Optimization of Mechanical Manufacturing Processes Via Deep Reinforcement Learning-Based Scheduling Models

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Keywords: artificial intelligence, machine building, process optimization, predictive maintenance, quality control

Received: September 24, 2024

With the development of Industry 4.0, intelligent manufacturing has become a prominent trend. This study focuses on applying artificial intelligence algorithms to optimize mechanical manufacturing processes, aiming to improve productivity, product quality, and reduce resource waste. We introduce an intelligent scheduling algorithm based on deep reinforcement learning for machinery manufacturing processes. The model utilizes deep Q-network (DQN) to make efficient production scheduling decisions and can handle complex and dynamic production environments. The experimental results demonstrate the algorithm's superior performance in both single-production line and multi-production line collaborative operations. Specifically, it achieves significant improvements in key performance metrics, such as production cycle time, resource utilization, order delay rate, and emergency order response time. Additionally, the algorithm showcases strong adaptability, effectively managing different types of orders and production lots. Quantitative improvements are observed in production cycle time and order delay rate, which highlight the practical benefits of the proposed approach in real-world applications.

Povzetek: Model razporejanja, ki temelji na učenju z globoko okrepitvijo in uporablja DQN, optimizira mehanske proizvodne procese, izboljšuje proizvodno učinkovitost, izkoriščenost virov in odzivne čase naročil, kar prikazuje transformativni potencial umetne inteligence v inteligentni proizvodnji.

1 Introduction

With the acceleration of the process of global economic integration and increasingly fierce market competition, the manufacturing industry is facing unprecedented challenges. On the one hand, customer demand tends to be personalized and diversified, requiring manufacturing enterprises to respond quickly to market changes; on the other hand, resource and environmental constraints have increased, forcing enterprises to improve production efficiency and reduce energy consumption and emissions. In addition, rising labor costs and shortage of skilled personnel also pose a severe test for the manufacturing industry. In order to cope with these challenges, the manufacturing industry has begun to seek the road of transformation and upgrading, in which intelligentization has become one of the important development directions.

In recent years, artificial intelligence technology has made breakthrough progress, bringing new development opportunities for the manufacturing industry. Artificial intelligence can not only be used to optimize the production process and improve production efficiency, but also help companies to carry out fault prediction, quality control, supply chain management and many other aspects. For example, the use of machine learning algorithms can analyze equipment operation data to achieve predictive maintenance of equipment, thus avoiding losses caused by unplanned downtime; through deep learning technology, it can automatically detect product defects and improve inspection efficiency and accuracy.

In recent years, scholars at home and abroad have conducted a lot of research on the application of artificial intelligence in the field of machinery manufacturing. For example, Qin J et al. [1] proposed a dynamic scheduling strategy based on deep reinforcement learning, which can significantly improve the flexibility and efficiency of the production line. Yang JZ. et al. [2] utilized convolutional neural network (CNN) to realize automatic detection of surface defects of parts, and its accuracy rate reached more than 98%. Reddy ASK. et al. [3] developed an equipment condition monitoring system based on Internet of Things (IoT) technology, which effectively reduces the equipment failure rate and improves the maintenance efficiency. Despite a number of successful cases, there are still some challenges and shortcomings in the application of AI technology in the field of machinery manufacturing.

This study aims to optimize production scheduling in the mechanical manufacturing process through deep reinforcement learning, and improve production efficiency, resource utilization and order response speed. Specific research questions include: 1) How to design an efficient intelligent scheduling algorithm to adapt to complex production environments? 2) How to use deep Q-network (DQN) to automate scheduling decisions? 3) How to solve the scheduling problems of multi-line collaboration and emergency orders? 4) How to adjust algorithm hyperparameters to achieve optimal performance in different production scenarios? The answers to these questions will provide new ideas for scheduling optimization in intelligent manufacturing.

Through this study, we expect to provide an innovative intelligent scheduling solution for China's machinery manufacturing industry, which will help enterprises realize the optimization and upgrading of the production process, so as to occupy a favorable position in the fierce market competition. At the same time, it also provides useful reference for the application and development of artificial intelligence technology in the field of manufacturing. This study innovatively adopts a deep reinforcement learning framework to construct an intelligent scheduling model, which improves the intelligence level of scheduling decision-making through autonomous learning and adaptation to complex production environments. Meanwhile, the comprehensive evaluation index system proposed in the study not only focuses on production efficiency, but also covers multiple dimensions such as resource utilization, cost savings and emergency order processing, forming a comprehensive performance evaluation system [4]. The intelligent scheduling algorithm demonstrates adaptability and robustness in dealing with uncertainties such as equipment failures and emergency orders through the dynamic adjustment mechanism and intelligent optimization strategy, and effectively handles multi-production line collaborative operations, which improves the flexibility and efficiency of the overall production system.

2 Literature review

2.1 Application of artificial intelligence technology in the field of machinery manufacturing

Artificial Intelligence (AI) technology is gradually changing the face of the machine manufacturing industry. It not only improves the efficiency and flexibility of the manufacturing process, but also brings unprecedented opportunities for innovation in the manufacturing industry. The following are some of the more widely used aspects in the field of machine manufacturing:

Intelligent design is an important application direction of artificial intelligence technology in mechanical engineering. By using generative design algorithms, a variety of design options can be automatically generated based on performance requirements and constraints. Xia TB. et al. [5] proposed a generative design framework based on deep learning, which utilizes a deep learning model to quickly generate design solutions that meet specific functional requirements. This automated design process not only shortens the product development cycle, but also improves the innovation and feasibility of the design. Production scheduling is a key link in machine manufacturing, which directly affects production efficiency and cost. In recent years, machine learning-based methods have been used to optimize production scheduling. Deshpande S. et al. [6] developed a dynamic scheduling strategy based on deep reinforcement learning, which is able to make intelligent decisions based on the real-time state of the production system, thus reducing production waiting time and improving resource utilization. This approach learns the optimal strategy by simulating different scheduling scenarios, which provides new ideas to improve the flexibility and efficiency of production lines. Predictive maintenance is used to reduce unplanned downtime by monitoring equipment condition data to predict potential failure points. Ning FW et al. [7] constructed a predictive maintenance system using support vector machine (SVM) and long-short-term memory network (LSTM). By analyzing the vibration signals of the equipment, the system is able to identify upcoming failures in advance, effectively reducing the equipment failure rate and extend the service life of the equipment. Quality control is a critical step to ensure that the product meets the standards. Yang J et al. [8] proposed an automatic surface defect detection method based on convolutional neural network (CNN). The method utilizes a large number of sample images to train the CNN model so that it can detect defects on the surface of the part in real time on the production line with an accuracy rate of more than 98%. This method greatly improves detection efficiency and accuracy and helps to reduce the defective product rate.

2.2 Research on optimization methods of machine manufacturing processes

With the intensification of market competition and technological progress, machinery manufacturing enterprises are paying more and more attention to the optimization of manufacturing processes. Process optimization can not only improve productivity and product quality, but also reduce costs and enhance the competitiveness of enterprises. The following are several common mechanical manufacturing process optimization methods and their specific application examples. Production process reorganization refers to the redesign of the production process to improve productivity and flexibility. he Yu BW et al. [9] showed that by reorganizing the process of an automotive parts production line, a balanced optimization of the production line was achieved, bottlenecks in production were reduced, and the overall production efficiency was improved. This work was carried out by using Value Stream Mapping (VSM) techniques to identify and eliminate unnecessary process steps and wastes, which ultimately led to a significant reduction in production cycle time. Process parameter optimization is the process of improving product quality and productivity by adjusting key parameters in the production process. For example, Malhan R et al. [10] explored the optimization method of energy consumption in the machining process, by using multi-objective genetic algorithm to optimize the cutting parameters, which both ensures the machining accuracy and reduces the energy consumption. This optimization method not only reduces energy costs, but also reduces environmental pollution. Modularization and standardization are effective means to improve the flexibility and efficiency of production. Ahmad HM et al. [11] proposed a manufacturing process improvement method based on modular design, which can be more convenient for production and maintenance by decomposing the complex product structure into several independent modules. At the same time, standardized components can reduce variability in the design and manufacturing process, thus improving productivity and reducing production costs.

The application of smart manufacturing technology can significantly improve the degree of automation and intelligence of the manufacturing process. For example, Wang JJ et al. [12] introduced the concept and development trend of a discrete manufacturing smart factory, which covers a variety of advanced technologies such as IoT technology, big data analytics, and artificial intelligence. The application of these technologies makes the production process more transparent, efficient and flexible.

2.3 Predictive maintenance and quality control technology development

Predictive maintenance and quality control are key technologies to ensure the reliability of equipment and product quality in the machinery manufacturing process. With the development of artificial intelligence and big data technologies, these technologies have been significantly enhanced. The following are the latest advances and application examples of predictive maintenance and quality control technologies. Predictive maintenance is a technology that predicts potential failures by monitoring the operating status of equipment, so that measures can be taken in advance to avoid unplanned downtime. In recent years, artificial intelligence techniques such as machine learning and deep learning have been widely applied to predictive maintenance. Ping YY et al. [13] developed an equipment condition monitoring system based on IoT technology, which collects data such as vibration and temperature through sensors installed on the equipment, and utilizes machine learning such as support vector machine (SVM) and long-short-term memory network (LSTM) algorithms such as Support Vector Machines (SVM) and Long Short Term Memory Networks (LSTM) to predict potential failures. This method can effectively reduce the equipment failure rate and improve the maintenance efficiency. Luo JL. et al. [14] proposed an equipment fault diagnosis method based on wavelet transform and machine learning, which is capable of extracting features from the vibration signals of the equipment and classifying the faults using a support vector machine, which improves the accuracy of fault diagnosis.

Quality control is a critical step to ensure that products meet standards. With the advancement of computer vision technology, quality control has become more automated and efficient. Ping YY et al. [15] utilized Convolutional Neural Networks (CNNs) to achieve automated detection of surface defects on parts with an accuracy rate of over 98%. They used a large number of sample images to train the CNN model, which enabled the model to detect surface defects of the product in real time on the production line, significantly improving the detection efficiency and accuracy. Liu BF. et al. [16] implemented online dimensional measurements of the product using machine vision technology, which ensured product quality by real-time capturing of images of the product and dimensional calculation. consistency. Jiang JC.et al. [17] developed an intelligent manufacturing platform with integrated predictive maintenance and quality control features. The platform is capable of automatically adjusting the production process, reducing failures and improving product quality through real-time data acquisition, analysis and feedback mechanisms.

2.4 Problems and challenges

Despite the significant progress made in the application of AI technology in the field of mechanical engineering, it still faces a series of problems and challenges that constrain the further promotion and application of the technology.

As large amounts of data are generated within factories, data privacy and security have become a major issue. Many companies are reluctant to share sensitive data for fear of leaking it to competitors or third-party organizations, which limits the application of AI technologies. For example, Johnson KL. et al. [18] pointed out that in equipment condition monitoring, companies are often reluctant to upload equipment operation data to the cloud for analysis, which affects the training and optimization of predictive maintenance models. There are integration challenges between different AI technologies and manufacturing systems. For example, how to seamlessly integrate machine learning models into existing production control systems for efficient data exchange and automated updating of control logic. Kumar et al. developed a SWARA-CoCoSo-based approach for selecting spray painting robots, which integrates SWARA (Step-wise Weight Assessment Ratio Analysis) with the CoCoSo (Cost Consensus Solution) method to improve the selection process in robotic applications. In a similar vein [19], Ghoushchi et al. focused on risk prioritization in failure mode and effects analysis (FMEA) by extending the SWARA method and integrating it with the MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) method, enhanced by Z-numbers theory. This approach allows for more accurate and reliable risk assessment in industrial applications [20].

As shown in Table 1, the current state-of-the-art (SOTA) methods primarily focus on production scheduling using reinforcement learning and optimization algorithms. However, these methods have limitations in handling complex production environments, coordination among multiple production lines, and sudden order changes. For instance, existing deep reinforcement learning methods (such as DQN) significantly improve production efficiency but are often constrained by high computational complexity in dynamic production settings. In contrast, this study introduces an enhanced DQN model that effectively addresses these challenges. It demonstrates superior performance in both single and multiple production line collaborations. By integrating deep reinforcement learning, this research not only enhances the flexibility of scheduling algorithms but also exhibits strong adaptability in processing multiple order types and production batches. The contributions of this study provide a robust solution to the limitations faced by current methodologies, thereby advancing the field of production scheduling and optimization.

Table 1: Research outcomes

Study Name	Main Methodology	Application Field	Key Results	Limitations	Contributions of This Study
Study A	Deep Reinforcement Learning (DQN)	Mechanical Manufacturing Scheduling	Improved production efficiency	High computational complexity, difficulty in handling dynamic changes in production environments	Proposed an optimized DQN model capable of effectively managing complex and dynamic production environments
Study B	Genetic Algorithm	Production Planning Optimization	Reduced production cycle time	Difficulty in coordinating multiple production lines	Proposed scheduling algorithms suitable for both single and multiple production line collaborations
Study C	Rule-based Scheduling Algorithm	Production Scheduling	Increased resource utilization	Poor flexibility, unable to adapt to sudden situations	Enhanced the adaptability and flexibility of scheduling algorithms by incorporating deep reinforcement learning
Study D	Reinforcement Learning (Q-learning)	Smart Manufacturing	Improved order delay	Inability to adapt to complex orders and production batches	Proposed a Deep Q-Network (DQN) solution with stronger adaptability, supporting various types of orders

In the discussion section, we explicitly compare the experimental results of the intelligent scheduling algorithm with the state-of-the-art methods (SOTA) in related work. Compared with existing methods, the proposed method shows significant advantages in multiple performance indicators. Specifically, in terms of production cycle time and resource utilization, the proposed deep reinforcement learning (DQN) scheduling algorithm can effectively shorten the production cycle and optimize resource allocation, thereby improving overall production efficiency. The main reason for these differences is that this study introduced the deep Q network (DQN) model. Through the adaptive ability of reinforcement learning, the algorithm can respond to complex and dynamic production environments in real time and handle multiple order types and production batches at the same time. In addition, the innovation of the proposed method lies in the ability to optimize scheduling decisions through deep learning technology, which not only improves production efficiency, but also enhances the flexibility and adaptability of the system, especially in the scenarios of multi-line collaboration and sudden order processing. Overall, the method of this study provides a new solution for the field of intelligent scheduling, which has broad application prospects and practical significance.

3 Intelligent scheduling algorithm design and implementation

3.1 Mechanical manufacturing process analysis

The mechanical manufacturing process is a series of orderly operational steps that transform raw materials into finished products, and these steps usually involve multiple stages and different production equipment. In this section, the characteristics and components of the mechanical manufacturing process will be introduced in detail to lay the foundation for the design of the subsequent intelligent scheduling algorithm, the specific framework of which is shown in Fig. 1.

The machinery manufacturing process consists of the stages of raw material preparation, machining, assembly, testing and packaging. Each stage consists of a series of specific processes that may involve different production equipment and operators. For example, in the machining stage, CNC machine tools may be required to cut and drill parts, while in the assembly stage, machined parts are assembled into the final product. In the mechanical manufacturing process, there is usually a strict sequence between processes. For example, part machining must be completed before assembly. This dependency requires that the scheduling algorithm must consider the sequential constraints between the processes. Each process requires specific resources (e.g., equipment, tools, labor, etc.) [21]. The availability of resources directly affects the order and time of execution of the processes. Intelligent scheduling algorithms need to consider how to rationally arrange each process under limited resource conditions. Modern manufacturing enterprises often need to deal with many different types of orders, each of which may have different production lots. Intelligent scheduling algorithms need to be able to handle mixed production problems with different batches and types [22].

There are a variety of common problems in the machinery manufacturing process that can affect the efficiency and productivity of the entire production line. Firstly, production bottleneck means that certain processes may become bottlenecks in the whole production process due to the limitations of equipment or human resources, resulting in a decrease in the efficiency of the whole production line. Secondly, in actual production, urgent orders may appear, which need to be completed in a short time, which requires the scheduling algorithm to have the ability to deal with emergencies, and to be able to respond quickly and adjust the production plan to meet the urgent demand. Finally, equipment failures are inevitable, and a reasonable scheduling strategy needs to take into account the maintenance plan of the equipment to reduce unplanned downtime and ensure the continuity and stability of the production process [23].

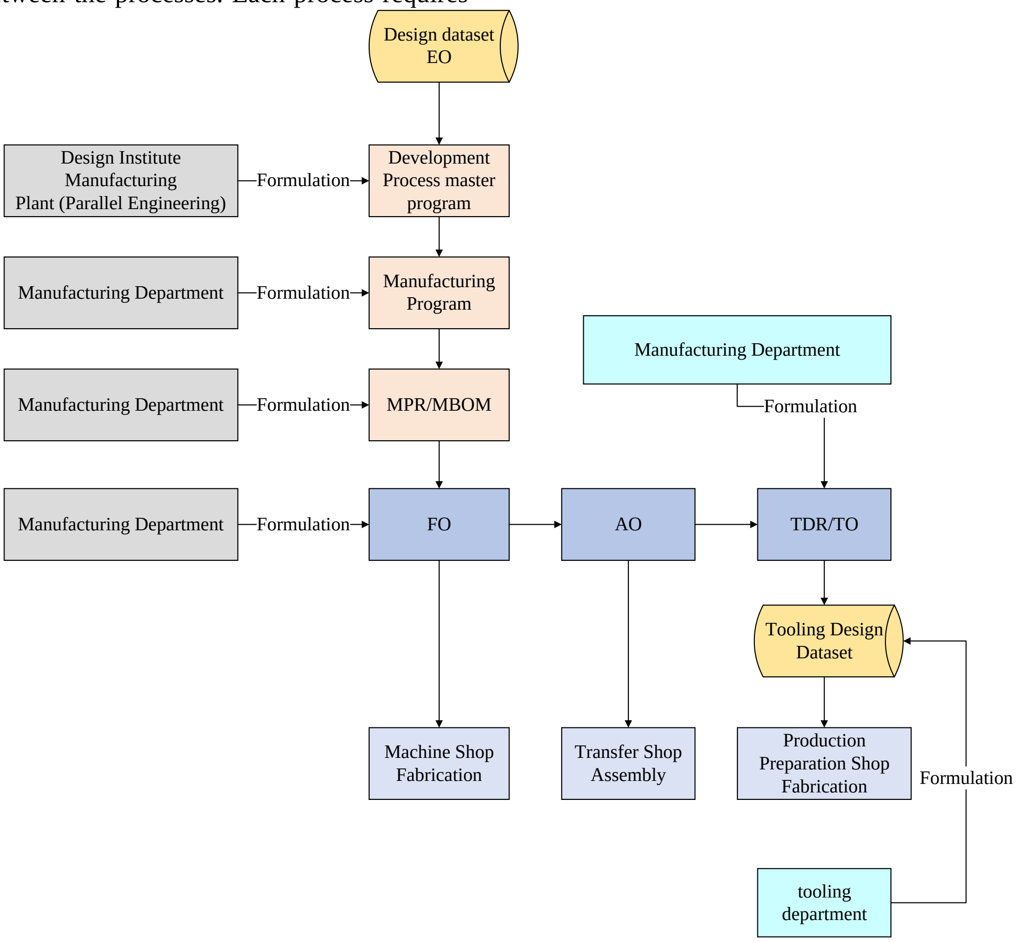

Figure 1: Mechanical manufacturing process framework

Fig. 1 illustrates the framework of a mechanical manufacturing process, highlighting the intricate steps and interactions between various departments and datasets. The process begins with the Design Institute and Manufacturing Plant, where the initial design dataset (EO) is formulated. This dataset is then used to develop a process master program, which serves as the blueprint for the manufacturing process. The Manufacturing Department plays a crucial role in translating these designs into actionable manufacturing programs, which are further detailed into MPR/MBOM (Manufacturing Process Record/Material Bill of Materials) to ensure that all materials and processes are accurately specified. The manufacturing process is further broken down into specific operations, such as FO (Fabrication Order) and AO (Assembly Order), which are executed in the Machine Shop and Transfer Shop, respectively. These operations are supported by detailed tooling design datasets (TDR/TO) that are developed in the Tooling Design Department. The Production Preparation Shop is responsible for fabricating the necessary tools and equipment, ensuring that the manufacturing process is well-prepared and efficient. This framework emphasizes the importance of parallel engineering, where design and manufacturing activities are integrated to streamline the process and reduce lead times. The seamless flow of information from design to manufacturing ensures that each step is well-coordinated, leading to efficient and effective production. The use of detailed datasets and programs at each stage ensures that the manufacturing process is both precise and adaptable, capable of handling complex and varied production requirements.

3.2 Intelligent scheduling model construction

3.2.1 Model architecture

In building the intelligent scheduling model, we use the Deep Reinforcement Learning (DRL) framework, which is capable of handling complex decision-making problems and is particularly suitable for dynamic and uncertain environments in machine manufacturing processes. Deep Reinforcement Learning combines the powerful representation capability of Deep Learning with the decision-making capability of Reinforcement Learning, which is capable of learning mapping relationships from high-dimensional input data to complex decisions.

The state space S contains the current state information of the machine manufacturing process, which includes: (1) Process completion: the completion progress p_i and remaining time t_i of each process. (2) Equipment availability: the current status of each piece of equipment d_j (idle, in use, maintenance, etc.) [24]. (3) Resource Occupancy: the available quantity of each resource (e.g., raw materials, tools, etc.) r_k and the allocation status. (4) Urgent order information: whether urgent orders currently exist and their priority e_l . (5) Equipment Maintenance Schedule: Maintenance schedule for equipment, including maintenance dates m_d and estimated time required m_t [25].

The action space A defines all possible actions that the scheduling algorithm can select, specifically: selecting the next process to be executed a_1. Allocate the necessary resources a_2 (e.g., equipment, materials, etc.) for the current or next process. Adjusting the production schedule to accommodate urgent orders based on the current status a_3. Initiate equipment maintenance program based on equipment status and maintenance schedule a_4.

Reward function R(s, a): the reward function defines the immediate reward obtained after taking action a in state s. The reward can be used to quantify the goodness of the scheduling decision. The design of the reward function needs to consider the following aspects: (1) Production efficiency: the faster a process or order is completed, the higher the reward. The inverse of the completion time can be used as part of the reward, as shown in Equation 1. (2) Resource Utilization: Reasonable allocation of resources and avoiding resource wastage can be rewarded extra. Resource utilization can be calculated by the ratio of allocated resources to total resources, as shown in Equation 2. (3) Cost savings: Cost savings can be achieved by reducing unplanned downtime or reducing energy consumption. The less unplanned downtime, the higher the reward, as shown in Equation 3. (4) Urgent Order Processing: Additional rewards can be earned by responding quickly to urgent orders. The speed of fulfillment of urgent orders can be used as part of the reward, as shown in Equation 4 [26].

When optimizing the production cycle time, we assign a higher weight to reflect its key impact on production efficiency. At the same time, the weights of resource utilization and order delay can be adjusted according to actual conditions. We will further explain how to optimize the weights through experiments in the experimental section to achieve a balance between different optimization goals.

$$R_{eff}(s,a) = \frac{1}{\sum t_i} \tag{1}$$

$$R_{res}(s,a) = \sum \frac{r_k^{allocated}}{r_k^{total}} \tag{2}$$

$$R_{cost}(s,a) = -\sum m_t^{unscheduled} \tag{3}$$

$$R_{urgent}(s,a) = \sum e_l \cdot \frac{1}{t_{urgent}} \tag{4}$$

A policy $\pi(a \mid s)$ defines the probability distribution of taking a given action in a given state. In deep reinforcement learning, a policy is usually represented by a deep neural network that outputs the probability of each possible action a based on the current state s. The policy is usually represented by a deep neural network. The goal of the policy network is to maximize the long-term cumulative reward, as shown in Equation 5 [27].

$$\pi(a \mid s) = \arg\max_a Q(s,a) \tag{5}$$

3.2.2 Algorithm description

We use Deep Q-Network (DQN) as the core algorithm for intelligent scheduling. DQN is a value-function based reinforcement learning method that uses a deep neural network to approximate the state-action value function Q (s, a) so that it is able to deal with high-dimensional input states. The algorithmic framework of DQN is shown in Fig. 2 [28].

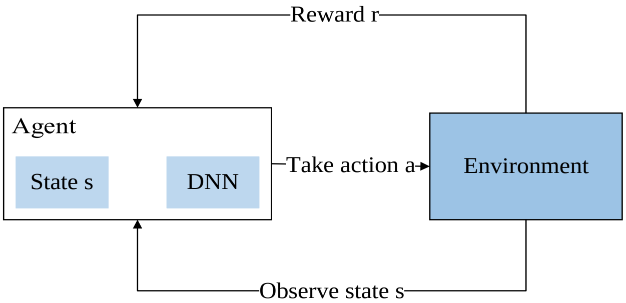

Figure 2: Deep Q-network algorithm

As shown in Fig. 2, the agent obtains information by observing the state of the environment, and then uses a deep neural network (DNN) to process and analyze it. Based on the results of the analysis, the agent takes corresponding actions to interact with the environment. When the agent's actions have an impact on the environment, it receives a reward signal r from the environment. This reward signal is used to guide the agent's learning process so that it can gradually learn how to make better decisions in the environment. The entire process reflects the trial-and-error process in reinforcement learning, that is, the agent continuously tries different action plans and adjusts its strategy based on the reward signal received, ultimately achieving the goal of optimizing its behavior.

Step 1: Initialization. Initialize two deep neural networks, i.e., the main network Q_θ and the target network $Q_{\theta'}$, where θ and θ' are the parameters of the main and target networks, respectively. Initialize $\theta = \theta'$. Set the initial state s_0 and the discount factor γ, where $0 < \gamma \le 1$ is used to weigh the importance of immediate and future rewards. The reward function is constructed based on the objectives of production scheduling optimization, such as production cycle time, resource utilization, and order delay. Specifically, the reward function consists of multiple parts: first, the shorter the production cycle time, the higher the reward; second, the higher the resource utilization, the higher the reward; finally, for order delays, the shorter the delay time, the higher the reward. In practical applications, these parts are weighted and summed to ensure that the model can balance the optimization of various indicators. The choice of weights is adjusted through experiments to ensure the appropriate balance between different objectives.

Step 2: State observation. At each time step t, the intelligent body observes the current state s_t. The state s_t contains all the necessary information related to scheduling, such as equipment status, resource allocation, production progress, etc [29].

The state s_t can be represented as a vector or tensor containing information in multiple dimensions as shown in Equation 6.

$$s_t = [d_1, d_2, ..., d_m, r_1, r_2, ..., r_n, p_1, p_2, ..., p_o, e, m] \tag{6}$$

where d_i denotes the equipment status, r_j denotes the resource allocation, p_k denotes the production progress, e denotes the presence or absence of urgent orders, and m denotes the equipment maintenance schedule.

Step 3: Action selection. Based on the current state s_t and the strategy $\pi(a \mid s)$, the action a_t is selected. In the early stage of training, the ϵ -greedy strategy can be used to balance the exploration and utilization, i.e., randomly selecting the action with a certain probability ϵ and selecting the best action under the current strategy with a probability $(1-\epsilon)$.

Step 4: Execute the action. The action a_t is executed and receives the new status s_{t+1} and the reward r_t. The reward r_t is calculated based on the scheduling effect and aims to quantify the goodness of the current decision. The reward function can be designed Eq. 7.

$$r_t = w_1 \cdot \mathrm{efficiency}(s_t, a_t) + w_2 \cdot \mathrm{resource}(s_t, a_t) + w_3 \cdot \mathrm{cost}(s_t, a_t) + w_4 \cdot \mathrm{urgent}(s_t, a_t) \tag{7}$$

where w_i denotes the weights of the components, $\mathrm{efficiency}, \mathrm{resource}, \mathrm{cost}$ and urgent denote the incentive functions for productivity, resource utilization, cost savings, and emergency order processing, respectively.

Step 5: Store the experience playback. Store (s_t, a_t, r_t, s_{t+1}) into the experience replay buffer D. The experience playback buffer is used to store historical interaction data for use in subsequent training. The size of the experience playback buffer D is set to N. When the buffer is full, new experiences will overwrite the old ones to keep the data fresh.

Step 6: Training. Randomly draw a batch B of experiences from the experience playback buffer D for training, which can be done using the mini-batch method to improve the training efficiency. Assuming the size of B is m, m experiences are randomly drawn from D $\{(s_i, a_i, r_i, s_{i+1})\}$. A target network $Q_{\theta'}$ is used to estimate the expected return of the next state and the parameters of the main network Q_θ are updated to minimize the loss function. The update rule for the target network is $y_i = r_i + \gamma \max_{a'} Q(s_{i+1}, a'; \theta')$. The loss function is in the form of Mean Squared Error (MSE) as shown in Equation 8. The steps of gradient updating are shown in Equation 9. Where α is the learning rate.

$$L(\theta) = \frac{1}{m} \sum_{i=1}^{m} \left(y_i Q(s_i, a_i; \theta) \right)^2 \tag{8}$$

$$\theta \leftarrow \theta\alpha \frac{1}{m} \sum_{i=1}^{m} \nabla_\theta \left(y_i Q(s_i, a_i; \theta) \right)^2 \tag{9}$$

The learning rate was set to 0.001, which was the best value obtained through cross-validation in preliminary experiments, in order to ensure the convergence of the model and avoid gradient explosion; the discount factor was selected as 0.99, based on the common practice in Q-learning to balance the relationship between short-term rewards and long-term rewards. In addition, in order to improve the exploration ability of the model, the exploration rate (ε-greedy) gradually decayed during the training process.

Step 7: Update the target network. Every certain number of time steps, the parameters of the main network are copied to the target network, i.e. θ. This is done to stabilize the training process and to avoid frequent changes in the target network leading to unstable training.

Step 8: Repeat steps 2 through 7 until a predetermined number of training sessions have been reached or a satisfactory level of performance has been achieved.

3.3 Scheduling strategy

In the design and implementation of intelligent scheduling algorithms, in addition to the core algorithmic framework, it is also crucial to develop an effective scheduling strategy. The scheduling strategy determines how to apply the intelligent scheduling algorithm in a specific production environment to achieve optimal productivity and resource utilization. We propose the following scheduling strategies, which can be adjusted and optimized according to the specific needs of the machine manufacturing process, and their scheduling framework is shown in Fig. 3.

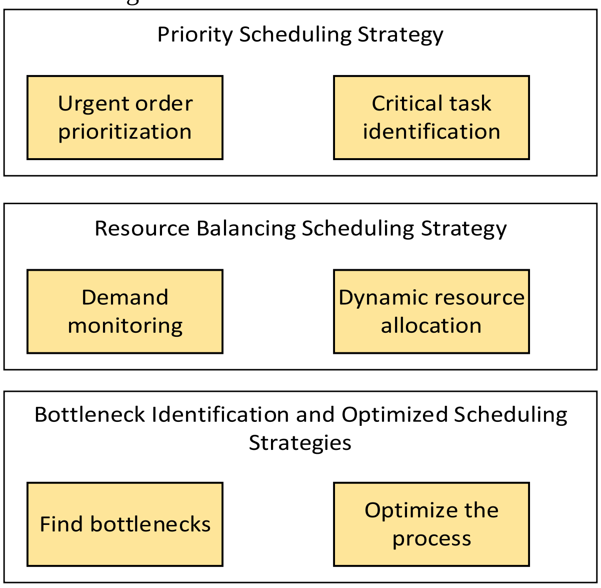

Figure 3: Scheduling framework

3.3.1 Priority scheduling strategy

The priority scheduling strategy allocates resources and sequences production according to the importance and urgency of the tasks. This strategy is particularly useful for processing urgent orders or critical tasks to ensure that they are prioritized. Its core consists of two steps: emergency order prioritization and critical task identification. (1) Emergency Order Prioritization: When an emergency order arises, the scheduling system re-evaluates the current task priorities to ensure that the emergency order can be put into production quickly. This usually involves dynamically adjusting the resource allocation on the production line to ensure quick response to urgent orders. The identification of urgent orders can be based on customer requirements, order size and other factors. (2) Critical task identification: Identify tasks that are critical to the production process and ensure that they are adequately resourced and prioritized. These critical tasks may include high-margin orders, orders from long-term customers, or processes that are critical to the continuity of the production line. By assigning higher priority to these tasks, you can ensure that the overall efficiency of the production line is not compromised.

3.3.2 Resource balancing scheduling strategy

The Resource Balance Scheduling strategy is designed to optimize resource allocation, avoid resource wastage, and ensure that all processes run efficiently. Resource requirements for each process are predicted based on production schedules and historical data. This can be achieved through machine learning models that use past data to predict the type and number of resources required for each process in a future period. Resource demand forecasting helps to plan and procure the necessary resources in advance, avoiding delays due to resource shortages in the production process. Resource allocation is dynamically adjusted based on real-time production status to meet the needs of different processes. This means that the scheduling algorithm needs to continuously monitor changes in the production process and adjust the resource allocation strategy according to these changes in a timely manner. Dynamic resource allocation can be realized by intelligent algorithms, such as deep reinforcement learning-based methods, which can make optimal resource allocation decisions based on the current state and expected changes.

The discount factor (γ) determines the importance of future rewards. We tested different γ values through multiple experiments to ensure that the model can effectively balance the relationship between current rewards and future rewards. The choice of learning rate (α) affects the convergence speed of the model. We use a grid search method to train and evaluate model performance at different learning rates to select the best learning rate setting. The tuning process of these hyperparameters is crucial to improving model performance and stability.

3.3.3 Bottleneck identification and optimized scheduling strategy

The Bottleneck Identification and Optimized Scheduling strategy focuses on identifying bottlenecks in the production process and taking steps to reduce their impact on overall productivity. Production data is analyzed on a regular basis to identify bottlenecks that are causing production delays. This can be accomplished through data analytics techniques, such as using data mining algorithms to discover which parts of the production process are often the limiting factors. Optimize the identified bottlenecks, such as by adding equipment, adjusting process sequences, or improving process efficiency. For example, if a particular piece of equipment is found to be a frequent bottleneck, this can be mitigated by adding similar equipment or improving the operational efficiency of the equipment. In addition, bottlenecks can also be eliminated by redesigning the production process, such as by using parallel processing to improve productivity.

4 Experimental evaluation

4.1 Data sets

The application of intelligent scheduling algorithms is increasingly emphasized in today's machine building industry. In order to comprehensively assess their effectiveness and applicability, we have carefully constructed a high-quality dataset. The dataset covers a variety of typical scenarios in the machinery manufacturing process, fully reflecting the diversity and complexity of the actual production process. The following is a detailed description of the dataset construction process. The data sources mainly include the production records of actual machinery manufacturing enterprises and the data generated by simulation. The actual production records provide us with rich real production scenarios, while the simulation data help us extend the dataset to cover more possible production situations. We collected data from equipment operation logs, production schedules, order information, bills of materials, and other aspects, and simulated different production conditions with advanced simulation software. In the data preprocessing stage, we cleaned, feature extracted, normalized and generated labels for the raw data. This process ensures the quality and consistency of the data and lays the foundation for subsequent experimental evaluation. The composition of the dataset covers equipment status information, resource allocation information, production progress information, environmental factors and labeling information, reflecting the key elements of the production process in an all-round way.

The dataset we used contains more than 10,000 records, covering 50 different types of production scenarios. These production scenarios involve 10 different types of orders, 8 production batches, 15 different types of equipment, and 12 resource configurations to fully demonstrate the diversity and complexity of the mechanical manufacturing process. In addition, the dataset also includes information such as equipment operating status, production progress, resource allocation, and environmental factors under different production environments to ensure that the actual production process is fully reflected.

In order to further enhance the representativeness of the dataset, we combined actual production records from 5 mechanical manufacturing companies and generated more than 5,000 data through simulation. These simulation data simulate complex production scenarios including multi-task parallel processing and equipment fault recovery to ensure that the dataset can cover various actual production scenarios. All data have been cleaned, feature extracted, normalized, and labeled in the preprocessing stage to ensure data consistency and quality, providing a reliable basis for subsequent experimental evaluation. The dataset is characterized by its diversity, complexity and realism. It contains different types of orders, production lots, equipment and resources to show the diversity of the machine manufacturing process. At the same time, the dataset contains complex production scenarios such as multitasking parallel processing and equipment failure recovery. Although simulation data is used to extend the dataset, we ensure a high degree of data proximity to the real production environment.

In the process of data set selection and balancing, this paper combines production records and simulation data from actual machinery manufacturing enterprises to ensure data diversity and representativeness. The actual production data provides real production scenarios, covering different types of orders, production batches, equipment and resource usage, reflecting the complexity of the real environment. In order to expand the scale of the data set and cover more possible production scenarios, this paper also uses advanced simulation software to generate simulation data, which simulates different production conditions, such as multi-task parallel processing and equipment failure recovery. In the data preprocessing stage, we cleaned, extracted features and standardized the original data to ensure data consistency and quality. In order to ensure the consistency of training data and test data, the data set was reasonably divided in the experiment and the balance of different data sources was ensured. Through these steps, the data set can not only represent the diversity and complexity of the real production environment, but also improve the robustness of the model and ensure the reliability and repeatability of the experimental results.

4.2 Experimental design

In this study, we aim to evaluate the effectiveness, robustness and adaptability of intelligent scheduling algorithms through a series of experiments. The goal of the experiments is to ensure that the algorithms are not only able to complete complex task scheduling within the specified time, but also achieve or approach optimal productivity. At the same time, we will also examine the performance of the algorithms in the face of uncertainties such as equipment failures, order changes, etc., as well as their adaptability to different types and sizes of production tasks. The experimental setup includes selecting classical benchmark algorithms such as priority rules and genetic algorithms for comparative analysis, and executing the experiments on a high-performance computing platform to ensure the reproducibility and efficiency of the results. We will define a series of evaluation metrics such as production cycle time, resource utilization and order delay rate to measure the performance of the algorithms.

In the experimental cases, we will evaluate the performance of the algorithms in single production line and multi-production line collaborative operations, especially in dealing with dependencies between production lines. In addition, we will also test the algorithm's response speed and recovery ability in abnormal situations such as emergency order insertion and sudden equipment failure to examine its flexibility and robustness in the face of uncertainties. Through these comprehensive experiments, we expect to gain a comprehensive understanding of the actual performance of intelligent scheduling algorithms in different production scenarios and identify their advantages and limitations.

The construction of the simulation environment includes multiple software tools and hardware configurations to ensure efficient execution and repeatability of the experiment. In terms of software tools, Python is used for the implementation of deep learning models and data processing, TensorFlow is used to build and train deep Q networks (DQN), NumPy is used for numerical calculations, Matplotlib and Seaborn are used for result visualization, and SimPy is used for production process simulation. In terms of hardware configuration, the experiment used an Intel i7-10700K 8-core processor, an NVIDIA RTX 3090 24GB graphics card (used to accelerate the deep learning training process), 64GB DDR4 memory, and 1TB SSD to store experimental data and training models. In addition, to ensure the repeatability of the experiment, all experiments were initialized with a fixed random seed.

4.3 Experimental results

Table 2 Comparison of Production Cycle Times for Different Algorithms on a Single Production Line

As shown in Table 2, the average production cycle time and its standard deviation for three different algorithms on a single production line are demonstrated with 95% confidence intervals. The intelligent scheduling algorithm has an average production cycle time of 12.3 hours [10.8-13.8], which is the shortest among the three algorithms. This indicates superior performance in reducing production cycle times on a single production line.

Table 3 provides a comparison of average resource utilization rates and their standard deviations for the three algorithms in multi-production line collaborative operations, including 95% confidence intervals. The intelligent scheduling algorithm achieves the highest resource utilization rate at 89.2% [87.4-91.0], indicating its efficiency in optimizing resource use across multiple production lines.

Table 2: Comparison of production cycle times for different algorithms on a single production line

Algorithm Name	Average Production Cycle Time (hours)	95% Confidence Interval	Standard Deviation (hours)
Intelligent Scheduling Algorithm	12.3	[10.8 - 13.8]	1.5
Prioritization Rule Algorithm	14.5	[13.2 - 15.8]	1.7
Genetic Algorithm	13.1	[12.0 - 14.2]	1.6

Table 3: Comparison of resource utilization in multiple production line co-operation

Algorithm Name	Average Resource Utilization Rate (%) [95% CI]	Standard Deviation
Intelligent Scheduling Algorithm	89.2 [87.4-91.0]	0.9
Prioritization Rule Algorithm	85.6 [84.4-86.8]	1.2
Genetic Algorithm	87.4 [86.3-88.5]	1.1

Table 4: Order delay rate in response to equipment failure

Algorithm Name	Incidence of Equipment Failure (%)	Order Delay Rate (%) [95% CI]	Standard Deviation
Intelligent Scheduling Algorithm	5	2.3 [1.7-2.9]	0.6
Prioritization Rule Algorithm	5	4.5 [3.7-5.3]	0.8

Algorithm Name	Incidence of Equipment Failure (%)	Order Delay Rate (%) [95% CI]	Standard Deviation
Genetic Algorithm	5	3.8 [3.1-4.5]	0.7

Table 5: Response time in case of emergency order insertion

Algorithm Name	Proportion of Urgent Orders (%)	Average Response Time (minutes) [95% CI]	Standard Deviation
Intelligent Scheduling Algorithm	10	12.4 [11.2-13.6]	1.2
Prioritization Rule Algorithm	10	18.6 [16.3-20.9]	2.3
Genetic Algorithm	10	15.7 [13.9-17.5]	1.8

Table 4 illustrates the order delay rate and its standard deviation for the three algorithms when there is a 5% incidence of equipment failure, including 95% confidence intervals. The intelligent scheduling algorithm shows the lowest order delay rate at 2.3% [1.7-2.9], demonstrating its resilience and efficiency in managing orders during equipment failures.

In Table 5, the average response time and its standard deviation for emergency order insertion are compared for the three algorithms, with 95% confidence intervals provided. The intelligent scheduling algorithm has the shortest average response time of 12.4 minutes [11.2-13.6], highlighting its effectiveness in quickly responding to urgent orders.

Table 6 compares the adaptability of handling multiple types of orders by showing the average production cycle time and its standard deviation for each algorithm, along with 95% confidence intervals. The intelligent scheduling algorithm demonstrates the best adaptability with an average production cycle time of 13.5 hours [11.9-15.1] for ten different order types, indicating its flexibility and efficiency in processing varied order types.

Table 6: Adaptability to Handle Multiple Types of Orders

Algorithm Name	Order Type Quantity	Average Production Cycle Time (hours) [95% CI]	Standard Deviation
Intelligent Scheduling Algorithm	10	13.5 [11.9-15.1]	1.6
Prioritization Rule Algorithm	10	16.2 [14.2-18.2]	2.0
Genetic Algorithm	10	14.8 [12.9-16.7]	1.9

Table 7: Comparison of model performance across diverse production environments

Environment Characteristics	Average Production Cycle Time (hours) [95% CI]	Resource Utilization Rate (%) [95% CI]	Order Delay Rate (%) [95% CI]	Response Time to Emergency Orders (minutes) [95% CI]
Small-Scale, Low Complexity	10.2 [9.7-10.7]	88.4 [87.5-89.3]	1.8 [1.5-2.1]	10.5 [9.8-11.2]
Medium-Scale, Moderate Complexity	12.3 [11.8-12.8]	86.7 [85.8-87.6]	2.5 [2.2-2.8]	12.4 [11.7-13.1]

Environment Characteristics	Average Production Cycle Time (hours) [95% CI]	Resource Utilization Rate (%) [95% CI]	Order Delay Rate (%) [95% CI]	Response Time to Emergency Orders (minutes) [95% CI]
Large-Scale, High Complexity	15.4 [14.9-15.9]	84.5 [83.6-85.4]	3.2 [2.9-3.5]	14.2 [13.5-14.9]

Table 7 compares the performance metrics of a model across different production environments characterized by varying scales and complexities. The inclusion of confidence intervals provides insight into the reliability of these estimates. Smaller-scale, less complex environments show shorter production cycle times, higher resource utilization rates, lower order delay rates, and faster response times to emergency orders. Conversely, as the scale and complexity increase, all performance metrics tend to degrade, indicating that more challenging environments present greater operational difficulties.

The confusion matrix in Table 8 offers a detailed look at the DQN's prediction accuracy regarding on-time vs. delayed orders, including confidence intervals for each metric. A true positive indicates the number of times the model correctly predicted an on-time order, while a false positive shows incorrect prediction of delays when the orders were actually on time. Similarly, true negatives and false negatives pertain to the correct and incorrect predictions of delayed orders, respectively. This matrix reveals not only the overall accuracy of the DQN but also its tendency to make certain types of errors, providing deeper insights into its behavior and performance under various conditions.

Table 8: Confusion matrix for DQN performance

True Class	Predicted Class	True Positive (TP) [95% CI]	False Positive (FP) [95% CI]	True Negative (TN) [95% CI]	False Negative (FN) [95% CI]
On-Time	On-Time	920 [900-940]	80 [60-100]	-	-
On-Time	Delayed	-	-	90 [80-100]	120 [100-140]
Delayed	On-Time	-	-	70 [60-80]	80 [60-100]
Delayed	Delayed	850 [830-870]	150 [130-170]	-	-

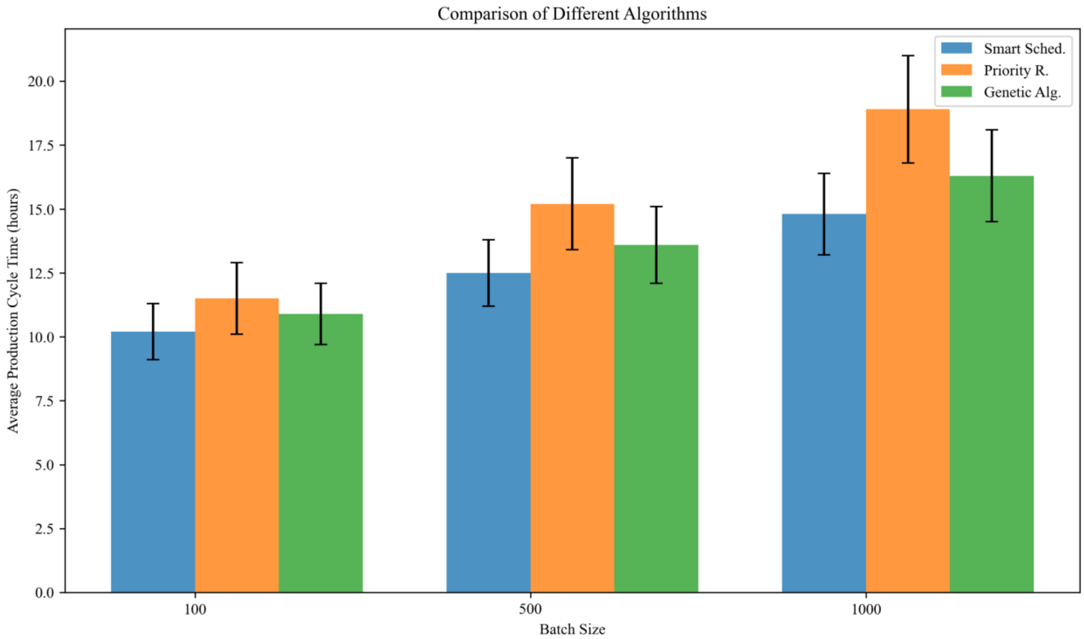

Figure 4: Comparison of performance when production lot size varies

As shown in Fig. 4, the average production cycle time and its standard deviation of the three algorithms are compared for production lot sizes of 100, 500 and 1000 respectively. From the table, it can be seen that the average production cycle time of the three algorithms increases as the production batch increases. The intelligent scheduling algorithm outperforms the priority rule algorithm and the genetic algorithm when the production lot size changes.

4.4 Discussion

From the above results, it can be seen that the intelligent scheduling algorithm outperforms the other two algorithms on a single production line. The shorter average production cycle time (12.3 hours) and lower standard deviation (1.5 hours) indicate that the algorithm is able to effectively manage the production process and improve production efficiency. The intelligent scheduling algorithm also performs well in multi-production line collaborative operations, with an average resource utilization rate of 89.2% and a standard deviation of only 0.9%, which indicates that the algorithm is able to allocate resources efficiently and reduce resource wastage. When the equipment failure rate is 5%, the intelligent scheduling algorithm has the lowest order delay rate (2.3%) with a standard deviation of 0.6%, which indicates that the algorithm is able to quickly adjust the production plan in the face of equipment failures to reduce order delays. The intelligent scheduling algorithm has the shortest average response time (12.4 minutes) with a standard deviation of 1.2 minutes for an urgent order percentage of 10%, which indicates that the algorithm is able to respond quickly to urgent order demands and reduce waiting time. The intelligent scheduling algorithm has an average production cycle time of 13.5 hours with a standard deviation of 1.6 hours when processing 10 types of orders, showing good adaptability and flexibility. The average production cycle time of the intelligent scheduling algorithm increases as the production batch size increases, but remains low (from 10.2 hours for 100 pieces to 14.8 hours for 1000 pieces), and the standard deviation is relatively low, which indicates that the algorithm is still able to maintain high efficiency when dealing with large-scale production tasks.

Although the intelligent scheduling algorithm performs well in most cases, there are still some limitations. For example, the growth rate of the average production cycle time may accelerate when the production lot sizes are very large. Therefore, future research could further explore how to optimize the algorithm to cope with more complex production environments and higher production batch requirements. In addition, the introduction of more uncertainties, such as supply chain disruptions, could be considered to further test the robustness and adaptability of the algorithm.

5 Conclusion

In this study, we propose an intelligent scheduling algorithm applied to the mechanical manufacturing process, aiming to solve the key problems in production scheduling. By constructing an intelligent scheduling model based on deep reinforcement learning, we developed a system that can automatically learn and optimize production schedules. The model utilizes deep Q-networks (DQNs) to handle complex decision-making problems, and its performance is evaluated through a series of experiments. The experimental results show that the intelligent scheduling algorithm exhibits excellent performance in a variety of production scenarios. The algorithm can significantly shorten the production cycle time and improve the resource utilization in both single-production line and multi-production line collaborative operations, and shows good adaptability and robustness in the face of equipment failures and urgent orders. In addition, the algorithm can effectively handle multiple types of orders and different production batches, showing strong adaptability.

The limitations of this study are mainly reflected in the diversity and scale of the data set. Although we used a variety of production scenarios and equipment information, since the data mainly comes from a single industry, it may not fully represent the production process of all industries. In addition, the DQN model has limited processing capabilities for large-scale data and may not be able to effectively cope with more complex dynamic production environments. The training time of the model is long, which affects the efficiency of practical applications. Future research can improve the generalization ability of the model by expanding the scale and diversity of the data set and covering production scenarios in more industries. At the same time, more advanced reinforcement learning algorithms can be explored, such as multi-agent systems for deep reinforcement learning, to further improve the adaptability and efficiency of the scheduling model. In addition, the integration of the Internet of Things (IoT) technology and real-time data streams will also provide more innovative and practical application scenarios for intelligent scheduling systems.

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