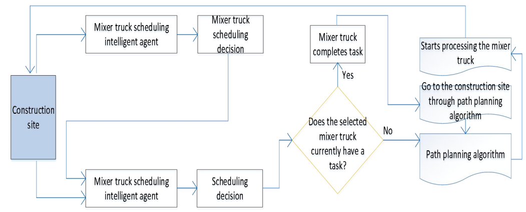
Programación adaptativa de camiones mezcladores en obras de construcción mediante una Red Q profunda mejorada



Adaptive Scheduling of Mixing Trucks in Construction Sites with an Improved Deep Q-Network

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The management of concrete mixing station distribution is evolving toward more intelligent and efficient methods. Additionally, in the context of the group operations of commodity concrete enterprises, the cooperation between each mixing station during the distribution process has become increasingly crucial. Therefore, establishing a scientific and effective cooperative scheduling system is of practical significance. This paper proposes a centralized hierarchical dispatch system for construction site mixer trucks, designed to meet the control requirements of cooperative transport. The upper computer control system handles single-vehicle scheduling tasks, while cooperative transport tasks are determined by the system based on task and environmental conditions. The system establishes the cooperative transport formation, with the primary vehicle responsible for both the assembly and scheduling paths. The "master vehicle" at the construction site identifies the "slave vehicles" and oversees control and coordination during collaborative operations. This study explores the scheduling method based on the Improved Deep Q-Network (IDQN) algorithm, leveraging a mathematical model of scheduling and a reinforcement learning environment. The paper details the basic principles of the DQN algorithm and outlines the learning process for the scheduling algorithm tailored to construction sites. Furthermore, it designs a local mechanism for the scheduling agent and an action selection method based on environmental state information specific to various construction sites. It also defines the interaction between scheduling agents, the scheduling algorithm, and the construction site mixer truck path planning algorithm. The simulation results show that the IDQN scheduling algorithm outperforms five other algorithms, demonstrating better performance, adaptability, and real-time responsiveness to environmental changes.

Keywords: Multi-load construction site mixer truck; Real-time scheduling; Improved Deep Q-Network; Action selection mechanism; Interaction mechanism

1. INTRODUCTION

The distribution of commercial concrete differs from logistics in other industries because it cannot store finished products, and concrete is prone to solidifying over time [1]. Additionally, while continuous pouring is required at construction sites, the demand is not fixed. Concrete mixer trucks, as specialized engineering vehicles, must continually mix the concrete during transportation to prevent solidification due to the hydration of cement [2]. This particularity of the commercial concrete industry makes scheduling and production arrangement significantly more complex [3, 4]. To maximize enterprise profits, manufacturers must efficiently deploy production sequences and transport vehicles for each construction site. Furthermore, to maintain the construction schedule, it is crucial to ensure the continuous unloading and pouring of commercial concrete [5, 6]. Therefore, developing an efficient and scientifically sound scheduling scheme is essential for improving resource utilization, enhancing construction site service quality, and integrating various factors.

Traditionally, mathematical programming methods have provided effective solutions to construction site mixer truck scheduling problems [7]. The core concept of this method is to find the optimal solution under resource constraints. Mathematical programming methods include integer programming, dynamic programming, and petri programming. While these methods offer stability and accuracy in small-scale scheduling tasks [8], they have limitations in large-scale, highly automated environments such as flexible workshops and wharves [9]. As the spatial dimension of the scheduling problem increases, the time required to solve it grows exponentially, leading to substantial resource waste [10].

Artificial intelligence methods typically address the construction site mixer truck scheduling problem by seeking optimal solutions while satisfying constraints. These methods guide mixer trucks to complete assigned tasks through embedded knowledge [11]. Approaches include expert systems, genetic algorithms, heuristic algorithms, neural network algorithms, and reinforcement learning algorithms [12]. Neural network and reinforcement learning algorithms have been extensively studied and applied in recent years [13].

In the context of artificial intelligence, Reinforcement Learning (RL), a type of unsupervised machine learning, is widely used in game system design, robot path planning, large-scale traffic signal control, and path planning for multi-automated guided vehicles [14-16]. In reinforcement learning, the interaction between an agent and the environment is modeled as a stochastic game, where state transitions and rewards depend on the agent's actions [17, 18]. Each agent continually interacts with the environment, aiming to maximize cumulative return and optimize its decision-making strategy based on the expected return [19, 20].

This paper presents a construction site mixer truck cooperative transport system. Using a centralized hierarchical control structure, we design the implementation scheme for the upper computer management system, wireless communication system, mixer truck vehicle control system, and cooperative handling system. The operation mode of the entire system is also described. For the construction site scheduling problem, we study the Improved Deep Q-Network (IDQN) algorithm for mixer truck scheduling. The mixer truck agent is designed to read the local environment and map it to the state parameters of the mixer truck. Based on these parameters, a scheduling list is generated, enabling the selection of actions from the workshop state to the mixer truck scheduling. The construction site mixer truck agent is designed to obtain handling parameters by reading the scheduling decisions and environmental data, enabling interaction between the agents. The relevant handling parameters and state information are mapped into scheduling weights to generate the scheduling list. Additionally, the interaction between the scheduling agent and path planning algorithm is designed. Simulation results show that the IDQN scheduling method offers excellent performance and adaptability to environmental changes, making it suitable for real-time scheduling in practical manufacturing environments.

2. Architecture design of construction site mixer truck cooperative transport control system

2.1 Functional requirement analysis of construction site mixer truck cooperative transport control system

The application object of this paper is an automatic material conveying system used for construction site mixer truck handling in multi-mixer truck mixed production workshop. The main mixer truck is carried by single construction site mixer truck, and some large parts need to be carried by construction site mixer truck cooperation to realize the automatic conveying of the mixer truck in the workshop. Therefore, the construction site mixer truck cooperative transport control system designed in this paper should meet the following requirements:

(1) System communication: All devices in the system, including host computers, construction site mixer trucks and workstations, achieve wireless interconnection and information exchange under a network;

(2) Autonomous mobile car control: Manage the autonomous mobile car in the system according to its status, including idle, busy and fault, control the construction site mixer truck to pick up and unload the goods between two workstations, and run according to the shortest route planned in real time;

(3) Human-computer interaction: With interactive interface, real-time display of construction site mixer truck distribution position in the system, detection of construction site mixer truck battery power, system fault warning, prompt fault solution;

(4) Mixed handling: Independent planning of handling forms for scheduling tasks within the system, single construction site mixer truck handling for small mixer trucks, collaborative handling for large mixer trucks;

(5) Task management: Manage the tasks issued by the system, add, execute and delete the tasks in the task list, reasonably plan the execution sequence, and optimize the efficiency of task execution;

(6) Operation management: Real-time monitoring of construction site mixer truck operation status, traffic management at traffic intersections to prevent path conflicts, reasonable planning of construction site mixer truck operation routes, early warning of traffic congestion, and route adjustment;

(7) Data storage: With data storage function, you can save a series of data in the production process, and analyze and export reports.

2.2 Architecture of construction site mixer truck control system

As shown in Figure 1, the centralized control structure means that the entire construction site mixer truck material conveying system is controlled by the central control center, and all the construction site mixer truckconstruction site mixer truck operation process and all the status information in the production workshop are summarized and processed in the control center, and after analysis and decision, the construction site mixer truck sends control and scheduling instructions.

For such a centralized control mode, the control system design requirements are relatively low, the framework is relatively simple, and the reliability is high. However, with the increase of equipment in the system, the computing requirements and data communication requirements of the control center will increase exponentially, when the system reaches a certain scale, the computing capacity of the control center and the bandwidth of the communication equipment will be unbearable. Therefore, the centralized control structure is mainly used in small and medium-sized construction site mixer truck systems.

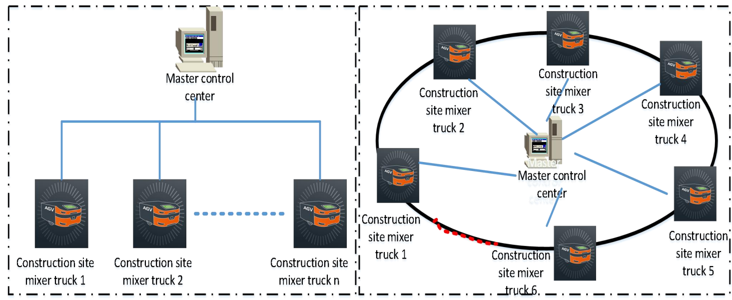

Figure 1 Construction site mixer truck system control architecture

Distributed control structure refers to a control structure that distributes the lower implementation units and controls them autonomously through remote monitoring of equipment production. The essential difference between the distributed control structure and the above two types is that the control mechanism is no longer the upper management system sends control instructions to the lower implementation unit according to the real-time state, but the implementation unit independently perceives and communicates with each other to make decisions.

The centralized hierarchical control structure is controlled by a total control center, but the total control center is not necessarily directly connected to the specific implementation unit, the implementation unit is first divided by region or type. The specific implementation unit is managed by several sub-control centers, and then the general control center issues instructions to the sub-control center. This control structure can greatly reduce the control burden of the total control center. The total control center only needs to issue global control instructions. By distributing specific control tasks to the sub-control center, the sub-control center will issue more specific control instructions, so the system robustness and reliability will be better. The data in the production process is summarized in the sub-control center, screened and calculated, and then uploaded to the total control center, which will greatly reduce the burden on data communication. The complexity of this control structure is between centralized and distributed, and it has good stability, robustness and response speed.

2.3 Structure design of construction site mixer truck cooperative transport control system

In order to meet the scheduling and control needs of the construction site mixer system, this paper analyzes the advantages and disadvantages of the three control structures, and decides to adopt the centralized hierarchical control structure. The upper layer is the upper computer, which integrates the various functions of the system. For tasks that do not require collaborative handling, all construction site mixer truck and work units are uniformly scheduled by the host computer. When the task is carried out in coordination, the system determines the main vehicle, and the path is sent to the main vehicle by the host computer. The master car then acts as a sub-control center, controlling and coordinating from construction site mixer truck, and the slave car works with the master car to complete the scheduling task. In the process of performing tasks, the slave car is subject to the coordination of the master car, rather than the host computer.

1) Host computer management system

The upper computer management system is a user software running in the Windows system, which can conveniently set task instructions, and the upper computer can schedule tasks, plan routes and manage traffic for construction site mixer truck. The system state is displayed in real time and the real-time data is detected during operation. The main working principle is as follows: When the system gets the task information, it reads the status and task information of each construction site mixer truck in the system, and selects the construction site mixer truck and transport form of the task according to the task assignment algorithm. If the host receives multiple tasks, it sorts them according to the scheduling rules. For construction site mixer trucks that need to execute tasks, the path from the initial point to the execution point is planned for them. After the construction site mixer trucks are assembled, the path from the task point to the target point is planned for the master vehicle. In the process of operation, the system always monitors the operation of the construction site mixer truck, when there is a possible collision, according to the traffic management rules to make appropriate adjustments; when the construction site mixer truck sends a low power warning, it sends the off-duty instruction to the construction site mixer truck to charge at the charging port; when the construction site mixer truck sends a fault alarm, the construction site mixer truck is controlled to enter the waiting area for manual maintenance.

2) Network communication system

The main function of the network communication system is to realize the transmission and exchange of communication data between the host computer management system and construction site mixer truck and other working units in the system. The communication data includes the instructions sent by the upper computer to the construction site mixer truck and the instructions returned by the upper computer of the construction site mixer truck. The command returned by the construction site mixer truck upward machine includes the construction site mixer truck hardware and software information (including the time stamp, construction site mixer truck number, real-time battery), and the construction site mixer truck running status information (including the moving speed, current position, and next node position).

3) construction site mixer truck collaborative transport architecture

As can be seen from Figure 2, the host computer determines whether the scheduling task is coordinated handling or ordinary handling. If it is ordinary handling, it is processed according to ordinary tasks; if it is coordinated transport, the transport formation is determined, and the construction site mixer truck main vehicle and slave vehicle are defined, and the command is sent to the construction site mixer truck through the wireless communication module to set it to the corresponding mode. After receiving the command from the upper computer, the construction site mixer truck main vehicle coordinates the slave vehicle formation, and reports the completion of the formation and related slave vehicle information to the upper machine. After confirmation by the host computer, the assembly path and handling path information are planned and optimized, and the newly formed cooperative handling team begins to assemble and perform the scheduling task. Once the task is over, the collaborative transport team is dissolved, the original mode is restored, and the new scheduling command is waiting for the host computer.

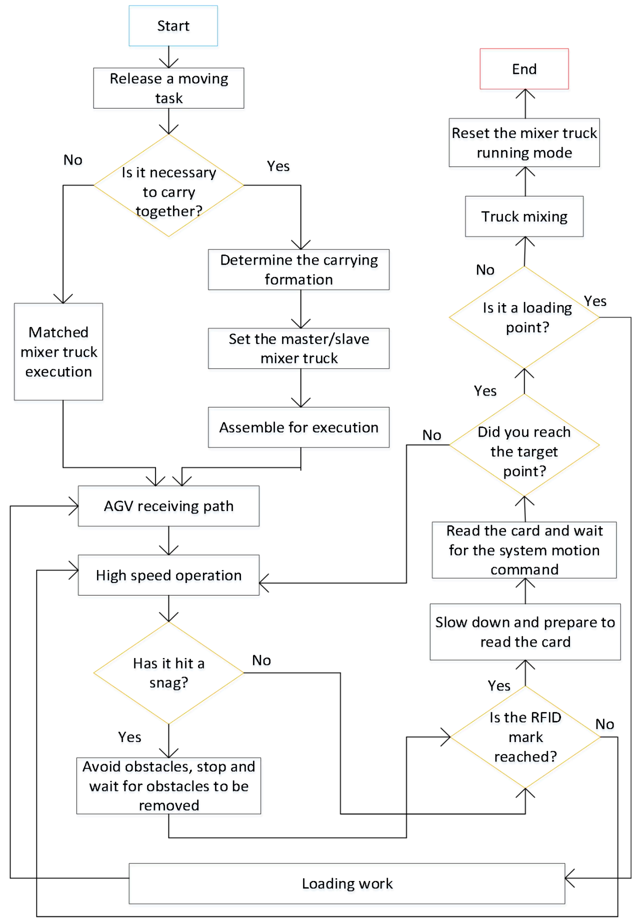

Figure 2 Flowchart for executing a collaborative transport task

3. Algorithm design

Construction site mixing truck scheduling algorithm flow

The traditional reinforcement learning algorithm, such as Q-learning algorithm, expresses the mapping relationship between action and value in the form of table. Since the table is discrete, it is difficult to represent continuous input variables, so the algorithm can only process them by discretization and dimensionality reduction. The tabular method can not be applied to the scheduling problem of construction site, which is a complicated problem of state and action space. The deep Q-Network (DQN) algorithm can replace the Q table by fitting the mapping relationship from the input state of the construction site to the corresponding scheduling action Q value of the construction site through the deep neural network, which solves the problem that the data volume and dimension of the table increase due to the complexity of the state and action space.

The scheduling problem of construction site is solved by scheduling algorithm based on DQN algorithm, and the algorithm solving process is shown in Figure 3.

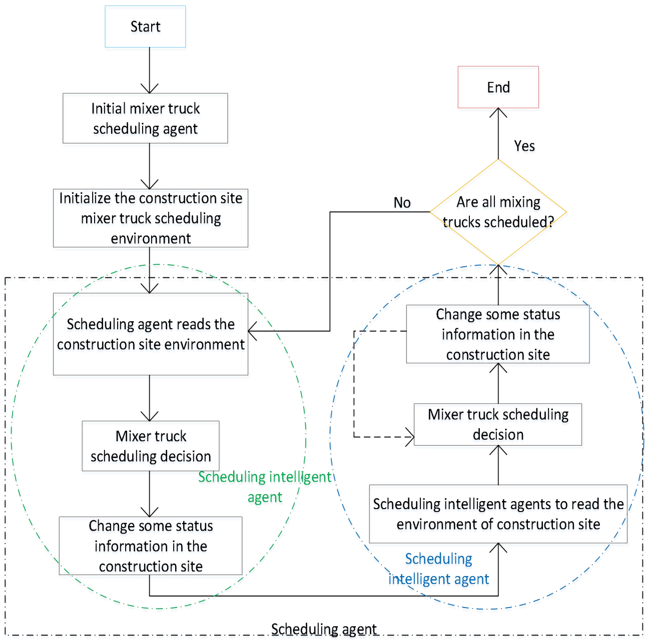

Figure 3 Flow chart of scheduling algorithm for construction site

3.2 Principles of DQN algorithm learning and optimization

The learning process of the scheduling agent based on DQN algorithm is to optimize its own network parameters by processing the empirical data generated in the scheduling process of the construction site.

The scheduling agent has two networks with the same organization structure, namely the evaluation network and the target network. The evaluation network realizes the mapping from the state of multi-resource input in the construction site to the action policy Q value. Evaluation network training is one of the two steps of DQN learning. The training of evaluation network takes place after Q-value iteration, which is also a step in the learning process of DQN. The form of Q-value iteration is similar to the iteration of Q-learning algorithm.

The target network is a replica of the evaluation network at a certain stage in the learning process, and its network structure is the same as that of the evaluation network. After a certain number of learning times, the target network will directly copy the network parameters of the evaluation network. The evaluation network and the target network work together to complete the Q value iteration. The iterative process is more stable and the convergence of the algorithm is improved effectively.

After the completion of iteration, DQN algorithm trains the evaluation network according to the difference of Q values before and after:

$$T = r_t + \gamma MaxQ(s_{t+1}, a_{t+1}; \theta_t) - Q(s_t, a_t; \theta_t) \tag{1}$$

Where, T is the deviation value of the time difference.

The training of neural network requires that the input samples are independent of each other, and an experience buffer is set for the algorithm. The experience buffer stores the states adopted by the algorithm in the past, the corresponding actions, the reward of the environment feedback after the execution of the actions, and the state after the execution of the actions. The experience playback mechanism in the experience pool is used to disrupt the sample so that the sample is not continuous scheduling experience data.

3.3 Learning process of scheduling algorithm

The mixer truck scheduling agent is only responsible for the scheduling decision of the mixer truck and selects the mixer truck to be scheduled. The construction site mixer truck scheduling agent is only responsible for the scheduling decision of the construction site mixer truck, and selects the mixer truck selected by the construction site mixer truck load handling part scheduling agent. The learning process of the scheduling algorithm is as follows:

Sets the number of iterations to learn and initializes the number of iterations. Two network parameters of the scheduling agent are randomly generated. Example Initialize the scheduling reinforcement learning environment. Judge whether all the mixer trucks in the workshop have been processed. If they are completed, the number of iterations is increased by one and jump to step9. If not, data is extracted from the experience pool to the two networks. The two networks read the data from the experience pool and output their action value function (Q function) respectively. The loss of two action value functions is found, and the optimizer is used to optimize the loss. The network parameters of the evaluation network are optimized according to the minimization of loss, and the parameters of the evaluation network are synchronized to the target network every certain iterations. The evaluation network makes scheduling decisions according to the current reinforcement learning environment, and the reinforcement learning environment changes its environment according to scheduling decisions. Determine whether the set number of iterations has been reached. If so, the network parameters of the evaluation network are output.

3.4 Implementation of scheduling algorithm learning process

The learning implementation of scheduling algorithm based on DQN algorithm is summarized as follows: At the beginning of each round of scheduling in the construction site, the status information in the workshop is reset to obtain the initial status. When t≤ T, the mixer truck scheduling agent will observe the current status, and the mixer truck scheduling agent performs the action.

After the action is performed, the global environment is updated to obtain the next state. The mixer truck scheduling agent gets the reward and stores the sequence into the experience pool of the job agent. The construction site mixer truck scheduling agent receives a reward to deposit the sequence into the construction site mixer truck agent's experience pool. When enough scheduling experience is stored in the two scheduling experience pools, a small batch of scheduling experience data is randomly selected to calculate the loss value between each sample evaluation network and the target network. The neural network parameter optimizer is used to optimize the loss value and update the evaluation network parameters.

3.5 Scheduling agent Mechanism

1) Local state, action space and local reward mechanism

In order to speed up the decision-making speed of mixer truck agents and construction site mixer truck agents and reduce the input of irrelevant information, the state spaces of mixer truck scheduling agents and construction site mixer truck scheduling agents are inconsistent and both are subspaces of the total state space of the environment.

The action space of reinforcement learning environment includes all the executable actions in scheduling. According to the different functions of the scheduling agent, the action space of the mixer truck scheduling agent is set as the subaction space of the mixer truck scheduling part, and the action space of the construction site mixer truck scheduling agent is set as the subaction space of the construction site mixer truck scheduling part. The two scheduling agents are independent of each other and get their own rewards according to the scope of decision-making in the learning process.

2) Scheduling agent decision-making process

The mixer truck scheduling agent adopts scheduling parameters such as the current process completion time of the mixer truck, the remaining processing time of the mixer truck, the processed process of the mixer truck, the remaining process of the mixer truck, and the distance that the mixer truck needs to be transported. For the construction site mixer truck scheduling agent, the scheduling parameters include the current transfer end time of the construction site mixer truck, the distance between the construction site mixer truck and the mixer truck position, and the number of construction site mixer truck transfers. For each scheduling parameter, the scheduling agent has an output neuron of the neural network corresponding to it.

The relevant parameters in the local state space of the scheduling agent are input, and the weight value of each scheduling parameter is output through the neural network. The weighted sum of the weight value and the normalized scheduling parameter is obtained to obtain the scheduling value of each scheduling object. The scheduling list is obtained after the scheduling value is sorted. Through the above processing, the scheduling list of scheduling objects can be obtained from the environmental state parameters of the construction site, and the decision of the agent can be realized by selecting the objects in the scheduling list.

3) Action selection mechanism

The scheduling agent can obtain the current maximum reward by using the known information of the environment, and the scheduling agent can obtain more environmental information of the construction site by exploring the environment to try to obtain a greater reward. The number of exploration and utilization needs to be balanced to achieve the maximum cumulative reward. The solutions of scheduling tasks are diverse, and different scheduling schemes may get the same completion time. Therefore, in the process of scheduling solution, the exploration of the workshop environment should be kept to promote the agent to find other or better scheduling schemes, so a fixed exploration environment probability is adopted. This article uses the s - greedy strategy to realize the exploration and utilization of two scheduling agent s - greedy strategy to a fixed in the process of solving the probability to explore on the environment. When the random value is greater than s, the scheduling agent schedules the object with the largest scheduling value in the current scheduling list. When the random number is less than or equal to s, the scheduling agent randomly selects an object from the scheduling list for scheduling.

$$\varepsilon - greedy = \begin{cases} random(schedule, list) & p < \varepsilon \\ Max(schedule, list) & p \geq \varepsilon \end{cases} \tag{2}$$

4) Interaction mechanism

In the scheduling problem of the construction site, information needs to be transferred between scheduling agents, and the scheduling agent also needs to interact with the construction site mixer truck path planning algorithm of the construction site to obtain the movement information of the construction site mixer truck in the construction site to obtain the time required for the construction site mixer truck to move in each location of the workshop. In a scheduling round, the interaction mechanism between scheduling agents is shown in Figure 4.

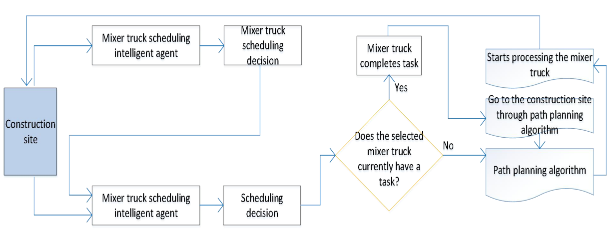

Figure 4 Scheduling agent interactions

The mixer truck scheduling intelligent agent reads the workshop environment to make mixer truck scheduling decisions, and provides the current location and the location of the next processing machine to the construction site mixer truck intelligent agent, scheduling mixer trucks to wait for construction site mixer truck reception. The scheduling intelligent agent makes construction site mixer truck scheduling decisions based on the information provided by the mixer truck scheduling intelligent agent and the workshop environment. If the construction site mixer truck selected by mixer truck scheduling currently has a scheduling task, after completing the scheduling task, the construction site mixer truck provides its own position information, and the mixer truck scheduling intelligent agent provides mixer truck position information to the construction site mixer truck path planning algorithm in the construction site. If the construction site mixer truck currently does not have a scheduling task, it directly provides its own position information and the position information of the mixer truck to the construction site mixer truck path planning algorithm.

After receiving the mixer truck, the construction site mixer truck provides the current position of the mixer truck and the machine position of the next process for the construction site mixer truck path planning algorithm. The construction site mixer truck path planning algorithm in the construction site can obtain the position information provided by the multi resource scheduling algorithm, which can solve for a path that has no collision with other construction site mixer trucks or machines and has the least number of turns. Based on the length of this path, the construction site mixer truck's handling and walking time can be obtained, providing information for the calculation of relevant parameters in the multi resource scheduling algorithm, and realizing the interaction between the multi resource scheduling algorithm in the construction site and the construction site mixer truck path planning algorithm in the construction site.

4. Simulation and Analysis

4.1 Simulation Settings

In order to verify that the IDQN method can self adjust in dynamic environments through reinforcement learning methods to adapt to changes in the environment, after comparing the scheduling performance under default parameter conditions, this paper also compared the performance of different scheduling methods under scheduling target weight coefficient conditions.

From the scheduling decision-making process of construction site mixer trucks studied in this article, it can be seen that the dispatch decision-making problem of construction site mixer trucks is quite similar to the scheduling problem of batch processing machines. In the batch processing scheduling problem, an important decision is how to determine the time for the batch processing machine to start a new batch processing process based on production demand, in order to fully utilize the processing capacity of the batch processing machine and improve processing efficiency.

In the workshop concrete mixing system, the scheduling method of construction site mixer trucks not only needs to consider the efficiency of the handling system, but also its impact on the construction site. Meanwhile, these methods do not take into account the changes in concrete ratio and scheduling target weights over time during the scheduling process.

In terms of material scheduling task generation, these scheduling methods can use static reorder point method and dynamic reorder point method respectively. Among them, for the static reorder point method:

$$T_i^R = \frac{1}{v}\left[Dist(i) + 2MaxDist\right] + RC \tag{3}$$

In the formula, RC is the parameter set to change the reorder point. Similarly, for the dynamic reorder point method:

$$T_i^L = \frac{1}{v}\left[Dist(i) + 2MaxDist\right] + RC^L \tag{4}$$

RC L also sets parameters for changing dynamic reorder points.

4.2 Comparison of Scheduling Performance Based on Default Parameters

To evaluate the performance of scheduling methods, we first construct an Ideal Scheduling Method (ISM). The so-called 'ideal' refers to the method that can complete all concrete mixing with the shortest distance without any delay. Specifically, it meets the following conditions:

(1) There were no delays in concrete mixing, and the construction site worked normally throughout the entire scheduling period;

(2) The inventory of parts on the construction site is always fully utilized;

(3) Every concrete mix takes full advantage of the mixing power of the mixer;

(4) The shortest evenly distributed scheduling distance of that part is always used to complete the scheduling. It should be pointed out that without any restrictions, in order to optimize concrete mixing costs, the concrete mixing system will not perform any material scheduling tasks, resulting in a minimum concrete mixing distance of 0. However, the scheduling system must immediately dispatch a tractor to perform the scheduling task when the construction site stops working due to a lack of parts. It can be seen that under this assumption, the shortest concrete mixing distance cannot be equal to 0.

Based on the above conditions, the scheduling objective function value of the ISM method can be calculated as follows:

If the total scheduling time is ST, then in an ideal situation (assuming that the online inventory of all parts can always meet the assembly demand), the maximum output that any scheduling method can achieve is:

$$TP^* = ST / CT \tag{5}$$

If the ratio conforms to m, then the average consumption rate URi of mixer truck Pi is:

$$UR_i = \sum_{j=1}^{N_m} \rho_j BOM(M_j, P_i) / CT \tag{6}$$

And its consumption is equal to the product of the total scheduling time and the average consumption speed URi, that is:

$$PA_i = ST \cdot UR_i \tag{7}$$

If the shortest unit scheduling distance of mixer truck Pi is UC *, then we can obtain:

$$f^* = \frac{w_M \times ST}{CT} + w_D \times ST \times \sum_{i=1}^{N_p} UR_i \cdot UC_i^* \tag{8}$$

F* is the optimal objective function value that the ISM method can achieve under the above conditions. UC * is a constant, and when the concrete ratio is given, URi is also a constant. Therefore, f * is determined by the concrete ratio, scheduling target weight, and total scheduling time, and is independent of the specific scheduling plan adopted.

In this simulation experiment, each scheduling method was tested 30 times, with each simulation lasting 80 hours, including 10 hours of warm-up time.

When yield is the only evaluation indicator, the IDQN method is the optimal scheduling method. The smaller the batch size, the higher the output. This is because waiting for the generation of the next scheduling task may result in a shortage of the parts that have already been generated, causing the construction site to shut down and production to decrease. For other methods, the performance (objective function value) of the system using the dynamic reorder point method is superior to that using the static reorder point method. This indicates that the dynamic reorder point method helps improve the performance of the scheduling system. From Figure 5, it can be observed that for this case, the performance of IDQN is relatively close to the theoretically optimal scheduling method.

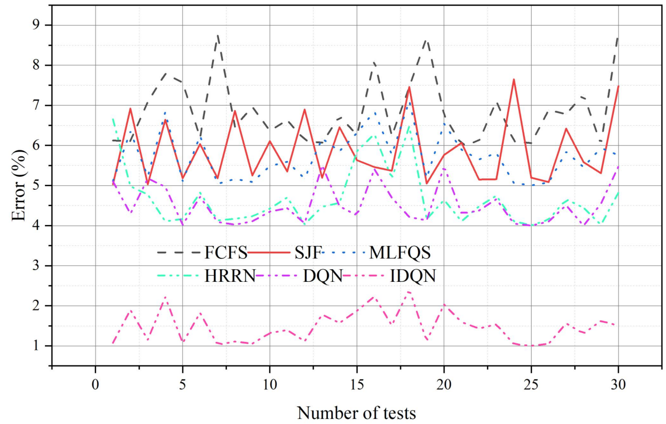

Figure 5 Error comparison between each scheduling method and ISM

4.3 Cost comparison between IDQN and other scheduling algorithms

This section continues to use simulation experiments to compare the scheduling costs of different methods. It can be seen from Figure 6 that IDQN has lower scheduling cost than FCFS, SJF, MLFQS, HRRN and DQN.

The benefits brought by IDQN are higher than those of other scheduling methods, which further shows that IDQN has a good economic advantage in scheduling.

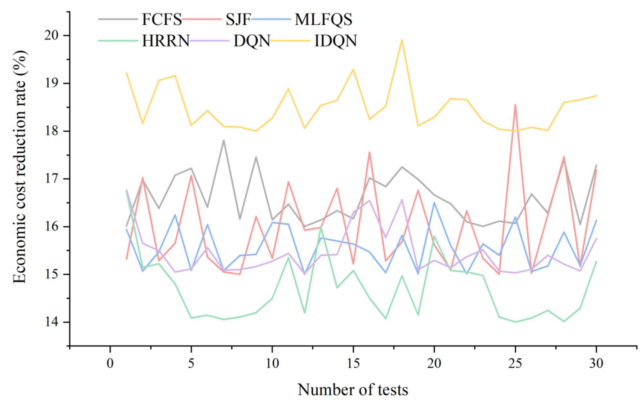

Figure 6 Comparison of economic performance of six scheduling methods

4.4 Performance comparison under different concrete ratios and scheduling target weights

In order to verify that the IDQN method can adapt to the environment with variable concrete ratio and scheduling target weight, this section compares the performance of each method under different concrete ratio and scheduling target weight Settings. Figure 7 shows the performance of the scheduling system using each method under these 25 different concrete ratio Settings. It can be seen from the figure that for the setting of the 25 different concrete ratios, the performance of IDQN method is superior to other scheduling methods participating in the experiment. This shows the adaptability of IDQN method in dynamic environment with variable concrete ratio.

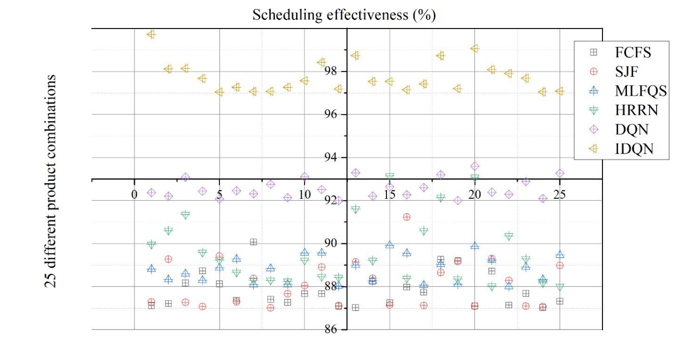

Figure 7 Comparison of scheduling performance under different concrete ratio settings

For different wM, IDQN can perform reinforcement learning according to wM in offline phase. As the weight of output increases, the value of the objective function of all scheduling methods increases. This is because an increase in wM means that the construction site earns more per unit of output. For FCFS, SJF, MLFQS, HRRN, the change of the objective function value is linear with respect to the change of wM. This is because these methods do not consider the scheduling target weight during scheduling, so the change of scheduling target weight has no impact on the scheduling process of these methods. However, the change of the objective function value of IDQN method is non-linear relative to wM. This is because the neural network learning and reinforcement learning of IDQN in the offline stage can adjust the scheduling policy according to the scheduling target weight, and the change of scheduling target weight has a very important impact on the scheduling process of IDQN.

In order to further understand the performance of each method under different scheduling target weights, the gap between them and ISM methods can also be compared. As can be seen from Figure 8, the gap between IDQN method and ISM is generally small. It can be seen that for the real-time scheduling problem of construction site mixer truck studied in this paper, IDQN method has better performance in general, which is not only better than other scheduling methods involved in comparison, but also has a small gap between its performance and the theoretical optimal scheduling method.

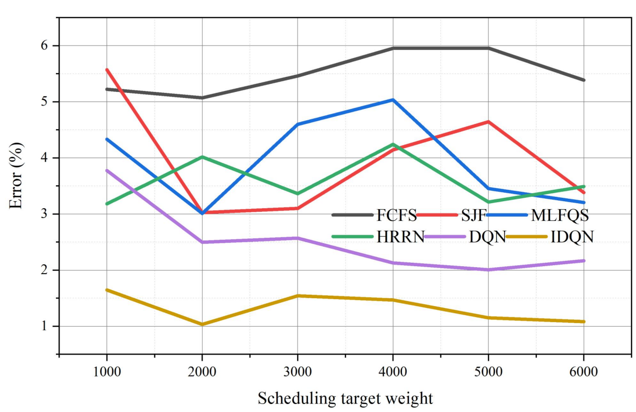

Figure 8 Error comparison of scheduling methods under different scheduling target weights

4.5 Comparison of calculation time of different scheduling methods

In order to verify whether the IDQN method proposed in this paper has good real-time response performance, Figure 9 compares the longest computation time for a scheduling decision of the various scheduling methods involved in this paper.

The maximum calculation time of IDQN is significantly lower than that of other scheduling methods. IDQN has higher computational efficiency and better real-time response ability, which meets the real time requirement of construction site mixer truck scheduling system.

5. Conclusions

Combined with the particularity of cooperative transport scheduling, the overall architecture of construction site mixer truck scheduling control system based on centralized hierarchical architecture is designed. This paper studies the scheduling method of construction site based on IDQN algorithm, analyzes the learning process of scheduling algorithm to extract scheduling information from experience pool and minimize output loss based on scheduling process, and designs mixer truck scheduling agent and construction site mixer truck scheduling agent to realize scheduling of shop. The mechanism of scheduling agent is studied, including the local state space, action space and local reward mechanism of mixer truck and construction site mixer truck scheduling agent based on scheduling function and mathematical model objective. The decision generation process is to map the job and construction site mixer truck scheduling information into weight information and synthesize scheduling list by neural network. It combines the ε-greedy action selection mechanism, the interaction mechanism between mixer truck and construction site mixer truck agent, scheduling algorithm and construction site mixer truck path planning algorithm. In order to evaluate the scheduling performance of IDQN, this paper compares IDQN with other 5 scheduling methods through simulation experiments. Simulation results show that the performance of IDQN is better than other scheduling methods. IDQN can adapt to the change of environment through reinforcement learning and has good adaptability. In addition, from the comparison of calculation time of each scheduling method, it can be found that IDQN can still meet the real-time requirement of the actual system, although the calculation efficiency is worse than other methods. Therefore, IDQN is a real-time scheduling method for multi-load construction site mixer truck in dynamic manufacturing environment.

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