Collaborative Optimization Algorithm for Multimodal Logistics System based on Artificial Intelligence

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***Abstract*—In view of the complexity and lack of coordination in transportation scheduling in multimodal logistics systems, this paper introduces a collaborative optimization algorithm for multimodal logistics systems based on artificial intelligence (AI). In order to achieve comprehensive optimization of transportation cost, time efficiency and resource utilization, a convolutional neural network (CNN) is used for demand forecasting, NSGA-II (Nondominated Sorting Genetic Algorithm II) based on genetic algorithm is used for multi-objective optimization, and the Q-learning algorithm in reinforcement learning is used for switching decisions between logistics modes. First, a collaborative optimization model of a multimodal logistics system is established, and CNN is used to accurately predict demand fluctuations and transportation status to provide data support for subsequent optimization. Secondly, the NSGA-II algorithm is used for multi-objective optimization to maximize the overall benefit of the system by selecting the optimal transportation path and resource allocation plan. Finally, the Q-learning reinforcement learning algorithm is used to adjust the switching strategy between different logistics modes to achieve flexible resource scheduling and further optimize the balance between transportation cost and time window. In multimodal logistics systems, the increase in "switching costs" and "switching time", such as from 200,000 yuan to 400,000 yuan, and from 5 hours to 9 hours, highlights the impact of high-frequency mode switching on logistics systems. The AI-based collaborative optimization algorithm for multimodal logistics systems proposed in this study has achieved remarkable results in solving local optimal and collaborative problems in traditional scheduling methods, and has strong application potential and promotion value. In the future, real-time data and adaptive learning strategies can be combined to further improve the dynamic response capability and robustness of the system.**

Keywords—artificial intelligence, multimodal logistics system, collaborative optimization algorithm, Q-learning reinforcement learning algorithm.

I. Introduction

In modern society, the logistics industry, as a vital component of the global economy, is undergoing profound changes. With the advancement of globalization and the booming development of e-commerce, logistics needs are becoming increasingly complex. Especially in the fields of bulk commodity transportation and international trade, how to effectively coordinate and dispatch multiple modes of transportation (such as railways, roads, aviation, etc.) has become an urgent problem to be solved. The coordination and scheduling efficiency of various transportation modes in the logistics system are poor. Nowadays, with the rapid development of AI technology, advanced algorithms such as deep learning, reinforcement learning, genetic algorithms, etc. are gradually being applied in logistics optimization. Researchers have tried to use these technologies to solve problems that traditional methods cannot overcome. However, although many studies have proposed corresponding optimization methods, they still face the problem of how to achieve coordinated scheduling and comprehensive optimization of various modes in complex and changeable transportation networks. How to break through the limitations of existing methods and improve the flexibility, adaptability and efficiency of the system is still a problem that academia and industry need to overcome.

This paper aims to solve the problems of low efficiency and poor collaboration in existing logistics scheduling methods when facing complex multimodal transportation networks based on AI and collaborative optimization algorithms. Most of the existing scheduling methods are limited to single-mode transportation or fail to effectively coordinate resource allocation between different modes. Traditional optimization algorithms, such as linear programming and simulated annealing, although they show certain advantages in certain specific scenarios, often have problems of high computational complexity and poor solution quality when dealing with large-scale and dynamically changing logistics networks. In addition, although existing methods such as reinforcement learning and genetic algorithms have achieved success in individual applications, they have failed to fully tap the inherent potential of the system due to the lack of a dedicated framework for multimodal collaborative optimization. To this end, this paper combines cutting-edge technologies such as deep learning, genetic algorithms and reinforcement learning to propose an integrated optimization framework that optimizes global cost, transportation timeliness and resource utilization by collaboratively optimizing demand forecasting, resource scheduling, mode switching and other links. This study fills the gap in the optimization research of multimodal logistics systems.

This paper is organized as follows: First, the background and related issues of multimodal logistics systems are introduced, the existing optimization methods and the application progress of AI in logistics scheduling are reviewed, and the deficiencies and challenges in previous studies are analyzed. Secondly, the research framework of this paper is proposed, and the core methods such as demand forecasting based on deep learning, multi-objective optimization of genetic algorithms, and mode switching strategies based on reinforcement learning are described in detail. This paper adopts CNN for demand forecasting to improve the system's responsiveness to changes in transportation demand. At the same time, NSGA-II is used to deal with the balance between transportation cost and timeliness in multi-objective optimization, thereby achieving global optimal resource scheduling. On this basis, the Q-learning reinforcement learning algorithm is combined to optimize the switching strategy between different modes to improve the dynamic adaptability of the system. Finally, this paper verifies the effectiveness of the proposed algorithm in a multimodal logistics system through simulation experiments.

II. Related Work

In the field of logistics system optimization, research on multimodal transport scheduling has gradually become a hot topic in recent years. Multimodal logistics systems can effectively utilize the advantages of different modes of transportation, such as the long-distance carrying capacity of railways and the fast transportation advantages of aviation, to achieve more flexible and efficient logistics services. Tang et al. [1] explored the multi-model vehicle configuration and path collaborative optimization scheme considering queuing factors. Wang et al. [2] studied the joint replenishment-distribution collaborative optimization technology of heterogeneous products based on Lipschitz continuity. Liu et al. [3] conducted the design and planning of the automated logistics system of plant factories. Winkelhaus & Grosse [4] realized the retrospective analysis of the new logistics system through logistics 4.0 technology. Park et al. [5] studied the cyber-physical logistics system framework for supply chain control based on digital twins. However, although these studies have achieved certain results in the optimization of specific modes, the existing methods still face problems such as poor coordination and insufficient adaptability, and fail to effectively deal with the complexity and dynamic changes in multimodal transportation systems.

The collaborative optimization of multimodal logistics has important application value. Guo et al. [6] explored the adaptive collaborative control technology of intelligent production logistics system. Lopes et al. [7] designed a framework for logistics systems that promote low-carbon production. Hu et al. [8] applied AI to logistics optimization. An et al. [9] studied the relationship between outward foreign direct investment and green logistics operations. Karakas et al. [10] studied the application of blockchain in logistics and supply chain. However, these methods often ignore the dynamic coordination among multiple modes and the optimization of the overall system, which makes it difficult for them to adapt to the complex changes in the logistics environment in practical applications.

III. Methods

A. Demand Forecasting and Data Modeling

In the collaborative optimization of multimodal logistics systems, accurate demand forecasting is the key to the efficient operation of the entire system. To this end, this paper first uses CNN to predict logistics demand [11-12]. CNN is commonly used for image recognition tasks, but its advantages in time series prediction have also been widely used. By designing a network structure with multiple convolutional layers and pooling layers, CNN can automatically extract characteristic patterns in logistics demand data and then make efficient predictions. Specifically, we implement demand forecasting through the following steps: Data preprocessing is to collect historical data of the multimodal logistics system, including order quantity, transportation time, transportation method, etc. The data is cleaned and normalized to remove noise and ensure the quality of the input data. Feature engineering is to extract relevant time series features, such as seasonal fluctuations and holiday effects, to ensure that the model can learn the underlying rules. CNN modeling uses convolutional layers to extract local features in the data, and reduces feature dimensions through pooling layers to enhance the generalization ability of the model. Finally, the fully connected layer is used to output the prediction results to predict logistics demand in the future. Through this process, the CNN model can extract hidden patterns from a large amount of complex historical data and accurately predict future fluctuations in transportation demand. The accuracy of this process directly affects the effect of subsequent resource scheduling and path optimization.

In demand forecasting, CNN is used to extract features from time series data and predict future logistics demand. Assuming the input data is X_t (input at time step t), the model output is $\hat{y}_{t+k}$ (demand forecast for the next k time steps), and the output of CNN is obtained through convolution and pooling layers is shown in Equation (1).

$$\hat{y}_{t+k} = f\big(Conv(X_t)\big) \tag{1}$$

Among them, $f(\cdot)$ is the activation function in the convolutional neural network, and $\mathrm{Conv}(X_t)$ is the feature extracted by convolution operation.

B. Multi-Objective Optimization and Resource Scheduling

In multimodal logistics systems, there are many optimization requirements such as transportation cost, time and resource utilization. In order to balance these objectives, this paper uses NSGA-II to balance multiple objectives. This algorithm seeks the Pareto optimal solution, maintains the diversity of solutions, and is suitable for multi-objective optimization.

In the specific implementation process of NSGA-II, the initial population is generated based on the actual situation of the transportation network. Each individual represents a resource allocation plan, including transportation routes, mode switching, etc. [13-15]. Individual fitness is calculated from the objective function. The objective function comprehensively considers transportation cost, transportation time and resource utilization, and performs weighted summation to reflect the priority of each goal. Through fitness evaluation, the quality of individuals can be quantified. The elite strategy preserves excellent individuals, cross combines parental genes to produce better offspring, and mutation assists in the generation of new individuals. The mutation operation simulates gene mutations in natural evolution, further enhancing the algorithm's exploration ability. Non-dominated sorting divides individuals into multiple levels through non-dominated sorting, ensuring that diversity is retained in each generation and constantly approaching the Pareto frontier. Iterative update: Through multiple generations of iterations, the resource scheduling plan is gradually optimized, and finally converges to a Pareto optimal solution set for multi-objective optimization. Through this optimization process, NSGA-II can effectively find a balance between multiple objectives, not only maximizing resource utilization, but also minimizing transportation costs and time.

In multi-objective optimization, genetic algorithm evaluates fitness using weighted sum objective function, which can be expressed in Equation (2).

$$F(x) = w_1 f_1(x) + w_2 f_2(x) \tag{2}$$

Among them, w_1 and w_2 are the weight coefficients of the objective function, $f_1(x)$ and $f_2(x)$ represent the transportation cost and time associated with the individual respectively.

C. Mode Switching and Reinforcement Learning Optimization

In multimodal logistics systems, Q-learning reinforcement learning algorithm optimizes transportation switching strategies and achieves optimal state action decisions through a model free approach. In multimodal logistics systems, Q-learning first defines a state space that covers the load, distance, and expected time of transportation modes, and then sets an action space for switching between different transportation modes. The reward function is designed based on the benefits of reducing transportation costs, improving efficiency, and increasing resource utilization, with positive or negative reward effects. The Q function is continuously updated through the Bellman equation and gradually converges to the optimal strategy. During training, the algorithm selects the maximum reward action based on the Q value, flexibly adjusts the transportation mode switching, and ultimately achieves the global optimal scheduling of the logistics system and maximizes resource utilization. The AI-based multi-mode logistics system collaborative optimization algorithm process is shown in Figure 1.

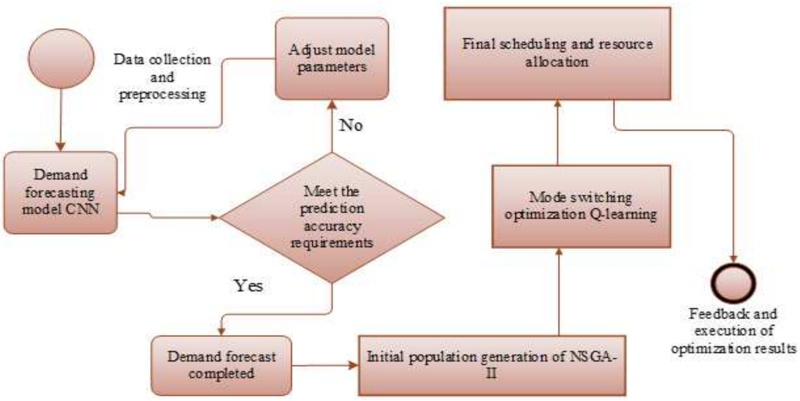

Fig. 1. AI-based multi-modal logistics system collaborative optimization algorithm process

In the Q-learning algorithm of reinforcement learning, the Q value is used to evaluate the long-term reward of taking an action in a given state.

The Q value $Q(s, a)$ is updated through the Bellman equation, and the Q value of each state-action pair is updated by the following formula shown in Equation (3).

$$Q(s_t, a_t) \leftarrow Q(s_{t-1}, a_{t-1}) + \alpha \left[r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right] \tag{3}$$

Among them, s_t and a_t are the current state and action respectively, r_{t+1} is the immediate reward obtained, γ is the discount factor, α is the learning rate, and $\max_{a'} Q(s_{t+1}, a')$ is the maximum Q value in the next state s_{t+1}.

IV. Results And Discussion

A. Experimental Setup

The experimental environment is based on a set of simulation logistics platform, using Python for modeling and simulation, using TensorFlow for deep learning model training, using genetic algorithm to optimize scheduling problems, and combining Q-learning algorithm to optimize mode switching strategy. All experiments are conducted under standard computer configuration, with Intel i7-9700K CPU, 32GB memory, 500GB SSD storage, and Windows 10 operating system. In terms of parameter setting, the demand forecasting model uses LSTM neural network, the learning rate is set to 0.001, and the training cycle is 1000 rounds. In the scheduling optimization experiment, the population size of the genetic algorithm is 50, the crossover probability is 0.8, the mutation probability is 0.2, and the maximum number of iterations is 500. The reinforcement learning of the mode switching strategy uses Q-learning, with the learning rate set to 0.1. In the experimental evaluation indicators, the scheduling efficiency and cost are evaluated by total cost, total time, and unit time cost; the mode switching strategy effect is evaluated by switching cost, switching time and overall system running time.

B. Results Analysis

1) Relationship between demand forecast accuracy and logistics system response time: The relationship between demand forecast accuracy and logistics system response time is shown in Figure 2.

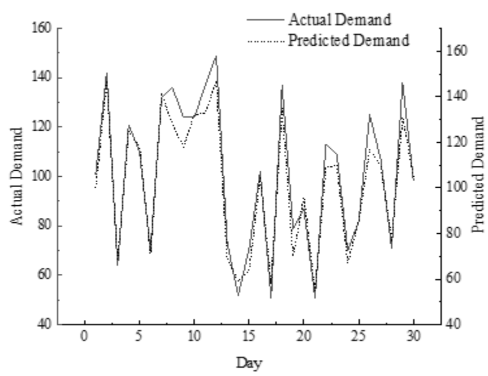

Fig. 2. Relationship between demand forecast accuracy and logistics system response time

There is a gap between actual demand and forecasted demand, and this gap fluctuates on different days. For example, the actual demand on the first day is 101, while the forecast demand is 100, resulting in a forecast error of only 1. This indicates a high level of accuracy in the model's predictions. The forecasting model demonstrates good accuracy for medium demand as well. For instance, on the 16th day, the actual demand is 102, while the forecast is 105, leading to a forecast error of 3. This performance illustrates a common trend in the model's predictions, reflecting its strengths and limitations.However, the volatility of the forecast error emphasizes the inherent complexity of demand forecasting. This complexity is particularly pronounced in environments characterized by rapidly changing market conditions, making it challenging for the model to fully capture the fluctuations in actual demand data. As demand patterns shift, the discrepancies between forecasted and actual demand can widen, complicating logistics planning and execution.

Further analysis reveals that the volatility of the forecast error has a direct impact on the response time of the logistics system. When demand predictions are accurate, the logistics system can prepare in advance, reducing response times and enhancing overall efficiency. Conversely, if the forecasting model consistently underestimates or overestimates demand, it can lead to delays, excess inventory, or stockouts, all of which adversely affect customer satisfaction and operational costs.

To address these challenges, it is crucial to focus on improving the accuracy of demand forecasting. By reducing errors and enhancing logistics response efficiency, organizations can better align their supply chain operations with actual market needs. Optimizing the prediction algorithm is a necessary step, especially during periods of demand fluctuations. Implementing advanced techniques such as machine learning models or adaptive forecasting methods can significantly enhance the model's ability to respond to changing conditions and improve its predictive accuracy.

2) Optimizing the trade-off between scheduling efficiency and cost: This experiment uses NSGA-II to evaluate the optimization effect of transportation scheduling, focusing on the trade-off between transportation cost and time efficiency. The experimental environment setting is the same as the first experiment, and the data set uses real-time logistics data from multiple warehouses. The experimental goal is to reduce transportation costs through optimization algorithms while ensuring that delivery time does not exceed the preset time limit. During the optimization process, we first generate the initial population and evaluate the target value of each individual through the fitness evaluation function. Then selection, crossover and mutation operations are performed until the predetermined termination condition is reached. Numbers 1 to 16 are Air, 17 to 28 are Rail, and 29 to 39 are Road. The relationship between cost and time is shown in Figure 3.

Figure 3 illustrates the relationship between cost and time for different modes of transport—Air, Rail, and Road—along with the corresponding number of each mode utilized. From the analysis of Figure 3, we can observe distinct differences between the transport modes, particularly regarding the trade-off between cost and time. For instance, air transport is characterized by a tendency for both cost and time to increase gradually as the number of air transports rises. This trend suggests that higher transportation volumes through air freight lead to increased expenses and extended time requirements, reflecting the inherent costs associated with expedited delivery.

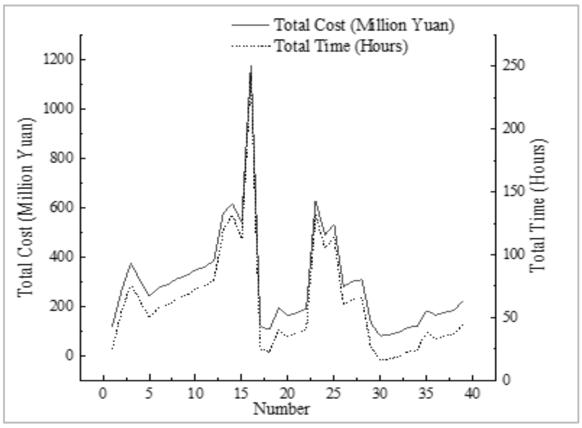

Fig. 3. Relationship between cost and time

In contrast, the rail and road transport modes appear to offer a more balanced and economical option. Rail transport, while generally less costly than air transport, shows a stable increase in both cost and time. For example, the total cost for railroad numbers ranging from 17 to 28 spans from 1.05 million yuan to 6.27 million yuan, while the total time required varies from 22.5 hours to 132 hours. This relatively predictable escalation underscores the efficiency of rail transport for medium to long distances.

Furthermore, when comparing rail to road transport, it becomes evident that road transport typically incurs lower costs and shorter transit times. This characteristic makes road transport an attractive option for businesses seeking to optimize their logistics operations, especially for last-mile delivery scenarios or short-haul shipments.

The decision-making process surrounding transport logistics must take into account not only the cost implications but also the timing requirements based on customer expectations. For instance, while air transport may be necessary for urgent deliveries, rail and road options can provide cost-effective solutions for less time-sensitive shipments.

3) Reinforcement learning optimization effect of mode switching strategy: This experiment focuses on optimizing the mode switching strategy in a multimodal logistics system through Q-learning. The experiment simulates a typical multimodal transportation system, which includes three modes: road transportation, rail transportation, and air transportation. The experimental environment is consistent with the previous two experiments, and the dataset used includes cost, time, and reliability data of various transportation modes. We design a Q-learning model based on state-action pairs to evaluate the impact of different mode switching strategies on the overall logistics system benefits. The model is trained using the Q-learning algorithm, and the design of state transitions and reward functions is based on actual transportation data. Starting from a state each time, the best action is selected and an immediate reward is obtained.

The reinforcement learning optimization effect data of the mode switching strategy is shown in Table 1.

TABLE I. REINFORCEMENT LEARNING OPTIMIZATION EFFECT DATA OF MODE SWITCHING STRATEGY

Mode A to B Cost (Million Yuan)	Mode A to B Time (Hours)	Mode B to C Cost (Million Yuan)	Mode B to C Time (Hours)	Switching Cost (Million Yuan)	Switching Time (Hours)
50	10	30	8	20	5
65	13	45	10	25	6
80	15	60	12	30	7
95	17	70	14	35	8
110	18	85	15	40	9
120	20	90	17	45	10
135	22	100	20	50	11
150	25	115	22	55	12
160	28	125	24	60	13
175	30	140	26	65	14

As the different mode switching strategies change, various costs and times show certain regularities. First, the relationship between "Mode A to B Cost" and "Mode A to B Time" shows a certain positive correlation. As the transportation volume from mode A to B increases, the cost and time required gradually increase. For example, the cost of mode A to B increases from 500,000 yuan to 1.1 million yuan, and the time also increases from 10 hours to 18 hours. Similarly, "Mode B to C Cost" and "Mode B to C Time" also show that as the transportation demand increases, the cost and time are both on the rise. Especially under high load conditions, the cost of switching to mode B to C gradually increases from 300,000 yuan to 850,000 yuan, and the time increases from 8 hours to 15 hours.

In a multimodal logistics system, the growth in transportation demand directly leads to a linear increase in resource consumption (cost and time), while mode switching also adds an additional burden. Specifically, the increase in "switching cost" and "switching time", such as from 200,000 yuan to 400,000 yuan, and from 5 hours to 9 hours, highlights the impact of high-frequency mode switching on the logistics system. In a high-load transportation scenario, frequent switching not only significantly increases costs, but also prolongs response time and reduces transportation efficiency. Therefore, it is crucial to optimize the mode switching strategy, aiming to reduce unnecessary switching or improve switching efficiency, thereby balancing cost and time and optimizing the overall performance of the logistics system.

V. CONCLUSION

This study focuses on AI-driven multi-modal logistics system optimization, innovatively integrating technologies such as reinforcement learning. Through accurate demand forecasting, efficient logistics scheduling and intelligent mode switching, the problem of high cost and low efficiency of traditional logistics has been effectively overcome. Experimental verification shows that this method not only significantly improves the accuracy of demand forecasting but also optimizes the scheduling process and achieves the optimal balance between cost and timeliness. In practice, this achievement has a far-reaching impact on express delivery, manufacturing supply chain and international trade transportation, and can help companies achieve refined operations, reduce logistics costs, speed up response speed, and thus improve customer satisfaction and enhance market competitiveness. In addition, the results of this study also provide policymakers with a theoretical basis for optimizing decisions in the field of multimodal transportation, especially in complex environments such as cross-border freight transportation and multi-city distribution management. In summary, this study not only explores the combination of AI and logistics optimization in theory, but also demonstrates great potential application value in practice, which has an important role in promoting the development of related fields.

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