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Optimization of Multi-Direction Material Supply Demand Based on Model Algorithm

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Abstract: The content of this study is to realize the real-time optimization of supply chain and improve the overall efficiency of supply chain by comprehensively considering various algorithms or models and comprehensively considering the needs of all parties in the supply chain. Through comparative experiments, this paper verifies that the proposed algorithm based on deep reinforcement learning has significant advantages in meeting the demand of multi-direction material supply. This study designed a series of key experiments to comprehensively evaluate the Deep Q-network DQN (Deep Q-Leaning Network) algorithm, GA (Genetic Algorithm) and PSO (Particle Swarm Optimization) algorithm and Q-Learning (Quintuple Learning) on multi-direction material supply chain optimization. In the benchmark performance test, the DQN algorithm has the lowest total supply cost of $1,200, the algorithm evaluation meets the demand in 2 hours, and the satisfaction rate reaches 95%, which is far higher than other algorithms. It can be seen from the dynamic demand adaptability experiment that DQN algorithm is highly adaptable and flexible in responding to market demand fluctuations. The average response time of DQN algorithm evaluation is 2 hours in season, and the response time of DQN algorithm can also be maintained at 2.2 hours in the case of demand surge caused by emergencies. The above data proves its superior performance in dynamic environments. The robust robustness of the DQN algorithm was also further confirmed in the robustness and exception handling experiments, where DQN showed the shortest recovery time of 1.5 hours and the lowest cost impact of a 5% cost increase in the face of anomalies such as supply point failures, demand surges and transportation delays. From the above experimental data, it can be seen that DQN algorithm shows excellent benchmark performance, dynamic adaptability and robustness in the multi-direction material supply chain optimization problem, which can be said to be an effective and reliable solution.

1. Introduction

Under the background of global economy, the complexity and dynamics of supply chain management are increasing day by day. Especially in the field of multi-direction material supply, how to effectively optimize the supply chain to improve efficiency and reduce costs has become the focus of enterprises and researchers. Traditional optimization methods are often unable to cope with complex and dynamic supply chain problems, and it is difficult to adapt to the rapidly changing market demand and sudden supply chain anomalies. In recent years, the rise of deep reinforcement learning provides a new way to solve this problem. As a typical algorithm in deep reinforcement learning, DQN algorithm of deep Q network shows great potential in supply chain optimization with its strong learning ability and decision optimization performance.

This paper focuses on the application of DQN algorithm in multi-direction material supply chain optimization. This paper comprehensively evaluates the performance comparison of DQN algorithm with GA algorithm, PSO algorithm and Q-Learning algorithm through the experimental design of benchmark performance test, dynamic demand adaptability test, robustness and exception handling ability test. The results show that DQN algorithm performs well in supply chain cost optimization, dynamic adaptability and robustness under abnormal conditions. The above experiments also provide an efficient and reliable optimization tool for supply chain management. The research in this paper not only expands the application of DQN algorithm in the field of supply chain optimization, but also provides valuable reference and inspiration for future research in related fields.

This paper first introduces the importance of supply chain optimization and the application potential of deep reinforcement learning in it, and highlights the background and significance of the research. Then this paper describes supply chain network optimization and DQN algorithm in detail, including the basic principle of supply chain network optimization and DQN algorithm. In the part of experimental results analysis, the paper compares the performance of DQN algorithm and other optimization algorithms in different tests, and discusses the results in detail. Finally, the paper summarizes the research findings and puts forward the prospect of future research directions. For this paper, the structure is clear, the logic is strict, in order to provide readers with a rich content, detailed information research paper.

2. Related Works

Previous studies have shown that many scholars have proposed various methods and models for supply chain management. For example, Rong Bo established a multi-objective integer linear programming model for the location of agricultural supply points and took the relationship between neighboring districts and counties as a constraint. He also discussed the selection of weights. Based on his experimental results, the location of agricultural product supply points can be optimized as a whole, thus reducing the sales and transportation costs of agricultural products and shortening the logistics time [1]. On the basis of the collaborative optimization model, Ma Bowen et al. further proposed a phased optimization method. His experimental results showed that the solution efficiency of the phased optimization method was significantly higher than that of the collaborative optimization method, which indicated its superiority in improving the transportation efficiency of the large-scale road network at the road bureau level [2]. Wu Di et al. designed and improved the genetic algorithm for solving the optimal cargo collecting route. The results showed that the improved genetic algorithm could get the approximate optimal solution. The optimized cargo transportation scheme had shown the characteristics of reducing cost and improving efficiency in practice, providing scientific theoretical basis and decision support for the cargo route planning and selection of cooperatives [3]. Zhang Yingting calculated the segmented route bottleneck model for the segmented route of ship logistics, obtained the bottleneck point coordinates of different transport sections, and then calculated the conflict diversion points of each transport section according to this bottleneck point coordinate data. Finally, she constructed the optimal path model by using stepwise genetic algorithm [4]. However, these studies often ignore the complexity of multi-direction material supply, and cannot effectively solve the balance and coordination of multi-party demand in the supply chain, resulting in poor practical application effect.

In the literature, some researchers try to use mixed integer linear programming model to optimize the supply chain to solve the problem of multi-direction material supply. For example, in order to improve the safety of dangerous goods storage and transportation, Kuang Yujie established a mixed integer multi-objective nonlinear programming model based on the locally connected urban road network. For the complexity of the model, she also designed a genetic stage solution algorithm based on the approximate ideal solution sorting method, and verified the effectiveness of the model and algorithm through numerical examples [5]. Wu Peng et al. first constructed a multi-objective mixed integer nonlinear programming model under different carbon emission policies, and converted it into an equivalent linear model according to the characteristics of the problem. Secondly, in order to effectively solve this model, he proposed an improved adaptive genetic algorithm for the characteristics of fusion problems and verified the effectiveness of the proposed model and algorithm [6]. However, these methods are often too complicated for practical application, so this paper thinks it is necessary to choose a new algorithm, which can not only effectively deal with complex data, but also solve the balance and coordination of multi-party demand in the supply chain. Therefore, this paper designs a model of optimizing material supply chain in different scenarios based on DQN algorithm.

3. Methods

3.1 Supply Chain Network Optimization

This section will focus on how to improve efficiency and maximize resource utilization by optimizing supply chain network structure and processes in order to reduce costs and achieve overall benefits. Supply chain network optimization plays a crucial role in modern logistics management. In the optimization of supply chain network, supplier selection and evaluation are very important. In this process, many factors such as supplier's price, on-time delivery rate and product quality should be taken into account, because only in this way can a comprehensive supplier evaluation model be established [7-8]. A good model can help find the optimal mix of suppliers, thereby optimizing the entire supply chain network. The supplier evaluation model can be calculated using the following weighted score method, as shown in formula (1):

$$\mathrm{S}_i = \sum_{j=1}^{n} w_j \cdot F_{ij} \tag{1}$$

In formula (1), the comprehensive score of supplier i is expressed as S_i, w_j represents the weight of the j-th evaluation index, and $F_{i,j}$ represents the score of supplier i on the j-th index.

Another key problem in supply chain network optimization is inventory management and ordering strategy optimization. This process requires the development of a rational inventory management strategy in order to minimize inventory costs while ensuring timely supply. Common inventory management models include EOQ (Economic Order Quantity) model based on dynamic programming and random inventory model based on random demand. Through these models, inventory can be managed more effectively and the overall efficiency of the supply chain can be improved. The mathematical representation of EOQ model is shown in formula (2):

$$\mathrm{Q}^* = \sqrt{\frac{2DS}{H}} \tag{2}$$

In formula (2), each order quantity is represented by Q^*, quantity required is D, S is the ordering cost, and H is the carrying cost.

Finally, supply chain network optimization also involves the optimization of resource scheduling and production planning. Through rational scheduling of production resources, production cost can be reduced and production efficiency can be improved. Common production planning methods include MRP (Material Requirements Planning) and ERP (Enterprise Resource Planning). Among them, MRP dynamically schedules the demand for raw materials and parts to meet the production needs of final products. ERP integrates the information flow of various departments within the enterprise to realize the effective use of resources and timely transmission of information [9-10].

According to the above content, supply chain network optimization involves many aspects such as supplier selection and evaluation, inventory management and ordering strategy, resource scheduling and production planning. It is necessary to comprehensively consider different factors and apply appropriate mathematical models and optimization algorithms to improve the overall benefits [11-12].

3.2 DQN Algorithm

Deep Reinforcement Learning (DRL) can be understood as a method that combines deep learning and reinforcement learning. It is used to solve problems with high complexity, uncertainty, and large-scale state spaces. In this paper, DQN algorithm in deep reinforcement learning is selected, which is mainly used as one of the main methods to solve the problem of multi-direction material supply demand [13-14].

The core idea of DQN algorithm is to approximate Q-value function by neural network to evaluate the expected cumulative reward of taking action in the state. Specifically, the Q-value function represents the expected cumulative reward for taking an action in the state. The DQN algorithm mainly uses a deep neural network to approximate the Q value function. By training the neural network, the output Q value can be approximated to the real Q value, so as to realize the prediction and selection of the action. The core update rule of DQN algorithm is shown in formula (3):

$$\mathrm{Q}(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)] \tag{3}$$

Among them, r represents the immediate reward obtained after performing action α, s′ represents the next state after performing action α, in the formula, α represents the learning rate, and γ is the discount factor. $max_{a'}Q(s',a')$ represents the largest Q value of all possible actions a′in the next state s′. In the above training process, DQN algorithm adopts the techniques of experience playback and fixed Q target to improve the stability and convergence of the algorithm.

In short, DQN algorithm, as an excellent deep reinforcement learning method, has important application value in solving the problem of multi-direction material supply demand. The Q-value function technology based on neural network enables it to deal with large-scale state space and highly uncertain environment effectively, and has obtained good experimental results.

4. Results and Discussion

4.1 Benchmark Performance Evaluation

The purpose of this benchmark performance experiment is to evaluate the performance of DQN algorithm, genetic algorithm GA, particle swarm optimization PSO and Q-Learning algorithm on multi-direction material supply demand optimization. The experiment is conducted in the supply chain environment, and then the effect of the algorithm on the three key performance indicators of total supply cost, time to meet demand and customer satisfaction is comprehensively investigated, in order to comprehensively evaluate the application potential and efficiency of each algorithm in the real world complex scenarios.

As can be seen from Figure 1, the DQN algorithm leads in total supply cost at $1,200, the GA algorithm at $1,300, the PSO algorithm at $1,250, and Q-Learning at $1,350. It also demonstrated significant advantages in terms of speed of meeting demand and customer satisfaction. The average time for DQN algorithm to meet the demand is 2 hours, while GA, PSO and Q-Learning are 2.5 hours, 2.3 hours and 3 hours, respectively. In terms of customer satisfaction, DQN algorithm reached 95%, GA algorithm reached 90%, PSO algorithm reached 92% and Q-Learning algorithm reached 85%. The details are shown in Figure 1:

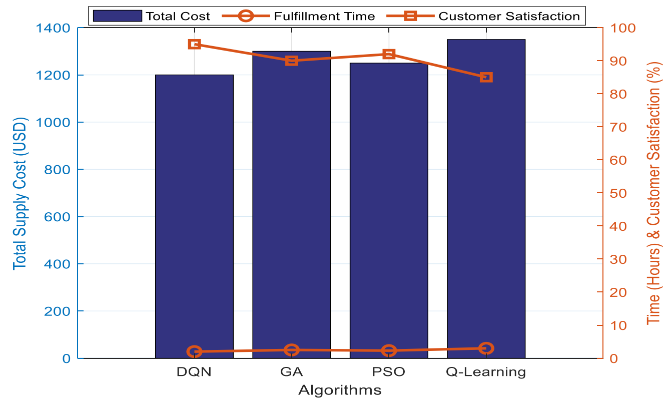

Figure 1: Benchmark performance assessment

4.2 Market Fluctuation Experiment Design

In the market volatility experiment, the experiment uses market volatility to evaluate the performance of DQN and other algorithms in response to changes in complex market demand. The experiment is carried out under two scenarios, including seasonal demand fluctuation and demand surge caused by unexpected events. The purpose of the experiment is to compare the performance of the algorithms in terms of response time, cost efficiency, and supply stability to reveal which of the tested algorithms is more effective in optimizing multi-directional material supply demand in dynamic and uncertain market environments. The details are shown in Figure 2:

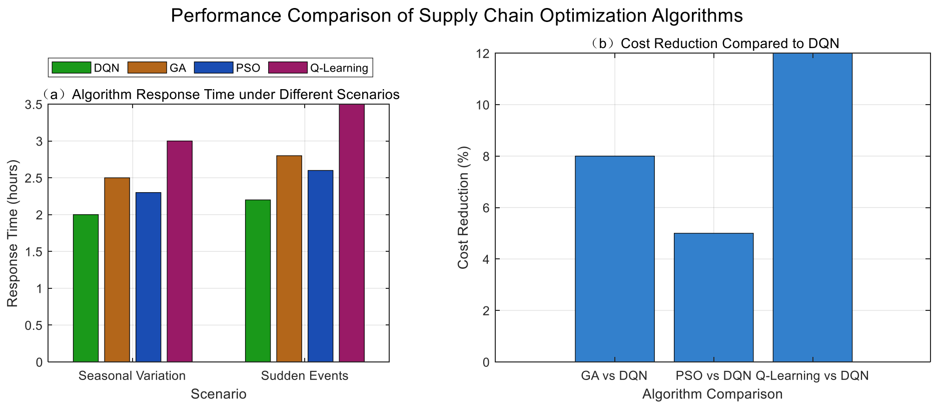

Figure 2: Market volatility assessment

Figure 2 (a) represents response time and Figure 2 (b) represents percentage cost reduction. As can be seen from Figure 2, in the market fluctuation experiment, the average response time of DQN algorithm under seasonal demand changes is 2 hours, while that of GA algorithm, PSO algorithm and Q-Learning algorithm is 2.5 hours, 2.3 hours and 3 hours, respectively. The response time of DQN is maintained at 2.2 hours, while the response time of other algorithms increases to 2.8 hours, 2.6 hours, and 3.5 hours, respectively. The total supply cost of DQN is 8%, 5% and 12% lower than GA, PSO and Q-Learning, respectively, throughout the trial period, which proves its excellent performance and cost-effectiveness in a dynamic market environment.

4.3 Robustness and Exception Handling Capability Evaluation

In the robustness and exception handling ability evaluation experiment, the experiment explores the robustness and exception handling ability of DQN, GA, PSO and Q-Learning algorithms in the face of supply chain disruptions such as supply point failure, demand surge and transportation delay. By comparing the recovery time of the algorithm and the cost increase due to abnormal conditions, the two indicators can evaluate the performance of each algorithm in maintaining supply chain stability and efficiency.

As can be seen from Figure 3, in the robustness and exception handling experiments, DQN algorithm performs well with the shortest recovery time of 1.5 hours and the lowest cost increase rate of 5%. The longest recovery time of Q-Learning is 3 hours, and the highest cost increase rate is 12%. In the GA and PSO algorithms, the recovery time of GA is 2 hours and the cost increase rate is 10%, while the recovery time of PSO is 2.5 hours and the cost increase rate is 8%. The results of the above experimental data show the advantages of DQN algorithm in fast adaptation and minimization of abnormal effects. Specific data display is shown in Figure 3:

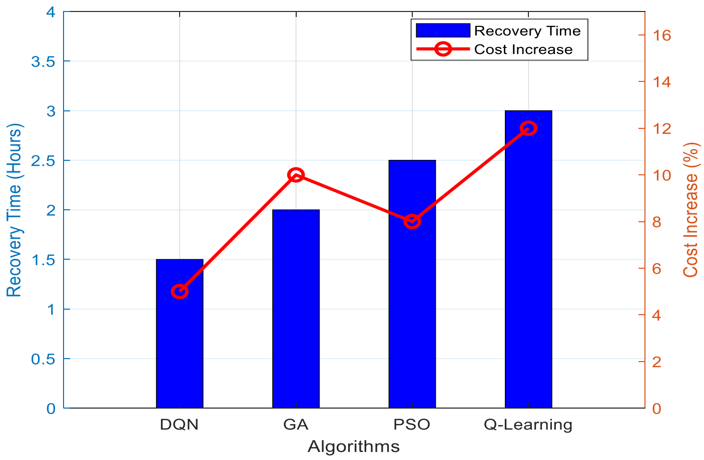

Figure 3: Robustness and exception handling evaluation

4.4 Scalability and Scale Adaptability Test

Finally, the scalability and scale adaptability experiments are designed to evaluate the ability of DQN, GA, PSO and Q-Learning algorithms to deal with supply chain problems of different scales. The experiment is gradually extended from a small network of 10 nodes to a large network of 50 nodes, in order to examine the scalability and scale adaptability of the algorithm. In this experiment, there are two performance indicators, total supply cost and algorithm running time, mainly to evaluate the performance and efficiency of each algorithm when the scale of supply chain increases. The detailed data are shown in Table 1:

It can be seen from the scale adaptability analysis of the algorithm in Table 1 that the DQN algorithm shows the best scalability and can maintain a low total supply cost and reasonable running time even in a large-scale network of 50 nodes. With the increase of network scale, the cost growth rate of DQN algorithm is lower than that of other algorithms, and the increase of running time is also relatively gentle. In contrast, the cost and time of GA, PSO and Q-Learning algorithms increase rapidly in large-scale networks, so the scalability and optimal adaptability of DQN algorithms can be seen.

Table 1: Algorithm scale adaptability analysis

Network Size	DQN_Cost (USD)	GA_Cost (USD)	PSO_Cost (USD)	Q-Learning_Cost (USD)	DQN_Time (Second)	GA_Time (Second)	PSO_Time (Second)	Q-Learning_Time (Second)
10	900	1000	950	1100	10	15	12	20
20	950	1200	1150	1300	12	18	15	23
30	1000	1400	1350	1500	14	21	18	26
40	1050	1600	1550	1700	16	24	21	29
50	1100	1800	1750	1900	18	27	24	32

5. Conclusion

Through the research of this paper, the DQN algorithm is successfully applied to the optimization of multi-direction material supply demand problem. First of all, this paper introduces the principle and core ideas of DQN algorithm in detail, and expounds its importance in solving supply chain management combined with the topic of the article at the beginning. Secondly, this paper designs corresponding experiments for the practical problems of multi-direction material supply demand. The performance of DQN algorithm is evaluated through 4 experiments in the experimental stage. The experimental results show that DQN algorithm can effectively reduce the total cost, shorten the response time of material supply and improve customer satisfaction, and provide a new optimization method for supply chain management. However, this paper also has some shortcomings, such as the simulation of experimental data may have some deviations, and the stability and convergence of the algorithm need to be further improved. In the future, we can further improve the experimental design, improve the performance and stability of the algorithm, and explore more cutting-edge deep reinforcement learning algorithms, so as to cope with more complex and diversified problems in supply chain management, and provide more effective solutions for practice.

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