply chain. This strategy can consider the mutual influence and restriction between design and supply chain and choose the optimal action plan in a given state. Through continuous training and optimization of intensive learning, the collaborative efficiency between design and supply chain can be significantly improved, thus achieving better business performance.

6 EMPIRICAL RESEARCH

6.1 Data Source and Experimental Design

In empirical research, data sourcing and processing are crucial. Our study's data primarily originates from actual operational data of a clothing enterprise, encompassing historical sales records, inventory data, production plans, and market demand information. To ensure data accuracy and consistency, we undertook data cleaning and preprocessing, which involved removing outliers, filling missing values, and standardizing the data.

Experimental design is the core of empirical research. Aligned with our research objectives, we devised an experimental scheme for a supply chain collaborative management model based on RL. Our experiment employed a control group and an experimental group design, where the control group used traditional supply chain management methods while the experimental group applied the RL-based model proposed in this paper. Throughout the experiment, we ensured a stable and controllable environment to minimize external factor interference. Post-experiment, we conducted a thorough analysis and discussion of the collected data.

Figure 3 illustrates the comparison of demand forecast accuracy between the control group and the experimental group.

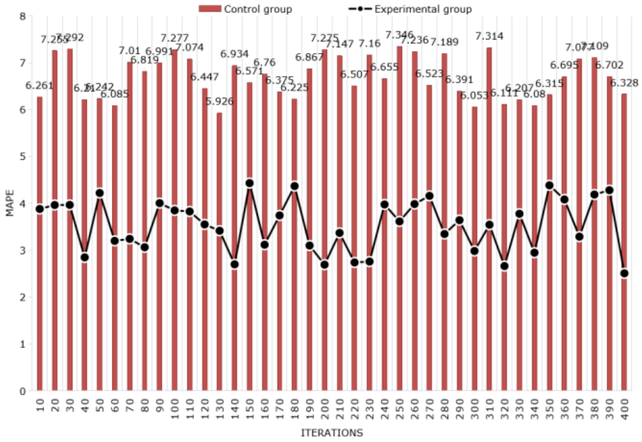

Figure 3: Accuracy comparison of demand forecast.

Upon calculating the deviation between predicted and actual demand, we found that the experimental group's MAPE (Mean Absolute Percentage Error) was 3.5%, compared to the control group's 6.8%. This indicates that the experimental group's demand forecast accuracy is significantly higher, with an error reduction of approximately 48.5%. This notable improvement demonstrates that the RL-based model can better capture market demand changes and provide more accurate information support for supply chain collaborative management.

Inventory turnover rate is a crucial metric for assessing supply chain operational efficiency, reflecting inventory flow speed and capital utilization efficiency. Figure 4 compares the inventory turnover rate between the control group and the experimental group.

The inventory turnover rate of the experimental group is about 12 times a year, while that of the control group is about 8 times a year. The inventory turnover rate of the experimental group has increased by 50%, which shows that the model based on RL can optimize inventory management more effectively, reduce inventory backlog and improve capital utilization efficiency.

Response speed refers to the response speed of the supply chain to market changes or customer needs. Figure 5 shows the comparison of response speed between the control group and the experimental group.

The average response time of the experimental group is approximately 120 minutes, whereas the control group's is around 360 minutes. This represents a 66.7% reduction in response time for the experimental group, indicating that the RL-based model can make decisions swiftly and better adapt to market changes and customer needs.

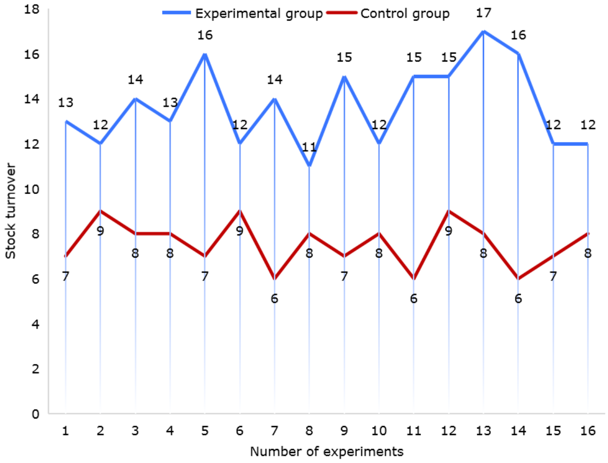

Figure 4: Inventory turnover ratio comparison.

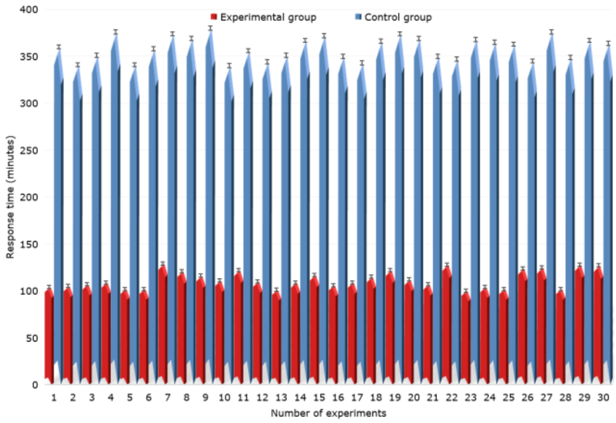

Figure 5: Response speed comparison.

6.2 Model Performance Evaluation and Comparison

To comprehensively evaluate the model's performance, this section employs multiple evaluation metrics such as accuracy, recall, F1 score, MAE (Mean Absolute Error), and MSE (Mean Squared Error). Additionally, it is benchmarked against other advanced supply chain management models to validate the proposed model's advantages and uniqueness. The results are presented in Table 1 and Table 2.

Fold	*Accuracy*	*Recall*	*F1 Score*	*MAE*	*MAP*
1	0.94	0.89	0.91	0.032	0.011
2	0.96	0.91	0.93	0.029	0.009
3	0.95	0.90	0.92	0.030	0.010
4	0.93	0.88	0.90	0.033	0.012
5	0.97	0.92	0.94	0.028	0.008
6	0.95	0.89	0.92	0.031	0.010
7	0.94	0.90	0.92	0.032	0.011

8	0.96	0.91	0.93	0.029	0.009
9	0.95	0.89	0.92	0.030	0.010
10	0.94	0.88	0.91	0.033	0.012
Avg	0.95	0.90	0.92	0.031	0.010

Table 1: Evaluation metrics of the rl-based supply chain collaboration management model using ten-fold cross-validation.

Model Name	*Accuracy*	*Recall*	*F1 Score*	*MAE*	*MAP*
RL-Based Supply Chain Collaboration Management Model	0.95	0.90	0.92	0.031	0.010
Deep Neural Network Supply Chain Prediction Model	0.92	0.88	0.90	0.035	0.013
Genetic Algorithm Optimized Supply Chain Model	0.89	0.85	0.87	0.040	0.016
Linear Regression Supply Chain Cost Prediction Model	0.85	0.80	0.82	0.050	0.020
Mixed Integer Programming Supply Chain Optimization Model	0.90	0.87	0.89	0.038	0.014
Machine Learning Ensemble Supply Chain Prediction Model	0.94	0.91	0.92	0.032	0.011

Table 2: Comparison of RL-based supply chain collaboration management model with other advanced models.

As can be seen from the data in the table: the cooperative management model of the supply chain based on RL performs well in accuracy, recall, F1 score, MAE and MSE, and its comprehensive performance is better than other models. This shows that RL has obvious advantages in dynamic decision-making optimization of the supply chain. Through evaluation and comparison, we further confirmed the effectiveness and advancement of the model based on RL in supply chain collaborative management.

6.3 Specific Application Cases of the Model in Supply Chain Management

Taking the new product design project of a clothing brand as an example, the brand has achieved close collaboration between design and supply chain by applying the strategy of collaboration between fashion design and supply chain based on RL, as shown in Figure 6. The proposed model can formulate an optimal design scheme and supply chain coordination strategy according to market demand, design trend, material cost and other factors. Taking the demand prediction and inventory optimization of this clothing brand as an example, the supply chain collaborative management model based on RL can predict the future demand by learning historical sales data and market demand trends, and optimize the inventory strategy according to the prediction results. The comparison of operating costs before and after using the model is shown in Figure 7.

Before applying the supply chain collaborative management model based on RL, the average operating cost of enterprises was about 1 million yuan per month. After applying the model, the average operating cost is reduced to about 800 thousand yuan per month. This means that the operating cost is reduced by 20%, which shows the remarkable effect of the model in optimizing supply chain management and reducing costs. Before and after applying this model strategy, the market response speed of new products is shown in Figure 8.

Before applying the model, the average market response time of new products is about 60 days. After applying the model, the average market response time was shortened to 30 days. This means that the market response time has been shortened by about 50%. This remarkable improvement shows that the model based on RL can respond to market changes more quickly, accelerate the listing and promotion of new products, and thus bring greater market competitive advantages to enterprises.

Figure 6: Management environment of clothing supply chain and some new product designs.

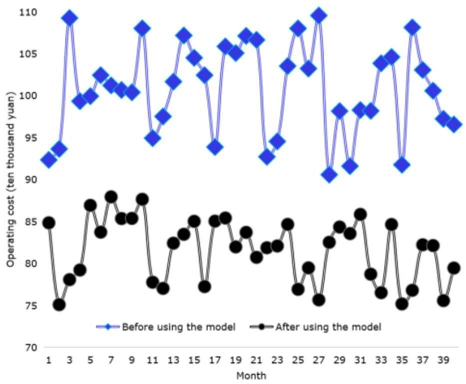

Figure 7: Comparison of operating costs before and after using the model.

Through the verification of the practical application effect, it can be found that this strategy can effectively improve the market response speed of new products, reduce inventory costs and production costs, and improve overall business performance. This is because the proposed model can make an optimal production plan and inventory strategy according to the current market demand, inventory level and production capacity, so as to minimize the inventory cost and maximize the satisfaction rate. Through the verification of practical application cases, we can find that this successful case proves the great application potential and value of RL in fashion design and supply chain collaboration.

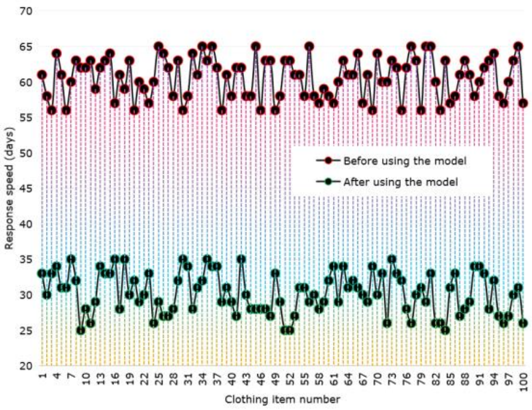

Figure 8: Response speed of supply chain.

7 CONCLUSIONS

In this study, the collaborative management model of supply chain based on RL is put forward around the problems of fashion design and supply chain collaborative management, and its effectiveness and advancement are verified by empirical research. In this paper, the design of state space, action space and reward function of the model, as well as the selection of RL algorithm and model training strategy are discussed in depth. At the same time, it also shows the obvious advantages of the model in demand forecasting and inventory optimization through practical application cases.

This study holds significant practical implications for fashion design and supply chain collaborative management. By implementing the RL-based model, enterprises can foster tight collaboration between design and supply chain operations, enhancing market response speed, decreasing operating costs, and boosting overall business performance. This, in turn, aids enterprises in distinguishing themselves in the competitive market and achieving sustainable growth.

While this study has yielded some accomplishments, there are numerous avenues worth exploring further. For instance, investigating how to integrate RL with other machine learning techniques to enhance model performance and stability presents a promising direction. Moreover, exploring the incorporation of additional supply chain factors into the model to facilitate more comprehensive collaborative management is another area for future research. As technology continues to advance and application scenarios expand, we anticipate that RL will play an increasingly pivotal role in fashion design and supply chain collaborative management.

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REFERENCES

[1] Alseaidy, H.: Color and line as creative elements in achieving movement in the design of woven fabrics for girls' clothing, International Design Journal, 10(1), 2020, 423-433. https://doi.org/10.21608/IDJ.2020.81752

[2] Cheng, Z.; Kuzmichev, V.; Adolphe, D.: A digital replica of male compression underwear, Textile Research Journal, 90(7-8), 2020, 877-895. https://doi.org/10.1177/0040517519883058
[3] Choi, T.-M.; Cai, Y.-J.; Shen, B.: Sustainable fashion supply chain management: a system of systems analysis, IEEE Transactions on Engineering Management, 66(4), 2019, 730-745. https://doi.org/10.1109/TEM.2018.2857831
[4] Cong, H.; Shen, Y.; Zhang, J.: Research on the virtual display of a weft-knitted seamless kneepad based on the free-form deformation model, Textile Research Journal, 92(19-20), 2022, 3545-3553. https://doi.org/10.1177/004051752210814
[5] GAN, L.; Liu, L.; Liu, L.: Accurate human parsing model by edge contour and pose feature, Journal of Computer-Aided Design & Computer Graphics, 33(9), 2021, 1428-1439. https://doi.org/10.3724/SP.J.1089.2021.18683--noPublish228
[6] Guo, H.; Ying, B.; Zhang, X.; Qi, J.: Acquisition of plate-making process knowledge for smart clothing CAD systems, Journal of Fiber Bioengineering and Informatics, 12(3), 2019, 137-145. https://doi.org/10.3993/jfbim00295
[7] Hu, L.: Design and implementation of a component-based intelligent clothing style CAD system, Computer-Aided Design and Applications, 18(S1), 2020, 22-32. https://doi.org/10.14733/cadaps.2021.S1.22-32
[8] Indrie, L.; Mutlu, M.-M.; Ork, N.: Computer-aided design of knitted and woven fabrics and virtual garment simulation, Industria Textila, 70(6), 2019, 557-563. https://doi.org/10.35530/IT.070.06.1659
[9] Ji, Y.; Li, X.; Wang, Q.: Investigating the structure and simulation of seamless weft knitted fabric, The Journal of The Textile Institute, 114(4), 2023, 633-638. https://doi.org/10.1080/00405000.2022.2059904
[10] Kim, J.; Kim, Y.-J.; Shim, M.; Jun, Y.; Yun, C.: Prediction and categorization of fabric drapability for 3D garment virtualization, International Journal of Clothing Science and Technology, 32(4), 2020, 523-535. https://doi.org/10.1108/IJCST-08-2019-0126
[11] Li, X.; Li, X.-R.; Li, Y.; Feng, W.: Review of cloth modeling and simulation for virtual fitting, Textile Research Journal, 93(7-8), 2023, 1699-1711. https://doi.org/10.1177/00405175221135625
[12] Liu, H.; Jiang, G.; Dong, Z.: Geometric simulation for warp-knitted tubular bandages with the mesh model, Textile Research Journal, 91(21-22), 2021, 2612-2623. https://doi.org/10.1177/00405175211013836
[13] Liu, H.; Jiang, G.; Dong, Z.: Mesh modeling and simulation for three-dimensional warp-knitted tubular fabrics, The Journal of The Textile Institute, 113(2), 2022, 303-313. https://doi.org/10.1080/00405000.2020.1871184
[14] Meng, S.; Pan, R.; Gao, W.; Yan, B.; Peng, Y.: Automatic recognition of woven fabric structural parameters: a review, Artificial Intelligence Review, 55(8), 2022, 6345-6387. https://doi.org/10.1007/s10462-022-10156-x
[15] Rolf, B.; Jackson, I.; Müller, M.; Lang, S.; Reggelin, T.; Ivanov, D.: A review on reinforcement learning algorithms and applications in supply chain management, International Journal of Production Research, 61(20), 2023, 7151-7179. https://doi.org/10.1080/00207543.2022.2140221
[16] Wang, Y.-M.; Sung, T.-J.: Application of knowledge management in costume design: the case of measure for measure, Journal of Integrated Design and Process Science, 23(4), 2021, 45-60. https://doi.org/10.3233/JID200001
[17] Wu, H.; Su, J.; Hodges, N.: Investigating the role of open costing in the buyer-supplier relationship: implications for global apparel supply chain management, Clothing and Textiles Research Journal, 41(2), 2023, 154-169. https://doi.org/10.1177/0887302X21993501
[18] Yan, Y.; Chow, A.-H.; Ho, C.-P.; Kuo, Y.-H.; Wu, Q.; Ying, C.: Reinforcement learning for logistics and supply chain management: Methodologies, state of the art, and future opportunities, Transportation Research Part E: Logistics and Transportation Review, 162(1), 2022, 102712. https://doi.org/10.1016/j.tre.2022.102712

[19] Yaghin, R.-G.; Sarlak, P.; Ghareaghaji, A.-A.: Robust master planning of a socially responsible supply chain under fuzzy-stochastic uncertainty (A case study of clothing industry), Engineering Applications of Artificial Intelligence, 94(9), 2020, 103715. https://doi.org/10.1016/j.engappai.2020.103715

[20] Zheng, P.; Jiang, G.: Modeling and realization for visual simulation of circular knitting transfer-jacquard fabric, Textile Research Journal, 91(19-20), 2021, 2225-2239. https://doi.org/10.1177/0040517521994