Reinforcement learning for online optimization of job-shop scheduling in a smart manufacturing factory

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Abstract
The job-shop scheduling problem (JSSP) is a complex combinatorial problem, especially in dynamic environments. Low-volume-high-mix orders contain various design specifications that bring a large number of uncertainties to manufacturing systems. Traditional scheduling methods are limited in handling diverse manufacturing resources in a dynamic environment. In recent years, artificial intelligence (AI) arouses the interests of researchers in solving dynamic scheduling problems. However, it is difficult to optimize the scheduling policies for online decision making while considering multiple objectives. Therefore, this paper proposes a smart scheduler to handle real-time jobs and unexpected events in smart manufacturing factories. New composite reward functions are formulated to improve the decision-making abilities and learning efficiency of the smart scheduler. Based on deep reinforcement learning (RL), the smart scheduler autonomously learns to schedule manufacturing resources in real time and improve its decision-making abilities dynamically. We evaluate and validate the proposed scheduling model with a series of experiments on a smart factory testbed. Experimental results show that the smart scheduler not only achieves good learning and scheduling performances by optimizing the composite reward functions, but also copes with unexpected events (e.g. urgent or simultaneous orders, machine failures) and balances between efficiency and profits.

Keywords
Job shop, online scheduling, multi-objective optimization, composite reward, reinforcement learning

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Introduction
In the last three decades, the world has experienced three times of industrial revolutions, enabling industry with automated machines and information systems to support rapid and innovative product design. The manufacturing industry plays an important role in the development processes of the economy and technology. Today, manufacturing companies face a large number of challenges in a turbulent environment originating from saturated markets, abrupt and unprecedented changes in market demands, an increasing number of product variants, and smaller lot sizes.\textsuperscript{1,2} This trend is intensified by production modes such as mass customization and individualization, which guarantee the creation of unique products to meet the requirements of almost every customer.\textsuperscript{3} The transformation of
traditional industrial markets inevitably leads to the evolution of manufacturing modes.

Production scheduling is a complex combinatorial problem, more specifically, a non-polynomial-hard (NP-hard) problem, which coordinates manufacturing resources to get optimal sequences and combinations. It is traditionally elaborated in a centralized manner using offline methods and considering the problems are static and deterministic. However, initial production plans often become invalid due to many unexpected events that come from internal (e.g., machine failures, operator absence), external (e.g., rush orders, unavailability of raw materials), or composite factors (e.g., time fluctuation, resource uncertainty). Therefore, scheduling algorithms are required to modify the original schedules for eliminating the disturbances. Early studies focus on rescheduling resources offline to achieve new schedules, which may suspend the manufacturing processes and increase the lead time. Simulation technologies (e.g., multi-agent system) build scheduling algorithms with empirical rules and historical data, but they are limited in achieving optimal schedules in a changeable manufacturing environment. Recently, artificial intelligence (AI) algorithms such as reinforcement learning (RL) are adopted to industrial manufacturing with regard to online scheduling. However, most RL-based scheduling algorithms are inefficient at learning to optimize the decision-making policies when multiple objectives are considered in a smart manufacturing factory. The overall performances of manufacturing systems are influenced by many factors such as order requirements, machine properties, and supply chain profits, which can be transformed into composite reward functions in RL-based scheduling systems. This paper realizes online scheduling based on RL with composite reward functions, which makes manufacturing systems to be more efficient and robust. Scheduling decisions are made online according to the operation attributes and machine states together. Composite rewards are given to the smart scheduler at all action moments, equipping smart manufacturing systems with self-learning and adaptation capabilities.

The remaining sections of this paper are organized as follows. Section 2 shows an overview of existing manufacturing scheduling approaches. Based on RL, Section 3 invites composite rewards and online methods to develop a system with self-learning abilities for job-shop scheduling. Section 4 designs an experimental testbed to conduct case studies on online scheduling. Section 5 expresses detailed experimental results and proposes the general relationships between composite rewards and manufacturing scheduling. Finally, Section 6 rounds up the paper with conclusions and prospects.

**Literature review**

The production scheduling problem has been widely studied, mainly due to its dynamic nature, highly combinatorial aspects, and applicability in manufacturing systems. In past years, researchers proposed many scheduling methods such as mathematical programming, rule-based dispatching, expert systems, heuristic search, or biomimetic algorithms. For example, Hou et al. formulated an integrated distributed production and distribution problem with a mixed integer programming model and developed an enhanced brain storm optimization algorithm to solve the model.

Fu et al. proposed an evolutionary algorithm and a local search method to solve a dual-objective stochastic hybrid flow shop deteriorating scheduling problem considering job deterioration and uncertain job processing time. However, these methods handle jobs or uncertainties with continuous iterations or periodic optimization, which takes extra computing time to adjust the initial plans offline and obtain newly optimal schedules. In addition, duplicated calculations for rescheduling resources may cause the whole system to shut down when the environmental states change frequently. When dealing with scheduling and rescheduling problems, some researchers used swarm intelligent algorithms to obtain optimal solutions from a large action space. In dynamic and uncertain environments, the optimized schedule produced by traditional scheduling methods can quickly become unacceptable, so dynamic rescheduling is required as fast as possible.

The fourth industrial revolution marked by intelligent manufacturing attracts researchers to a new research area of intelligent scheduling. Agent technologies provide a natural way to conduct production scheduling in distributed manufacturing environments. Many socialized interactive mechanisms, such as contract net protocol, game theory, auction mechanism, are used to coordinate machines in multi-agent systems, where resources can acquire rational dynamic schedules autonomously based on specific rules. In traditional multi-agent systems, machines participate in negotiation and interaction with each other according to specific rules. Such agent-based or holonic scheduling systems implement distributed manufacturing, but they require the support of sophisticated rules and have poor adaptability. Rule-based scheduling methods provide a platform for machines to realize real-time job-shop scheduling; however, historical data and future circumstances cannot be stored and anticipated. Hence, some evaluation factors are used to record operation logs such as capability, self-confidence, activity, and robustness. These
factors provide guidance for prospective decisions, but they can only mark down the participation times of machines in the decision platform. Thus, such improvements are weak in providing comprehensive and rapid decision mechanisms for machine interaction, and it is difficult to improve the scheduling performance substantially. Distributed scheduling integrates discrete units or factories and enables them to operate independently, which improves the operating efficiency of the whole manufacturing system. However, the distributed manufacturing manner may cause environmental fluctuation and local optimum.

Currently, innovative online scheduling methods are needed to follow the trend of mass customization of products. These methods have one or more typical features such as self-organized operation, self-adaptation adjustment, and self-learning optimization. With the success of Alpha Go, RL aroused the interest of researchers, and many of them tried to apply RL to production scheduling. Zhang et al. addressed a dynamic unrelated parallel machine scheduling problem with a mean weighted tardiness objective, but unexpected events, order details, and rewards in addition to tardiness are not involved. Shiue et al. proposed a scheduling algorithm based on RL using multi-agent RL for makespan and cost optimization to guide the scheduling performance for reducing the average lead-time of production orders. However, it is difficult for basic Q-learning algorithms to adapt to problems with a large action space. Wang et al. used correlated equilibrium to propose a multi-agent RL algorithm for makespan and cost optimization to guide the scheduling of multi-workflows over clouds, but many real events and factors existing in real manufacturing conditions are neglected. Such research brought new approaches to manufacturing scheduling, dealing with dynamic task assignments, and solving uncertainties well in job-shop scheduling problems. Nevertheless, the researches mentioned above are mainly concerned with optimizing makespan and costs from the operational research aspect, regardless of an overall study of various disturbances, reward-scheduling mechanisms, and industrial implementation. Meanwhile, most approaches to job-shop scheduling own fake real-time characteristics without online features that are largely influenced by job numbers and computing efficiency.

This current paper concentrates on establishing an online scheduling system to deal with the tendency of globalized and individualized manufacturing. A smart factory testbed was built to realize communication between machines and the smart scheduler. RL is used to establish a smart scheduler for online scheduling orders and handling unexpected events, which equips the self-organized manufacturing system with self-adaptive abilities. The smart scheduler improves its comprehensive capabilities through operating processes guided by innovative composite rewards. An instant reward is given to the smart scheduler after a scheduling action is taken rather than after all orders are completed, which increases the training efficiency of the smart scheduler.

Research methodology

Model description

An order contains only one job denoted by \( J_i \), and a job has one or more operations denoted by \( O_{i,j} \), where \( J_i \) denotes the \( i \)th job and \( O_{i,j} \) denotes the \( j \)th operation of the \( i \)th job. The total number of jobs is \( N_J \), and the total number of operations of job \( J_i \) is \( N_{O_i} \). The attributes of an operation \( O_{i,j} \) include initialization time \( T_{A_{i,j}} \), operation type \( C_{i,j} \), workload time \( T_{I_{i,j}} \). The first operation of a job is initialized when the job is generated at time \( T_{A_i} \) (i.e. \( T_{A_i} = T_{A_{i,1}} \)). The completion time and estimated completion time of a job are respectively denoted as \( T_{C_i} \) and \( \hat{T}_{C_i} \), and they are \( T_{C_{i,j}} \) and \( \hat{T}_{C_{i,j}} \) for operation \( O_{i,j} \). The initialization time, completion time, and estimated completion time of the operations of job \( J_i \) are shown in Figure 1, where scheduling moments are marked by red circles. Job \( J_i \) is initialized at time \( T_{A_{i,1}} \) and completed at time \( T_{C_{i,N_{O_i}}} \).

The total number of machines is denoted by \( N_M \). The attributes of a machine include machine type \( C_{m} \), machining speed factor \( K_{MT} \), energy consumption factor \( K_{ME} \). Each machine is equipped with a buffer, whose remaining length is \( B_{L_m} \), for holding the unprocessed jobs.

Some constraints are set up to keep the shop floor operating robustly. First, the chosen machine is capable of undertaking the corresponding operations, that is \( C_{m} \) matches \( C_{i,j} \). Second, the sequence of operations should be in accordance with designed requirements.
that is $T_{A_{i,j}} \leq T_{C_{i,j}}$. Third, the number of tasks assigned to a machine should be no more than $B_{lm}$. Fourth, the makespan of each order is supposed to satisfy the target completion time $T_{C_i}$.

Jobs are generated in real time and are automatically added to the job list, ensuring that the actual machining conditions are met. As shown in Figure 2, each block represents an operation of a job marked by a time label with initialization time and completion time, and the boundaries of blocks in the job list represent scheduling moments. As the former operation of a job is completed, the next operation of this job is initialized and added to the operation list. The scheduler handles operations along the dash line in the operation list of Figure 2. For example, job $J_1$ is decomposed into two operations (i.e. $O_{1,1}$ and $O_{1,2}$) after process planning; operation $O_{1,1}$ is initialized at time $T_{A_{1,1}}$ and completed at time $T_{C_{1,1}}$; operation $O_{1,2}$ is initialized at time $T_{A_{1,2}}$ and completed at time $T_{C_{1,2}}$. The job list is sequenced by the generating time of jobs, and the operation list is sequenced by the initialization time of operations. Scheduling moments are at the initialization or completion time of each operation. When an operation is completed, the next operation of the same job will be initialized and appended to the operation list.

**RL for online scheduling**

**Reinforcement learning.** RL is a series of algorithms to learn how to map situations to actions so as to maximize a numerical reward signal. RL can be formalized as Markov decision process (MDP) which is a straightforward framework of learning from interactions with a dynamic environment to maximize the total reward. A typical RL model comprises two parts of agent and environment. The agent learns to choose an action $a$ from the action space $A$ according to the environment state $s$ from the state space $S$. At a decision time step $t$, the agent takes an action $a_t$ based on the observation $s_t$ derived from the environment and receives a reward $r_t$. The environment state is updated to $s_{t+1}$ after taking the action $a_t$. The agent learns a policy $\pi$ that maps state $s$ to action $a$, that is $a = \pi(s)$, from the interactions with the environment. The objective of an agent is to master an optimal policy $\pi^*$ for achieving more discounted future rewards as follows:

$$G_t = \sum_{\tau=t}^{T} \gamma^{\tau-t} r_{\tau}, 0 \leq \gamma \leq 1$$  \hspace{1cm} (1)

where $\gamma$ is the discount rate that denotes the contribution of future rewards to the current action value; $T$ is the terminal time step.

Many algorithms are designed to obtain optimal policies of MDPs such as temporal difference (TD), dynamic programming (DP), and Monte Carlo (MC) methods. Like DP, TD methods update estimates individually or partly rather than waiting for an eventual result, which increases the efficiency of calculation. Like MC methods, TD methods interact directly with environments to acquire their statuses, which avoids depending on the transition possibility of models. Industrial environments need high stabilization, swift reaction, and low latency, so TD methods are appropriate for the operation of smart factories. Q-learning is an off-policy TD algorithm that incorporates the advantages of DP and MC methods. The iterative equation of Q-learning is shown as follows:

$$q(s_t, a_t) \leftarrow q(s_t, a_t) + \alpha [r_{t+1} + \gamma \max_a q(s_{t+1}, a) - q(s_t, a_t)], 0 \leq \alpha \leq 1$$  \hspace{1cm} (2)

where $\alpha$ is the learning rate that denotes the iterative speed.

In a Q-learning algorithm, the maps from the state space to the action space are recorded in a Q-table. If the state space is so large, a neural network can be used to take place of the Q-table, that is Deep Q-Network (DQN) is invented. The DQN has two neural networks: a target network and an evaluation network. The loss function of DQN, shown in equation (3), is used to update the parameters of the evaluation network. Parameters of the target network are copied from the evaluation network at every few steps.

$$L(\theta) = E[(\hat{y} - q)^2]$$  \hspace{1cm} (3)

$$\hat{y} = r_{t+1} + \gamma \max_a \hat{q}(s_{t+1}, a_t + 1)$$  \hspace{1cm} (4)

where $\hat{q}$ is an action-value given by the target network, and $q$ is an action-value given by the evaluation network.
The iterative equation of DQN can be rewritten as follows:

\[
q(s_t, a_t) \leftarrow q(s_t, a_t) + \alpha [r_t + 1 + \gamma \max_{a_{t+1}} q(s_{t+1}, a_{t+1}) - q(s_t, a_t)]
\]

(5)

From RL to job-shop scheduling problem. The precondition of solving scheduling problems with RL methods is turning scheduling problems into multi-step decision problems. In a job-shop scheduling problem, there are three main characters, including jobs, machines, and schedulers. Jobs are assigned to appropriate machines by schedulers. To implement online scheduling, schedulers should make decisions as soon as jobs are generated, which is a continuous single-step decision manner. Online scheduling is dependent on the current state of shop floors, and this scheduling approach turns a conventional JSSP into an RL model. The relationships between RL and JSSP models are listed in Table 1. The environment of a shop floor contains machines, material handlers, warehouses, etc. All jobs come from warehouses, and they will be brought back to them when the last operation is finished. Material handlers transport jobs between machines or between machines and warehouses. Machines play an important role in the processing of jobs.

State space of the shop floor. In a job-shop scheduling system, all machines are interconnected to build an environment for machining jobs and give back rewards for the scheduling actions. Each action can receive a reward, and all the rewards of a workpiece constitute a value for estimating the trace. A smart scheduler helps workpieces choose the appropriate machines according to the current state of the shop floor. The state space is made up of the attributes of schedulable operations and machines. The detailed state features of the shop-floor environment are listed in Table 2.

Rewards for scheduling optimization

Evaluation criteria of manufacturing scheduling methods come from three aspects including productivity (e.g. time and flow efficiency), cost (e.g. resource consumption), and customer satisfaction (e.g. tardiness and quality). Most researches aim at only one objective that minimizes the makespan which belongs to the first aspect. Actually, resource consumption should be considered along with shortening the machining period, which not only meets customers’ satisfaction but also saves manufacturing costs. Increasing utilization rate of machines or choosing high-efficiency machines can minimize the makespan of jobs. Generally, it is necessary to balance increasing efficiency and saving costs to get higher profits.

Shortening makespan. One of the optimization objectives is to minimize the mean tardiness rate of all jobs as follows:

\[
\text{minimize } T = \frac{1}{N_{JC}} \sum_{i=1}^{N_{JC}} \frac{T_{Ci} - \hat{T}_{Ci}}{T_{Ci} - T_{Ai}}
\]

(7)

where \(N_{JC}\) denotes the total number of completed jobs. The equation for calculating the target completion time of job \(J_i\) is:

\[
\hat{T}_{Ci} = T_{Ai} + K_{Di} \cdot \sum_{j=1}^{N_{i}} T_{i,j}, 1 \leq i \leq N_{J} \text{ and } K_{Di} > 0
\]

(8)

where \(K_{Di}\) is the urgency factor of job \(J_i\).

Saving production costs. The other optimization objective is to minimize the mean consumption of resources. The amount of resource consumption rises along with the elevation of machining efficiency. The resource consumption \(e_{ij}\) of operation \(O_{ij}\) depends on the energy consumption factor \(K_{EM}\) and actual machining time \(K_{MTm}\cdot T_{i,j}\), and its calculation equation is:

\[
e_{ij} = K_{EM} \cdot K_{MTm} T_{i,j}, K_{EM} > 0 \text{ and } K_{MTm} > 0
\]

(9)
Profits increase with the reduction of costs. Machines with higher speed can complete operations swiftly, but consume more resources. The prices of orders depend on the workload time $T_{i,j}$ and urgency factor $K_{DI}$. We define the price $P_{RI,j}$ of operation $O_{i,j}$ as:

$$P_{RI,j} = K_{PRI} T_{i,j}$$

where $K_{PRI}$ is a price factor that increases with the decrease of urgency factor $K_{DI}$.

The profit $P_{Vi,j}$ of operation $O_{i,j}$ can be calculated by equation (11).

$$P_{Vi,j} = P_{RI,j} - c_i = (K_{PRI} - K_{ME} K_{MTM}) T_{i,j}$$

**Increasing machine utilization rates.** Different machines have different properties, and schedulers are willing to choose efficient machines that complete tasks quickly. If a large number of tasks are assigned to specific capable machines, it may cause system congestion and workload imbalance. Some bottleneck resources can also slow down the operating efficiency of manufacturing systems. It is necessary to balance the workloads among the targeted machines. The standard deviation of the utilization rates of machines of type c, shown in equation (12), is an important criterion of workload distribution.

$$U_c = \sqrt{\frac{1}{N_{Mc}} \sum_m (u_m - \bar{u}_c)^2}, \quad C_m = c$$

where $N_{Mc}$ is the total number of machines of type $c$; $u_m$ denotes the utilization rates of machine $m$ ($m = 1$ and 2, ..., $N_M$); $N_M$ is the total number of machines; $\bar{u}_c$ is the mean value of the utilization rates of machines of type $c$.

The utilization rate of machine $m$ can be calculated by equation (13).

$$u_m = \frac{1}{T} \sum_{n=1}^{N_m} T_n$$

where $T$ denotes the production duration; $N_m$ is the total number of operations completed by machine $m$; $T_n$ is the machining time of the $n$th operation conducted on machine $m$.

**Composite reward functions.** There are many evaluation criteria and optimization objectives on job-shop scheduling for different working conditions, including time, cost, machine utilization, and system capacity. The machining time of each workpiece is recorded. One of the important objectives is to minimizing the makespan to guarantee the delivery time of orders. Many methods aim to reduce the flow time of workpieces, such as improving machining efficiency and shortening waiting time. High-speed machines can complete tasks rapidly, but require higher costs. Low-speed machines consume lower equipment costs, but need more time for machining workpieces. A workload balance is supposed to be maintained among machines with different working abilities. The operating time and idle time of each machine are recorded to calculate the utilization rate of each machine, and a comparison is made among machines. It is necessary to balance workloads among machines and improve their utilization rates. The warehouse downloads orders from the order system and stores them in its buffers. If there are some spare targeted machines, the warehouse will assign tasks to them. If the shop floor is always busy and the task buffers are full of tasks all the time, the scheduling system can provide improvement suggestions to entrepreneurs.

According to the above criteria, the optimization objectives of job-shop scheduling problems mainly contain three types, including lead time, resource consumption, and machine utilization rates. Most researches on job-shop scheduling optimization are concerned with time parameters such as makespan, tardiness, switching time, deadline, etc. Therefore, under actual conditions, resource consumption should be taken into consideration as well. Thus, a multi-objective optimization measure is invited into the RL-based scheduling method, where makespan and resource consumption are considered together. Such approaches are not restricted to minimizing the makespan of orders to guarantee the target completion time, but they conform to actual machining conditions as well.

When a scheduler takes an action at time step $t$, it will get an immediate reward $r_{t+1}$ which constitutes the value function. Optimization objectives are used to regulate the performances of schedulers and help them learn useful knowledge for enriching their experience. The reward $r_{t+1}$ is a weighted value that is formed as equation (14).

$$r_{t+1} = \sum_{i=1}^{n} k_i \cdot r_{i,t+1}, \quad \sum_{i=1}^{n} k_i = 1 \text{ and } k_i \geq 0$$

where $k_1$, $k_2$, ..., $k_n$ are weights of rewards $r_{1,t+1}, \quad r_{2,t+1}, \ldots, r_{n,t+1}$ corresponding to different optimization objectives. The composite reward function includes rewards for time saving rate $R_d$ in equation (15), energy saving rate $R_p$ in equation (16), machine utilization rate $R_u$ in equation (17), and workload distribution deviation $R_v$ in equation (18). The composite reward $R$ is
defined as equation (19). To get denser rewards at scheduling moments, each operation can give back rewards according to order details.

\[ R_D = \left( \frac{T_{C_i,j} - T_{A_i,j}}{T_{C_i,j} - T_{A_i,j}} \right)^{-K_{D_i,j}} + K_{D_i,j} \tag{15} \]

\[ R_P = K_{PRI} - K_{MEM} K_{MT} \tag{16} \]

\[ R_U = \frac{1}{N_{mc}} \sum_{m} u_m; \quad C_m = c \tag{17} \]

\[ R_V = -U_c; \quad C_m = c \tag{18} \]

\[ R = K_1 \cdot R_D + K_2 \cdot R_P + K_3 \cdot R_U + K_4 \cdot R_V \tag{19} \]

The weights \( K_1, K_2, K_3, K_4 \) own the same value normally, but they differ in specific conditions. For example, if some urgent orders are generated or the deadline approaches, \( K_1 \) and \( K_3 \) increase as \( K_2 \) decreases. Thus, the reward for time saving rate \( R_D \) contributes more to the total weighted rewards and scheduling decisions are adjusted autonomously for adapting to the new manufacturing condition. If the remaining completion time of orders is so long, the weight \( K_2 \) can be raised slightly for saving energy.

**Scheduling actions**

Scheduling methods aim to achieve a balance between jobs and machines to obtain optimized combinations and sequences of these two resources. In general, the actions of a scheduler include two types of scheduling and machining, which can change the state of the shop floor. Detailed steps are shown in Figure 3 to illustrate the online scheduling processes based on DQN algorithms. The scheduler should take actions at scheduling moments, including the operation initialization moments and completion moments. At these moments, the scheduler collects all the states of related machines and makes decisions based on operation attributes and machine states. As a scheduling action is chosen, the job will be transported to the target machine. The states of machines are updated and a reward for the action is given. Between two scheduling moments, the scheduler and machines do nothing but process operations. If there is no operation to do or all the operations are finished, machines will be in a standby mode and take no action. If all machine buffers are occupied, scheduled jobs have to wait until a job is finished and a buffer is released. In these operation actions, the scheduler moves the timeline and updates all machine states to the next scheduling moment.

Regarding scheduling actions, when a new order is generated or the current operation is finished, the scheduler will choose a machine for its next operation. Apart from scheduling actions, the environment will not move until the operations on a machine are finished. The RL method simplifies scheduling models, and all conditions will not be ignored, as shown in Figure 4. Figure 4 is a real-time Gantt chart that is used for the explanation of action types. It is assumed that there are three millers, three lathes, and a...
warehouse on the shop floor, and each machine has a buffer whose length is 4. The horizontal axis is a timeline and the vertical axis represents machines. Above the timeline, operations that have been scheduled are marked by rectangles in bold lines, and operations that will be scheduled are in double dot-dash lines. The operations waiting for being scheduled are below the timeline and the solid bricks represent that they are processed without delay. At time $t_1$, an operation is initialized at the shop floor. If it is a milling operation, it can be scheduled on Miller 2 and processed immediately, that is, ActM2. It can also choose to queue up behind the operation lists of Miller 1 or Miller 3. Miller 3 needs more waiting time than Miller 1, but it needs less machining time on the same operation. If it is a lathing operation, optional machines are Lathe 1 and Lathe 2. It cannot choose Lathe3 because the remaining buffer length of Lathe 3 is 0. At time $t_1$, a new operation in the warehouse is scheduled and arrives at the shop floor. At time $t_2$, the current operation on Lathe 2 is completed and scheduled for the next operation. At time $t_3$, an operation in the warehouse ends its waiting status and is scheduled to be machined. At time $t_4$, an operation on Lathe 3 is finished, but it has to remain still until $t_5$ when there is a vacant machine for its next operation. Between the adjacent scheduling moments, all the machines just process operations and the scheduler moves the timeline.

Neural networks are used to establish a mapping relationship between operation-machine states $s_t$ and scheduling action $a_t$. As shown in Figure 5, the neural network is composed of an input layer, a hidden layer, an output layer, and each layer comprises several neurons. At a scheduling moment, the scheduler chooses an action from ($a_0$, $a_1$, $a_2$, ..., $a_m$), where $a_0$ denotes waiting and $a_1$ to $a_m$ respectively denote target machines. After being processed by the interconnected neurons, a tuple $[q(s_t, a_0), q(s_t, a_1), q(s_t, a_2), ..., q(s_t, a_m)]$ is obtained, and the optimal action $a_t$ is given by the maximum $q(s_t, )$ in this tuple. Actions are chosen based on the $\varepsilon$-greedy policy, $\varepsilon \in [0, 1]$, that is, the optimal action is selected by the probability of $\varepsilon$, and a stochastic action is selected by the probability of $1 - \varepsilon$. As the optimal machine is chosen for the current operation, the state space of the manufacturing system will be updated to $s_{t+1}$, and a corresponding reward $r_{t+1}$ is derived from the environment by a comprehensive evaluation system. The states of all machines are updated to provide real-time observations for subsequent tasks. The evaluation network is used only for getting the optimal scheduling policy instantly. A target network with previous parameters of the evaluation network is used to provide the next observation $s_{t+1}$ for training the evaluation network.

**Experimental design**

**Manufacturing resource specifications**

**Smart factory testbed:** As shown in Figure 6, a testbed of the smart manufacturing system is established to verify the performances of the proposed methodology and other scheduling methods. Apart from the cloud, the shop floor includes a warehouse ($m = 0$), three millers ($m = 1, 2, 3$), three lathes ($m = 4, 5, 6$), an AGV ($m = 7$), and two robot arms ($m = 8, 9$). The buffer length of each machine is 4, and the total length of machine buffers is 24. The automated warehouse is used to place workpieces, and it has an exit numbered 0 and an entrance numbered 1. The AGV transports workpieces among the warehouse and machine buffers. When jobs enter the buffer of a machine, a robot arm...
can transit it between the machine and its affiliated buffers. The supervisor coordinates all machines and gathers the operating data of them.

**Order attributes:** The RL-based scheduling system improves its decision-making abilities at any time by interacting with the environment, and a trained scheduler can schedule resources instantly. On the shop floor, two typical workpieces of shafts and panels are chosen as the products. A shaft has two operations of lathing and milling, and a panel has only one milling operation. As shown in Table 3, it is assumed that $K_{Di} = 3$ (i.e. $P_{Ri} = 3$) represents a normal order, and $K_{Di} = 2$ (i.e. $P_{Ri} = 4$) represents an urgent order.

**Machine attributes:** As shown in Table 4, there are six machines (i.e. $N_M = 6$) in the smart factory including three lathes ($m = 1, 2, 3$) and three millers ($m = 4, 5, 6$). The former three machines do the lathing operations, while the latter three machines do the milling operations. Each machine has a buffer zone with a capacity of four jobs ($B_{Lm} = 4$) to hold the unprocessed or schedulable jobs. The machining speed of machines is depicted by the machining speed factor $K_{MTm}$, and the energy consumption rate is depicted by the energy consumption factor $K_{MEM}$.

**Case studies for the scheduling model**

**Parameter specifications:** Several case studies are conducted to test the overall performances of a smart scheduler. The parameters of DQN are set as: learning rate $\alpha = 0.01$, discount rate of rewards $\gamma = 0.9$, greedy rate $\epsilon = 0.9$. According to equation (6), the state dimension for the dynamic attributes of operations and machines is 34. At a scheduling moment, the smart scheduler chooses one from six machines for processing the next operation, otherwise the operation waits for the next scheduling moment. The neural network has an input layer with 34 neurons, a hidden layer with 200 neurons, and an output layer with seven neurons.

**Learning abilities:** Orders contain different customer requirements, including product quality and delivery time. To validate the self-learning abilities of schedulers, several study cases are designed to test their performance. Four reward functions are designed to help schedulers operate effectively, including time saving rate $R_D$, energy saving rate $R_E$, machine utilization rate

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**Table 3. The details of orders for scheduling.**

| $i$ | $j$ | $T_{Ai,j}$ (s) | $C_{i,j}$ | $T_{ij}$ (s) | $K_{Di}$ | $T_{Ci}$ (s) | $P_{Ri}$ |
|-----|-----|--------------|---------|------------|---------|-------------|---------|
| 1   | 1   | 10 Lathe 35  | 3       | 115 3     | 3       |             |         |
| 2   | 1   | 45 Lathe 32  | 3       | 141 3     | 3       |             |         |
| 2   | 2   | Mill 10 3    | 3       | 171 3     | 3       |             |         |
| 3   | 1   | 70 Mill 43  | 2       | 156 4     |         |             |         |
| 4   | 1   | 95 Mill 38  | 3       | 209 3     |         |             |         |
| 5   | 1   | 125 Mill 47  | 3       | 266 3     |         |             |         |
| 6   | 1   | 150 Mill 30  | 2       | 210 4     |         |             |         |
| 7   | 2   | Mill 14 2    | 2       | 238 4     |         |             |         |
| 7   | 1   | 175 Lathe 33 | 3       | 274 3     |         |             |         |
| 2   | 2   | Mill 15 3    | 3       | 319 3     |         |             |         |
| 8   | 1   | 190 Mill 50  | 2       | 290 4     |         |             |         |
| 9   | 1   | 200 Lathe 39 | 3       | 317 3     |         |             |         |
| 2   | 2   | Mill 17 3    | 3       | 368 3     |         |             |         |
| 10  | 1   | 210 Mill 29  | 3       | 297 3     |         |             |         |
| 11  | 1   | 235 Lathe 33 | 3       | 334 3     |         |             |         |
| 2   | 2   | Mill 13 3    | 3       | 373 3     |         |             |         |
| 12  | 1   | 260 Mill 44  | 2       | 348 4     |         |             |         |
| 13  | 1   | 270 Mill 38  | 3       | 384 3     |         |             |         |
| 14  | 1   | 295 Lathe 29 | 3       | 382 3     |         |             |         |
| 2   | 2   | Mill 10 3    | 3       | 412 3     |         |             |         |
| 15  | 1   | 320 Lathe 26 | 3       | 398 3     |         |             |         |
| 2   | 2   | Mill 9 3     | 3       | 425 3     |         |             |         |
| 16  | 1   | 350 Lathe 28 | 2       | 406 4     |         |             |         |
| 2   | 2   | Mill 10 2    | 2       | 426 4     |         |             |         |
| 17  | 1   | 370 Mill 35  | 3       | 475 3     |         |             |         |
| 18  | 1   | 385 Mill 37  | 3       | 496 3     |         |             |         |
| 19  | 1   | 430 Lathe 31 | 3       | 523 3     |         |             |         |
| 2   | 2   | Mill 16 3    | 3       | 571 3     |         |             |         |
| 20  | 1   | 495 Lathe 34 | 3       | 597 3     |         |             |         |
| 2   | 2   | Mill 17 3    | 3       | 648 3     |         |             |         |

**Table 4. The inherent attributes of machines.**

| $m$ | $C_m$ | $B_{Lm}$ | $K_{MTm}$ | $K_{MEM}$ |
|-----|-------|----------|-----------|-----------|
| 1   | Lathe | 4        | 0.5       | 2.0       |
| 2   | Lathe | 4        | 1.0       | 1.0       |
| 3   | Lathe | 4        | 2.0       | 0.5       |
| 4   | Mill  | 4        | 0.5       | 2.0       |
| 5   | Mill  | 4        | 1.0       | 1.0       |
| 6   | Mill  | 4        | 2.0       | 0.5       |
machinery failures, the fourth machine in Table 4 is shut down. To validate the adaptive ability for a scheduling algorithm can handle such unexpected events without downtime. The factors $K$ and $R$ are set with the values shown in Table 4. On the one hand, the urgency factor $K_D$ is put into practice, and the factors $K_{MTm}$ and $K_{Mea}$ of each machine still keep the same value 1.0. Under real manufacturing conditions, more than one order may be generated at the same time. The scheduler should choose a machine with a shorter waiting time and higher efficiency. Sometimes, urgent operations will be moved to the head of the waiting list if it is necessary. The factors $K_{MTm}$ and $K_{Mea}$ of each machine are set with the values shown in Table 4. On traditional shop floors, a failure machine can stop the operation of the entire system, while the RL-based scheduling algorithm can handle such unexpected events without downtime. To validate the adaptive ability for machine failures, the fourth machine in Table 4 is shut down.

**Experimental results and discussion**

**Learning performance of the smart scheduler**

Composite reward functions are designed to help the smart scheduler improve its decision-making ability. Different reward functions bring different scheduling results, and combinations of reward functions may obtain better improvements than a single component. The composite reward $R$ is constituted by rewards $(R_D$, $R_p$, $R_U$, $R_V)$, and the components are respectively applied in the smart scheduler. The learning curves show the changing rates of the costs between $\hat{q}$ and $q$, which can be derived from equation (3). Each RL-based scheduling model has been trained for 300 episodes, and the learning curves of them are shown in Figure 7.

At the very beginning, the scheduler may have many attempts many steps to schedule the orders in an episode. With the accumulation of experience, its decision-making abilities improved a lot during these training episodes, and it can make scheduling decisions instantly with its rich experience. Figure 7(a) to (d) are learning curves of the model based on $R_D$, $R_p$, $R_U$, $R_V$. These four curves all converge within 300 episodes, and the convergence points of them are respectively near the episodes of 170, 240, 175, 120. Although machining speed and energy consumption are not considered in this study case, the learning curve of the $R_p$-based scheduler also converges with the help of the discount rate $\gamma$. The learning curves of the $R_D$, $R_U$, $R_V$-based schedulers show rapid convergence, and their detailed performances are elaborated in the following paragraphs. The learning curve of composite reward $R$ is shown in Figure 7(e) and converges near episode 70. The heights of the curves are influenced by the weights $(K_1, K_2, K_3, K_4)$ of the components.

After an order is completed, reward $R_D$ can be calculated using equation (15). In most cases, it is advisable to shorten the lead time of orders to meet the completion time set by customers. Figure 8 shows the learning processes of an $R_D$-based scheduler. All the time saving rates of each episode are summed up, and all the total rates of the former 300 episodes are put together in Figure 8(a). According to the fitting curve, the total time saving rates increase from 11.51 to 12.97 by 12.69%. The Gantt chart of the scheduling results in the 300th episode is shown in Figure 8(b). The trained scheduler with reward $R_D$ for time saving rates attempts to schedule operations on free machines for minimizing the lead time so that the target completion time is well guaranteed. Each operation is processed as soon as it is initialized, but the workload distribution of machines is unbalanced.

The reward $R_D$ depends on the difference between the completion time and target completion time that is influenced by the efficiency and current state of machines. Another criterion showing the utilization rates of machines is the waiting time of jobs. The reward $R_U$ helps shorten the waiting time of jobs by increasing the utilization rate of the target machine between two adjacent time steps. All the waiting time of jobs in each episode is summed up, and all the total values of the former 300 episodes are put together in Figure 9(a). The Gantt chart of the scheduling results in the 300th episode is shown in Figure 9(b). According to the fitting curve, the total waiting time decreases from 221.56 to 41.90 by 69.72%. The actual waiting time of the 300th episode is 0, which means that all the operations are conducted without delay.
The workload balance of machines is a significant criterion for evaluating the performance of shop floors. The standard deviations of the machine utilization rates, given by equation (12), is a useful parameter for illustrating the workload balance of machines. Standard deviations of machine operating time are respectively calculated on lathes and millers, and all the results of the former 300 episodes are shown in Figure 10(a). Both the fitting curves of lathes and millers show a decreasing trend. The standard deviations of lathe operating time decrease from 70.48 to 23.92 by 66.06%, and these of millers decrease from 92.82 to

![Figure 7. Learning curves of all the components of composite rewards: (a) reward for time saving rate, (b) reward for energy saving rate, (c) reward for machine utilization rate, (d) reward for workload distribution deviation, and (e) composite rewards.](image)

![Figure 8. Learning processes of the scheduler based on time saving rates: (a) time saving rates and (b) scheduling processes of the scheduler.](image)
30.34 by 67.31%. As shown in Figure 10(b), the scheduler trained with reward $R_V$ gradually acquires the ability to balance the workloads among machines, but some operations still waste time waiting to be processed, because reward $R_V$ pays more attention to global workload distribution rather than the performance of a single operation.

The composite reward $R$ considers shortening the lead time and balancing workloads at the same time. It combines many optimization objectives to achieve global optimization of the shop floor. The scheduling results with the help of composite rewards are shown in Figure 11. Figure 11(a) is the Gantt chart of the untrained scheduler, and Figure 11(b) is the Gantt chart of the trained scheduler. The scheduler shows poor performances at the very beginning of training. After being trained by 300 episodes, its scheduling abilities have improved significantly. The standard deviations of operating time of lathes and millers respectively decrease from 62.47, 125.86 to 26.45, 62.76, by 57.66%–50.14%. The total waiting time of jobs decreased from 292 s to 0 by 100%. The total time saving rates of orders increase from 11.09 to 13.3 by 20.20%. Integrating the typical features of all components, the scheduler trained with composite rewards shows an overall good performance. The excellent performances are shown by the smart scheduler autonomously in real time, and the smart scheduler can perceive the states of the environment to make optimal schedules.

Figure 9. Learning processes of the scheduler based on machine utilization rates: (a) waiting time of jobs and (b) scheduling processes of the scheduler.

Figure 10. Learning processes of the scheduler based on workload distribution deviations: (a) the standard deviations of workloads and (b) scheduling processes of the scheduler.
According to the above experimental results, the trained scheduler performs well in scheduling processes. Thirty new orders are created stochastically to evaluate the adaptive abilities of a trained scheduler. The smart scheduler is trained with composite rewards $R$. Gantt charts of Figure 12 show the comparison of the scheduling results between the untrained and trained schedulers. As the untrained scheduler (i.e. Figure 12(a)) turns into a well-trained scheduler (i.e. Figure 12(b)), the standard deviations of lathe operating time decrease from 100.15 to 28.64 by 71.40%, and these of millers decrease from 182.10 to 12.25 by 93.27%, the total waiting time decreases from 653 to 77 by 88.21%, and the total remaining deadline rates increase from 14.87 to 19.46 by 30.87%. Their detailed results are recorded in the first two rows of Table 5. Although the features and sequences are not the same as before, they are scheduled with good performance. It is obvious that a trained scheduler can schedule new tasks well with the knowledge accumulated during its training period in the past.

Machine failures are common in production processes, and such problems are inevitable and may disturb shop floors. The scheduler faces great challenges in dealing with these unexpected technical failures. According to the Gantt chart in Figure 13, the smart scheduler perceived the failure of Miller 1 and scheduled the following milling operations to the other normal millers. In comparison with Figure 12(b), utilization rates of the normal millers increased a lot while the actions of three lathes almost keep the same.
Standard deviations of lathe utilization rates decrease from 26.86 to 27.40 by 4.33%, and those of millers increase from 12.25 to 22.00 by 79.59%. The total waiting time of jobs increases from 77 to 250 by 224.68%. The total time saving rates decrease from 19.46 to 18.26 by 6.17%. Detailed results are recorded in the third row of Table 5. Obviously, the smart scheduler can eliminate the effects of machine failures and keep the stability of the manufacturing system.

Large amounts of orders may be generated simultaneously. As shown in Figure 14, 30 orders are assumed to be generated at the same time. Jobs queue to be processed without delay, and the utilization rates of all machines are very high. The detailed scheduling results of simultaneous orders are recorded in the last row of Table 5. Although the total waiting time is so long, the target completion time can be guaranteed as well. Although the scheduler has not met such events before, it still keeps a preferable and robust performance in handling machine failures. Hence, the smart scheduler has good adaptability for scheduling different kinds of orders online according to the real-time statuses of machines on a shop floor.

Adaptive performance for different objectives

On most occasions, there are various machines with different machining abilities and efficiency on the shop floor. The efficiency of machines is denoted by the machining speed factor $K_{MT_m}$ in Table 4, and machines with smaller $K_{MT_m}$ can finish jobs more efficiently. All the testing orders in this section are obtained from Table 3. Only the reward $R_D$ for time saving rates is adopted in the training process. Scheduling results considering order urgency and machine efficiency are shown in Figure 15. Figure 15(a) shows the operating time of each machine, and Figure 15(b) shows the scheduling actions of a trained scheduler. As the training continues, more orders are scheduled on Lathe 1 and Miller 1 than on the low-efficiency machines. The total operating time of lathes and millers decreases with the help of high-efficiency machines. In Figure 15(b), the
urgent operations are marked by white characters with black tags. The trained scheduler is capable of scheduling tasks on high-efficiency machines, and all urgent orders are scheduled on the most efficient machines autonomously.

As shown in Table 6, the total operating time of machines changes during the training period of the smart scheduler. The operating time of Lathe 1 and Miller 1 increases dramatically by 324.41%–750.81%. Meanwhile, the operating time of other machines decreases to some extent. The total utilization time of lathes and millsers decreases by 62.06%–66.58%. The scheduling performance of the smart scheduler improved a lot during the training period considering order urgency and machine efficiency.

The production objectives of companies include not only improving operating efficiency but also saving costs to increase profits. The energy consumption factor $K_{ME_m}$, shown in Table 4, is considered separately at this time. Machines with smaller $K_{ME_m}$ consume fewer resources while processing the same operations. Only the reward $R_p$ for energy saving rates is adopted in the training period. Scheduling results considering profits (i.e. energy savings) and energy consumption factors are shown in Figure 16. Figure 16(a) shows the profit of every machine, and Figure 16(b) shows the scheduling actions of a trained scheduler. As the training period continues, more orders are scheduled on Lathe 3 and Miller 3 than on machines with high resource consumption rates. The total profits contributed by lathes and millsers increase continuously. In Figure 16(b), the urgent operations marked by white characters with black tags are neglected by the scheduler, because order urgency and machine efficiency are not considered in this case.

As shown in Table 7, the total profits of machines increase from 2190.76 to 2392.20 by 9.19% during the training period of the scheduler. Profit factors contributed by Lathe 3 and Miller 3 respectively increase from

### Table 6. Operating time of machines considering order urgency and machine efficiency.

| Machines | Operating time (s) | Change rate |
|----------|-------------------|-------------|
|          | Untrained         | Trained     |             |
| Lathe 1  | 39.50             | 167.64      | +324.41%   |
| Lathe 2  | 119.70            | 5.06        | -95.77%    |
| Lathe 3  | 321.87            | 9.84        | -96.94%    |
| All lathes | 481.07      | 182.54      | -62.06%    |
| Miller 1 | 27.93             | 237.63      | +750.81%   |
| Miller 2 | 256.84            | 11.60       | +95.48%    |
| Miller 3 | 519.21            | 19.47       | -96.25%    |
| All millers | 803.98     | 268.70      | -66.58%    |

### Table 7. Machine profits considering resource consumption rates.

| Machines | Profits (i.e. energy savings) | Change Rate |
|----------|-------------------------------|-------------|
|          | Untrained                     | Trained     |             |
| Lathe 1  | 76.87                         | 7.29        | -90.52%    |
| Lathe 2  | 310.59                        | 260.50      | -16.16%    |
| Lathe 3  | 504.25                        | 678.65      | +34.59%    |
| Miller 1 | 83.18                         | 65.38       | -21.40%    |
| Miller 2 | 700.72                        | 666.78      | -4.84%     |
| Miller 3 | 515.15                        | 713.59      | +38.52%    |
| All Machines | 2190.76     | 2392.20      | +9.19%     |
Meanwhile, profits from other machines show a certain reduction to some extent. Apparently, the trained scheduler considering energy saving rates is capable of scheduling operating on machines with lower energy consumption rates autonomously.

Scheduling performances of the scheduler considering machining efficiency and resource consumption has been separately verified in the previous parts of this section. In real manufacturing processes, efficiency and profits should be taken into consideration at the same time. In this part, these two criteria are considered simultaneously by considering all the components of composite reward $R$ and initializing machines with parameters in Table 4. The order attributes are the same as before in this section. After 300 training episodes, the scheduler can schedule operations among machines in consideration of the attributes of orders and machines. The scheduling results considering order urgency and resource consumption are shown in Figure 17. In Figure 17, the urgent operations are marked by white characters with black tags. All the urgent orders are assigned on the most efficient machines, while most normal orders are autonomously placed on the machines with lower energy consumption rates. The composite rewards show excellent performance in optimizing the comprehensive scheduling actions.

Comparison of different scheduling methods

Most production scheduling methods aim at achieving time-related objectives that are concerned with the order sequence and completion time. RL-based scheduling with composite rewards (RL-C) is compared with some common online or offline scheduling methods. About 100 orders with 152 operations are generated stochastically to evaluate the scheduling performances of Genetic Algorithm (GA), Shortest Processing Time First (SPTF), First Come First Serve (FCFS), and RL-based methods. FCFS is a common rule-based method for dynamic manufacturing scheduling. GA is an offline heuristic method that can be used to obtain optimal schedules offline. Another offline scheduling method, SPTF, is adopted to obtain a schedule with the shortest waiting time in total. FCFS is an online method and schedules jobs according to their initialization time. A basic RL-based scheduling method (RL-B) is also adopted to make a comparison, while aiming to minimize the idle time of machines. The experimental algorithms belong to three typical categories of scheduling methods, including iterative optimization (i.e. GA), rule-based simulation (i.e.

![Figure 16. Scheduling results considering profits and energy consumption: (a) profits contributed by machines and (b) scheduling actions for saving energy.](image1)

![Figure 17. Scheduling results considering order urgency and resource consumption.](image2)
SPTF and FCFS), and AI-based self-learning (i.e. RL-B and RL-C).

The learning performances of three online scheduling methods (i.e. FCFS, RL-B, and RL-C) are shown in Figure 18, where the performance metric is the total waiting time of 100 orders in each episode. The waiting time of an order is from the scheduling completion moment to the machining start moment. FCFS schedules orders based on specific rules and is not capable of improving decision-making abilities during scheduling processes. At the very beginning, RL-based scheduling methods (i.e. RL-B and RL-C) learn to minimize the waiting time of orders in real time. The learning curves of RL-B and RL-C converge near episode 270 and episode 170. RL-C converges faster than RL-B and needs 37.0% fewer training episodes than RL-B. Therefore, the proposed RL-C scheduling method shows better learning performances than the traditional rule-based method and basic RL scheduling method.

GA and SPTF are offline scheduling method that reschedule the jobs when unexpected events (e.g. urgent orders and machine failures) happens in the manufacturing environment. FCFS, RL-B, and RL-C are online scheduling methods that schedule jobs and handle unexpected events in real time. The calculation time and makespan of each scheduling method are recorded in Table 8. GA can give the best schedules, but it takes a long time to get the result by a complex iteration period, and some unexpected events may cause an incredible increase in computing time. As 10 urgent orders are generated stochastically, online methods can handle the events well with a negligible increase in computing time and makespan. As a machine breaks down, all the scheduling methods can reschedule the operations on normal machines with an increase of makespan. As shown in Figure 19, the curves of RL-C nearly coincide with the results of GA and are more robust than other scheduling methods. Composite rewards improve the online decision-making abilities of the smart scheduler.

**Conclusions and future work**

This paper presents a smart scheduler for online scheduling low-volume-high-mix orders in a smart manufacturing factory. RL algorithms equip the smart scheduler with the abilities of self-organization, self-learning, and self-adaptation. A new composite reward function enables the smart scheduler for online optimization of multiple scheduling objectives. A series of experiments are performed to evaluate how the reward functions (i.e. \( R_D, R_P, R_U, R_V \)) influence the learning performances and optimize the scheduling performances. Experimental results show that the proposed scheduling model not only effectively optimizes scheduling policies but also handles unexpected events such as simultaneously generated orders, urgent orders, and machine failures.

Low-volume-high-mix orders and unexpected events bring a large number of uncertainties to real-world production environment. RL and composite reward functions help the smart scheduler learn autonomously to schedule manufacturing resources with dynamic features in real-time. The smart scheduler can adapt to different real case situations by optimizing the components of the composite reward function. Therefore, engineers do not need to spend much time rescheduling resources when the attributes of orders or machines vary in the dynamic manufacturing environment, which reduces the human costs, computing resources, and lead time.

Real production processes are more complex than experimental environments, and various factors (e.g. transition time and transportation optimization) existing in real working conditions should be considered in

**Table 8.** Comparison of different scheduling methods (values: computing time/makespan; units: s).

|         | GA    | SPTF  | FCFS  | RL-B  | RL-C  |
|---------|-------|-------|-------|-------|-------|
| Normal  | 431/983 | 15/1034 | 12/1095 | 9/1001 | 7/990 |
| Urgent Order | 496/1002 | 21/1130 | 16/1208 | 11/1046 | 7/1014 |
| Machine Failure | 532/1310 | 23/1630 | 17/1703 | 15/1452 | 8/1347 |
future researches. To share the computing tasks with the centralized scheduler, the researches on improving the decision-making abilities of each machine are being conducted by the authors of this paper. In addition, we will delve into how to optimize the framework and parameters of DQN or other RL-based scheduling algorithms.

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References
1. Mehrabi MG, Ulsoy AG, Koren Y, et al. Trends and perspectives in flexible and reconfigurable manufacturing systems. J Intell Manuf 2002; 13: 135–146.
2. Zaeh MF and Ostgathe M. A multi-agent-supported, product-based production control. In: 2009 IEEE international conference on control and automation, Christchurch, New Zealand, 2009, pp.2376–2383. IEEE.
3. Bannat A, Bautze T, Beetz M, et al. Artificial cognition in production systems. IEEE Trans Autom Sci Eng 2011; 8: 148–174.
4. Leitão P and Restivo F. A holistic approach to dynamic manufacturing scheduling. Robot Comput Integr Manuf 2008; 24: 625–634.
5. Yuan M, Li Y, Zhang L, et al. Research on intelligent workshop resource scheduling method based on improved NSGA-II algorithm. Robot Comput Integr Manuf 2021; 71: 102141.
6. He Y and Stecke KE. Simultaneous part input sequencing and robot scheduling for mass customisation. Int J Prod Res 2021; 59: 1–16.
7. Luo S, Zhang L and Fan Y. Dynamic multi-objective scheduling for flexible job shop by deep reinforcement learning. Comput Ind Eng 2021; 159: 107489.
8. Shen W. Distributed manufacturing scheduling using intelligent agents. IEEE Intell Syst 2002; 17: 88–94.
9. Gershin SB. Hierarchical flow control: a framework for scheduling and planning discrete events in manufacturing systems. Proc IEEE 1989; 77: 195–209.
10. Webster S and Azzoglu M. Dynamic programming algorithms for scheduling parallel machines with family setup times. Comput Oper Res 2001; 28: 127–137.
11. Kutanoglu E and Sabuncuoglu I. Routing-based reactive scheduling policies for machine failures in dynamic job shops. Int J Prod Res 2001; 39: 3141–3158.
12. Sabuncuoglu I. A study of scheduling rules of flexible manufacturing systems: a simulation approach. Int J Prod Res 1998; 36: 527–546.
13. Park J, Mei Y, Nguyen S, et al. An investigation of ensemble combination schemes for genetic programming based hyper-heuristic approaches to dynamic job shop scheduling. Appl Soft Comput 2018; 63: 72–86.
14. Ruiz D, Cantón J, María Nougués J, et al. On-line fault diagnosis system support for reactive scheduling in multipurpose batch chemical plants. Comput Chem Eng 2001; 25: 829–837.
15. Metaxiotis KS, Askounis D and Psarras J. Expert systems in production planning and scheduling: a state-of-the-art survey. J Intell Manuf 2002; 13: 253–260.
16. Zhou H, Feng Y and Han L. The hybrid heuristic genetic algorithm for job shop scheduling. Comput Ind Eng 2001; 40: 191–200.
17. Lin TL, Horng SJ, Kao TW, et al. An efficient job-shop scheduling algorithm based on particle swarm optimization. Expert Syst Appl 2010; 37: 2629–2636.
18. Reisen K, Teschemacher U, Niehues M, et al. Biomimetics in production organization: a literature study and framework. J Bionic Eng 2016; 13: 200–212.
19. Hou Y, Fu Y, Gao K, et al. Modelling and optimization of integrated distributed flow shop scheduling and distribution problems with time windows. Expert Syst Appl 2022; 187: 115827.
20. Fu Y, Zhou M, Guo X, et al. Scheduling dual-objective stochastic hybrid flow shop with deteriorating jobs via Bi-population evolutionary algorithm. IEEE Trans Syst Man Cybern Syst 2020; 50: 5037–5048.
21. Wang C and Jiang P. Manifold learning based rescheduling decision mechanism for recessive disturbances in.

Figure 19. Comparison of the makespan of different scheduling methods.
RFID-driven job shops. *J Intell Manuf* 2018; 29: 1485–1500.
22. Park HS and Tran NH. An autonomous manufacturing system based on swarm of cognitive agents. *J Manuf Syst* 2012; 31: 337–348.
23. Jiang Z, Yuan S, Ma J, et al. The evolution of production scheduling from Industry 3.0 through industry 4.0. *Int J Prod Res* 2021; 59: 1–21.
24. Shen W and Norrie DH. Agent-based systems for intelligent manufacturing: a state-of-the-art survey. *Knowl Inf Syst* 1999; 1: 129–156.
25. Wang S, Wan J, Zhang D, et al. Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. *Comput Netw* 2016; 101: 158–168.
26. Wong TN, Leung CW, Mak KL, et al. Dynamic shop-floor scheduling in multi-agent manufacturing systems. *Expert Syst Appl* 2006; 31: 486–494.
27. Li K, Zhou T, Liu BH, et al. A multi-agent system for sharing distributed manufacturing resources. *Expert Syst Appl* 2018; 99: 32–43.
28. Yeung WL. Agent-based manufacturing control based on distributed bid selection and publish-subscribe messaging: a simulation case study. *Int J Prod Res* 2012; 50: 6339–6356.
29. Zhang Y, Wang J and Liu Y. Game theory based real-time multi-objective flexible job shop scheduling considering environmental impact. *J Clean Prod* 2017; 167: 665–679.
30. Wang LC, Cheng CY and Lin SK. Distributed feedback control algorithm in an auction-based manufacturing planning and control system. *Int J Prod Res* 2013; 51: 2667–2679.
31. Hsu CY, Kao BR, Ho VL, et al. Agent-based fuzzy constraint-directed negotiation mechanism for distributed job shop scheduling. *Eng Appl Artif Intell* 2016; 53: 140–154.
32. Fu Y, Hou Y, Wang Z, et al. Distributed scheduling problems in intelligent manufacturing systems. *Tsinghua Sci Technol* 2021; 26: 625–645.
33. Silver D, Huang A, Maddison CJ, et al. Mastering the game of go with deep neural networks and tree search. *Nature* 2016; 529: 484–489.
34. Silver D, Schrittwieser J, Simonyan K, et al. Mastering the game of Go without human knowledge. *Nature* 2017; 550: 354–359.
35. Zhang Z, Zheng L, Li N, et al. Minimizing mean weighted tardiness in unrelated parallel machine scheduling with reinforcement learning. *Comput Oper Res* 2012; 39: 1315–1324.
36. Shiue YR, Lee KC and Su CT. Real-time scheduling for a smart factory using a reinforcement learning approach. *Comput Ind Eng* 2018; 125: 604–614.
37. Shahrabi J, Adibi MA and Mahootchi M. A reinforcement learning approach to parameter estimation in dynamic job shop scheduling. *Comput Ind Eng* 2017; 110: 75–82.
38. Kardos C, Laflamme C, Gallina V, et al. Dynamic scheduling in a job-shop production system with reinforcement learning. *Procedia CIRP* 2021; 97: 104–109.
39. Wang Y, Liu H, Zheng W, et al. Multi-objective workflow scheduling with deep-Q-network-based multi-agent reinforcement learning. *IEEE Access* 2019; 7: 39974–39982.
40. Sutton RS and Barto AG. *Reinforcement learning: an introduction*. Cambridge, MA: MIT Press, 2018.
41. Watkins CJCH. *Learning from delayed rewards*. Ph.D. Thesis, King’s College, London, UK, 1989.
42. Mnih V, Kavukcuoglu K, Silver D, et al. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602* 2013.