IoT Real-Time Production Monitoring and Automated Process Transformation in Smart Manufacturing

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ABSTRACT

Conventional automobile manufacturing plants involve intricate assembly, testing, and debugging processes heavily reliant on manual operations. This study aims to explore the application of industrial internet of things (IIoT) and deep learning algorithms to achieve process automation in manufacturing. Firstly, utilizing IIoT technology, OPC UA, and point cloud fitting techniques, a comprehensive modeling of most equipment and materials within the factory is conducted, constructing a digital twin (DT) model as a virtual representation of actual equipment. Subsequently, the study innovatively introduces the deep Q network algorithm, facilitating the automatic transition of the production process and improving production efficiency. Through comparison with ten baseline models, the proposed model demonstrates an improvement in production efficiency of at least four percentage points compared to other models. Experimental validation confirms the effectiveness of the proposed model in the smart factory for electric vehicle manufacturing.

KEYWORDS

Digital Twin, DQN, IIoT, Process Automation, Smart Factory, Smart Manufacturing

INTRODUCTION

The establishment of intelligent factories has emerged as a significant global trend in the manufacturing sector, aimed at enhancing production efficiency, reducing costs, and achieving more flexible and sustainable manufacturing processes through the adoption of advanced technologies and digital solutions. Illustrative construction cases, such as the intelligent manufacturing transformation implemented by China's Haier Corporation, which involved technologies like the Internet of Things (IoT), cloud computing, and big data analytics, have resulted in the development of intelligent home appliance manufacturing facilities. This intelligent factory construction project has elevated the flexibility and adaptability of production lines, facilitated customized manufacturing, reduced product time-to-market, and strengthened market competitiveness. The process automation of electric

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vehicle manufacturing factories is currently a highly prominent research direction in the intelligent manufacturing landscape (Bathla et al., 2022). The investigation into this technology encompasses various aspects such as the enhancement of factory production efficiency, optimization of production resource utilization (Zhang & Dilanchiev, 2022), and the promotion of environmentally friendly manufacturing (Yang et al., 2022). First, it is poised to significantly enhance production efficiency. Traditional automotive manufacturing plants involve intricate assembly, testing, and debugging processes heavily reliant on manual operations. The introduction of automation technologies (Li et al., 2022b), such as robots and intelligent assembly lines, can substantially reduce the time devoted to manual operations and elevate the operational efficiency of production lines. The improvement in production efficiency aids in reducing manufacturing costs, facilitating quicker and more flexible production responses to rapidly changing market demands. Secondly, it is expected to contribute to the improvement of the quality and consistency of electric vehicles (Jiménez-Ramírez et al., 2023). Given the intricate nature of the components and systems in electric vehicles, errors during manufacturing can result in a decline in product quality. The introduction of automated processes can mitigate human errors and variations, ensuring more precise manufacturing and consequently enhancing overall product quality and consistency. Thirdly, it holds the potential to reduce energy consumption (Salman et al., 2022) and carbon emissions (Kumar et al., 2022). Automation technologies enable the optimization of production processes, precise control of energy usage, and the reduction of unnecessary waste, thereby rendering the manufacturing process more environmentally friendly and aligning with the overall eco-friendly philosophy of electric vehicles. Fourthly, it aids in driving the digitization transformation of the manufacturing industry (Favoretto et al., 2022). Through the integration of advanced technologies such as intelligent manufacturing and big data analytics, production shop floors can achieve higher levels of digital management and monitoring. This not only facilitates real-time tracking of production processes and optimization of resource allocation but also enhances production efficiency through data analysis, providing a more scientifically grounded basis for business decision-making. Therefore, research into the automation of processes in electric vehicle manufacturing plants holds crucial reference value for a nation's industrial strategy formulation. With the increasing global attention on the electric vehicle industry, an in-depth investigation into the application of artificial intelligence technologies in electric vehicle manufacturing can provide robust support for the development of national industrial policies (Srivastava et al., 2022). On a global scale, this contributes to elevating a nation's industrial competitiveness and strengthening its technological leadership in the field of electric vehicles.

Currently, deep learning technology has found numerous applications in the automation of factory production processes (Tercan & Meisen, 2022), and these innovative applications have profound impacts on enhancing production efficiency (Salman et al., 2022), improving product quality, reducing costs, and driving digital transformation. Due to its capability to learn and comprehend vast amounts of production data, deep learning enables intelligent decision-making, resource optimization, and waste reduction through real-time monitoring and analysis of data on the production line, thereby achieving a higher level of production efficiency. Deep learning empowers production systems with autonomous learning and adaptability, fostering the progression of factories toward intelligent manufacturing. This enhances the autonomy and adaptability of production systems, reducing dependence on human intervention and achieving a more highly automated production process (Zhou et al., 2022a).

Given that deep learning technology allows real-time monitoring and control of product quality through the analysis of sensor data and image recognition, it is often utilized to predict potential quality issues, take preemptive measures, reduce defect rates, and enhance the stability of product quality. At the level of each module within a factory, deep learning technology holds significant potential in energy management subsystems. By intelligently adjusting equipment operation based on the analysis of energy usage data in the production process, the system can optimize energy utilization, reduce energy consumption, and achieve a more environmentally friendly and sustainable manufacturing process (Musbah et al., 2022).

Furthermore, deep learning technology contributes to monitoring and analyzing the safety conditions within a factory (Moradi et al., 2022). By real-time identification of hazards and monitoring employee behavior, the system can preemptively alert potential safety risks, thereby ensuring the safety of the factory's production processes. In summary, the application of deep learning technology in factory production processes not only injects new vitality into traditional manufacturing but also provides innovative directions for the future of manufacturing. Through the integration of advanced technologies such as big data and cloud computing, it becomes possible to construct a more intelligent, flexible, and sustainable manufacturing system, propelling the manufacturing industry towards digitization and intelligence. The current commonly employed deep learning models for the construction of smart factories include:

1. **Convolutional Neural Network (CNN):** Primarily used for image recognition and processing, it is suitable for handling visual information in factories. In smart factories, CNNs are employed for tasks such as product quality inspection, defect identification, and real-time monitoring on production lines. Their advantage lies in their ability to extract features from images, enabling efficient and accurate visual analysis (Hsu et al., 2022).
2. **Recurrent Neural Network (RNN):** Suited for processing sequential data, such as time series or continuous data in processes. In smart factories, RNNs can be utilized for predicting equipment failures, detecting anomalies in production lines, and modeling dynamic changes during the production process. Their advantage lies in possessing memory capabilities, allowing them to handle data with strong temporal dependencies (Kannen & Subasi, 2023).
3. **Long Short-Term Memory (LSTM):** A specialized type of RNN designed for handling long sequential data, addressing the issues of vanishing, and exploding gradients in traditional RNNs. In smart factories, LSTMs find applications in modeling time series data, such as predicting equipment performance and optimizing energy consumption. Their advantage lies in better capturing long-term dependencies (Wahid et al., 2022).
4. **Generative Adversarial Network (GAN):** Mainly used for generating new data samples, commonly employed for data augmentation and synthesis. In smart factories, GANs can be used to simulate production environments, generate virtual data for model training, and enhance the generalization performance of models. Their advantage lies in generating realistic data (Zhou et al., 2022b).
5. **Reinforcement Learning (RL):** Employed for decision-making, RL learns optimal strategies through interaction with the environment. In smart factories, RL can be applied to optimize production scheduling, formulate equipment control strategies, and optimize resource allocation. Its advantage lies in its ability to autonomously learn and adapt to complex production environments (Lei et al., 2023).

This study is aimed at exploring the application of Industrial Internet of Things (IIoT) (Gupta et al., 2022) and deep learning algorithms to achieve production process automation in an established Chinese smart factory for electric vehicles. The design rationale of the proposed method encompasses several key steps. Firstly, leveraging IIoT technologies, OPC UA (Domínguez et al., 2022), and point cloud fitting techniques (Fan & Zhang, 2022) to model most devices and materials within the factory. This initial step aims to comprehensively model factory equipment by integrating IoT-based advanced physical information gathering and Poisson surface reconstruction-based three-dimensional point cloud technologies, constructing a digital twin (DT) model (Wang et al., 2022b). Secondly, by using a specific mapping algorithm, the DT model serves as a virtual mapping of the actual devices, providing real-time and highly accurate references for subsequent production process automation. Utilizing DT technology, the factory undergoes equipment behavior modeling and real-time monitoring of equipment status (Nie et al., 2021). By monitoring and analyzing real-time data from the digital twin model, the system can accurately simulate and predict equipment behavior, facilitating real-time monitoring of equipment status within the factory. This capability offers crucial support for achieving refined management and an immediate response to potential issues. Finally, within the Manufacturing Execution System (MES) (Shojaeinasab et al., 2022), the innovative introduction of the deep Q-network algorithm (Zeng et al., 2022) facilitates the automated transformation of the production process and enhances production efficiency. The incorporation of the deep Q-network algorithm enables the system to optimize decisions within the production process, realizing autonomous control and optimization of the production process. This innovative approach provides robust technical support for the intelligent production of the smart factory.

This study presents a novel solution through the integration of DT technology and deep learning algorithms for the automation of production processes in a Chinese electric vehicle smart factory. There are three main innovations:

1. **Comprehensive Application of DT Models:** The system innovatively employs a comprehensive approach using Industrial Internet of Things (IIoT) technology, OPC UA, and point cloud fitting techniques to extensively model the equipment and materials within the factory, constructing a DT model. This integrated application establishes a highly accurate mapping relationship between the virtual model and the actual devices. The DT model not only facilitates real-time monitoring of device status but also provides a real-time and accurate reference for subsequent production process automation, thus laying a solid foundation for the intelligence of the factory.
2. **Application of DT Technology in Equipment Behavior Modeling and Real-Time Monitoring:** Through the application of DT technology, the system engages in equipment behavior modeling and real-time monitoring of equipment status within the factory. The innovation lies in the system's ability to accurately simulate and predict equipment behavior by monitoring and analyzing real-time data from the DT model. This capability provides crucial support for achieving refined management and immediate responses to potential issues.
3. **Introduction of the Deep Q Network Algorithm in the Manufacturing Execution System:** The introduction of the deep Q network algorithm into the Manufacturing Execution System (MSE) represents the third innovation in this system. This algorithm innovatively achieves the automation transformation of the production process and enhances production efficiency. Through the deep Q network algorithm, the system can learn and optimize decisions within the production process, realizing autonomous control and optimization. This autonomous learning and optimization capability provides robust technical support for the intelligent production of the smart factory, offering valuable insights for the future development of industrial intelligence.

The proposed methodology demonstrates a thoughtful and practical approach, offering valuable insights for the intelligent transformation of the industrial sector.

This article is organized as follows: We will introduce the recently related work in Section 2. Section 3 presents the proposed methods: overview, digital twin modeling for factories based on OPC UA and point cloud fitting, real-time monitoring of factory status based on digital twins, automation of production processes based on digital twins, and deep learning. Section 4 introduces the experimental part, including practical details, comparative experiments, and a case study. Section 5 includes a conclusion and an outlook.

RELATED WORK

Industrial Internet of Things and Digital Twin

The application of IIoT and DT technology in smart manufacturing injects new vitality into modern manufacturing, offering enterprises a more efficient, intelligent, and sustainable production approach. The deep integration of information technology and physical systems, as exemplified by the IIoT, facilitates interconnectivity among devices. Through real-time data collection from sensors, equipment, and process flows, IIoT establishes a production environment characterized by real-time monitoring and control. DT technology further enriches this concept by virtually representing physical systems, creating a digital counterpart known as a DT model. The establishment of a DT model typically involves digitizing, connecting, and continuously updating representations of physical equipment. The entire application process can be delineated into steps such as data collection, data transmission, data processing, and model updates, ensuring synchronization between the DT and the actual physical systems (Chen et al., 2023a).

DT technology brings multiple advantages to smart manufacturing. Firstly, real-time monitoring and data analysis empower manufacturing enterprises to swiftly respond to changes in the production environment, enhancing production line flexibility and adaptability. Secondly, through the combined use of IIoT and DT technology, enterprises can achieve remote monitoring and maintenance of equipment, reducing downtime and maintenance costs. The comprehensive understanding of equipment status provided by the DT model aids in preemptively addressing potential faults and making informed decisions for intelligent maintenance. Currently, DT technology finds widespread applications across various facets of the manufacturing industry. In production planning and scheduling, enterprises can intelligently optimize the allocation of production resources through digital modeling and real-time monitoring of the entire production process. In quality control, the high-precision simulation of production processes by DT models facilitates real-time monitoring and prediction of product quality, thereby enhancing the stability of product quality. Regarding equipment maintenance, the integration of sensor data collection from IIoT and model updates from DT technology enables remote monitoring and intelligent maintenance of equipment, reducing downtime and improving equipment utilization rates.

Furthermore, in the development of smart factories, OPC UA (Open Platform Communications Unified Architecture) technology is extensively applied, offering an efficient, secure, and highly interoperable solution for industrial automation systems. Functioning as a communication protocol, OPC UA facilitates seamless integration among diverse devices and systems in smart factories through a unified information model and standardized data exchange mechanisms. In practical application scenarios, OPC UA supports various communication mechanisms, including publish-subscribe and request-response, enabling the collaborative operation of devices from different manufacturers and enhancing the coordination and flexibility of the production process. Moreover, OPC UA provides robust security mechanisms encompassing encryption and authentication, ensuring the confidentiality and integrity of data, and effectively addressing the escalating network security threats in smart factory environments. Simultaneously, OPC UA supports the standardization of information models in smart factories, enabling devices and systems to share consistent data structures and semantics, thereby simplifying the complexity of data interpretation and integration. This standardization not only enhances system maintainability but also reduces the costs associated with system integration.

DT and Production Process Modeling

DT technology demonstrates outstanding application prospects in the modeling of production processes in smart factories. Through the utilization of DT technology, enterprises can achieve a highly accurate reproduction and simulation of physical production systems, providing real-time and comprehensive digital representations of production processes. This capability enables enterprises to conduct real-time monitoring, analysis, and optimization of production processes. Additionally, DT models can be employed to simulate various production scenarios, offering decision-makers comprehensive data support. The modeling process of DT typically includes steps such as digital representation, connecting the model to the physical world, and real-time data updates to ensure synchronization between the model and the actual production system. Initially, digital representation involves digitizing physical elements such as actual equipment and process flows to construct a virtual DT model. The connecting phase involves utilizing Industrial Internet of Things (IIoT) technology to establish a connection between the DT model and actual equipment, collecting real-time data on equipment operations, production parameters, and more. The real-time update phase involves continuously updating the DT model through feedback mechanisms to maintain synchronization with the actual production process. This modeling approach enables DT models to promptly reflect changes in actual production, providing decision-makers with an accurate data foundation.

However, there are some limitations in the current application of DT technology. Firstly, there are constraints related to data quality and real-time capabilities. Building accurate and trustworthy DT models necessitates high-quality production data that needs to be continuously updated to maintain the model's authenticity. In certain circumstances, due to limitations in data collection and transmission, DT models may not fully and accurately reflect the actual production status, potentially impacting decision-making accuracy. Furthermore, the implementation of DT technology requires significant technological investment and specialized knowledge. Establishing DT models involves knowledge from multiple domains, including IoT technology, data analytics, simulation modeling, and more. For some small and medium-sized enterprises, this may result in high costs and resource-intensive requirements (Li et al., 2022a).

Intelligent Automation of Production Processes

The application of intelligent production planning algorithms in modern manufacturing holds the promise not only to enhance production efficiency and optimize resource utilization but also to reduce costs, providing significant competitive advantages for businesses. Common intelligent production planning algorithms include genetic algorithms, simulated annealing, particle swarm optimization, and ant colony optimization. From existing research, these algorithms demonstrate outstanding performance, particularly in precision and real-time capabilities. By integrating advanced data collection techniques and big data analytics, these algorithms can monitor and analyze key parameters in the production process in real-time, enabling rapid responses to change in market demands and fluctuations in the manufacturing environment. Furthermore, these algorithms exhibit intelligent and personalized production planning capabilities. Through technologies like deep learning and machine learning, algorithms can learn from historical data, predict market trends, and formulate more flexible and efficient production plans, thereby improving resource utilization and efficiency. Additionally, intelligent production planning algorithms contribute to optimizing supply chain management, ensuring smooth circulation of raw materials, semi-finished goods, and finished products, reducing inventory costs, and enhancing product delivery efficiency (Zhou et al., 2022a).

However, there are notable drawbacks to the application of intelligent production planning algorithms. Firstly, the implementation of these algorithms may require substantial data and technological investments. Obtaining high-quality production data and maintaining complex algorithmic systems could result in high construction costs compared to potential profits. Secondly, the robustness and stability of these algorithms need further improvement. In complex and dynamic manufacturing environments, algorithms may be susceptible to noise and outliers, leading to instability in production planning. Therefore, further research and innovation in intelligent production manufacturing process automation algorithms are necessary to overcome these challenges and further propel the development of smart manufacturing.

METHOD

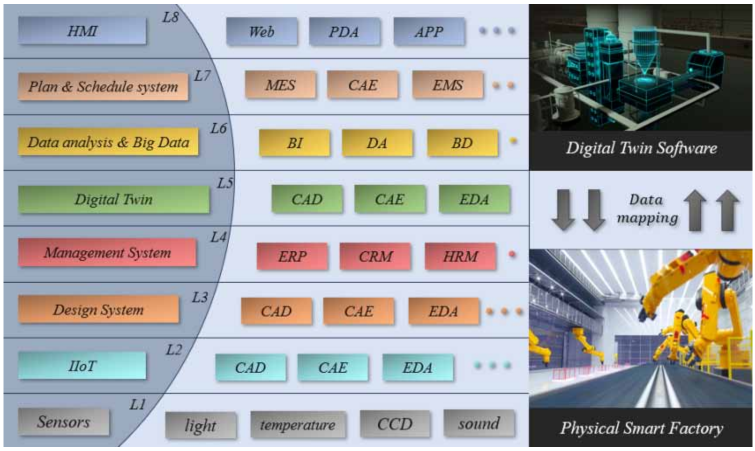
System Overview

In the automated production factory of electric vehicles, the design and implementation of the core software system cluster are crucial for improving production efficiency, optimizing resource utilization, and ensuring product quality. This cluster typically includes multiple subsystems, and the systems discussed in this article encompass the following key subsystems:

1. **Production planning and scheduling subsystem (Oluyisola et al., 2022):** This forms the foundation of the core software system, including the development of Manufacturing Execution Systems (MES), Advanced Planning and Scheduling Systems (APS), Energy Management Systems (EMS), Predictive Health Management Software (PHM), and Maintenance, Repair, and Operations (MRO) software. This component is responsible for translating market demands and ordering information into specific production plans and optimizing the allocation of production resources through intelligent scheduling algorithms. The production planning and scheduling system needs to be closely integrated with the supply chain management system to ensure accurate supply of raw materials and components, thereby ensuring the continuous and stable operation of the production line. Among these, the Manufacturing Execution System (MES) serves as the central control of the entire production process. The MES system, connected to equipment control systems and sensor networks on the production line, achieves real-time monitoring, control, and data collection of the production process. This system has a high level of automation and is capable of adjusting production parameters, monitoring equipment status, and providing timely feedback to the Production Planning and Scheduling System, achieving intelligent and adaptive production processes.
2. **Enterprise management subsystem:** This forms the foundation of factory management and includes the development of Enterprise Resource Planning Systems (ERP), Supply Chain Management Systems (SCM), Customer Relationship Management Systems (CRM), Human Resources Management (HRM), Quality Management Systems (QMS), Asset Performance Management Systems (APM), and other software.
3. **Data analysis and big data subsystems (Wang et al., 2022a):** This is an emerging component in the core software system. By collecting, storing, and analyzing vast amounts of data generated during the production process, the factory can gain profound insights, optimize production processes, and improve production efficiency. Data analysis and big data technologies also provide predictive maintenance capabilities for smart factories. By analyzing equipment operational data, potential faults can be identified in advance, reducing downtime and improving equipment availability.
4. **Design subsystem:** This subsystem is essential for ensuring the factory can manufacture high-quality products. It includes model libraries for automobile design, process libraries, basic knowledge libraries, and comprehensive optimization software for the entire process in the automobile industry. It also encompasses the integrated platform software for the design, production, and operation/maintenance of automobiles, as well as comprehensive control platform software for automobile production. Additionally, it includes some generic software such as Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), Computer-Aided Process Planning (CAPP), Computer-Aided Manufacturing (CAM), Electronic Design Automation (EDA), Product Data Management (PDM), and others.
5. **Quality management subsystem:** This subsystem is a crucial component to ensure the quality of electric vehicle production. The system conducts quality inspection and control at various nodes in the production process, ensuring that products meet standard requirements. The Quality Management System collaborates with the MES system to respond in real-time to any anomalies in the production process, preventing an increase in defective rates.
6. **Human-Machine Interaction (Bathla et al., 2022) Subsystem:** This subsystem is vital for presenting information from the entire core software system to operators in an observable and comprehensible manner. The HMI subsystem, through intuitive graphical interfaces, displays key information such as production plans, equipment status, and quality data, facilitating operators in making rapid decisions.

A detailed system architecture is shown in Figure 1.

Figure 1. A detailed architecture of this smart manufacture system



Digital Twin Modeling for Shop Floor Based on OPC UA and Point Cloud Fitting

This system employs OPC Unified Architecture (OPC UA) technology for real-time data collection in the factory and constructs a digital twin model based on point cloud fitting. The entire process can be divided into the following detailed steps: The first step involves clearly defining the objectives and scope of shop floor digital twin modeling, including the equipment, processes to be modeled, and the required real-time monitoring and control information. The key to this step is ensuring clear modeling objectives, which aid in the subsequent design and implementation of the system. In the second step, deploy OPC UA servers within the shop floor to ensure effective communication between the servers and various types of equipment in the shop floor. Configure device interfaces to enable the OPC UA server to obtain real-time data from the equipment, including but not limited to temperature, humidity, and equipment status. The third step entails deploying laser scanners or other 3D sensors on the equipment in the shop floor to capture point cloud data from the surfaces of the devices. This step needs to cover all equipment that requires modeling to ensure comprehensive 3D information is obtained. In the fourth step, process the collected point cloud data, removing noise and outliers. Subsequently, apply point cloud fitting algorithms to fit the processed point cloud data into highly accurate 3D models. This system utilizes a Poisson surface reconstruction (PSR) algorithm to achieve high-precision fitting of shop floor equipment:

$$M = \left(V, E, F\right) \tag{1}$$

where V denotes points, E denotes edges, and F denotes faces. Firstly, the objective implicit function $F\left(x\right)$ is computed so that the gradient of $F\left(x\right)$ at each P point is the normal vector V at that point, and the dispersion is taken to get the Poisson equation:

$$\nabla \cdot \left(\nabla F\right) - \nabla \cdot V = 0 \Leftrightarrow \Delta F = \nabla \cdot V \tag{2}$$

The $F\left(x\right)$ is represented by adaptive octree, and the marching cube is applied to extract the isosurfaces of the function, and the resulting Mesh mesh data contains topological information, domain information.

Due to occlusion, the point cloud data obtained from a certain angle is incomplete. In this study, a machine learning algorithm is used to predict the set of points at the occluded location to maximize the possible information complementation of the modeled object. The fifth step involves integrating real-time data collected by OPC UA with the 3D models obtained through point cloud fitting to construct the digital twin model of the shop floor. By mapping real-time data to the corresponding equipment models, the digital twin model can accurately reflect real-time information on the status and operating parameters of the equipment on the shop floor. Perform validation of the digital twin model by comparing it with the actual scene and checking for accuracy. If discrepancies are identified, make appropriate optimizations and adjustments to ensure the digital twin model accurately reflects the actual shop floor situation. In the sixth step, achieve real-time synchronization between the digital twin model and the actual shop floor equipment using OPC UA technology. Feed real-time data, such as equipment status and production parameters, back into the digital twin model to maintain its real-time nature. Simultaneously, if changes occur in the shop floor equipment, such as adding new equipment or adjusting equipment positions, use point cloud fitting technology to model new equipment or refit adjusted equipment, ensuring a high degree of synchronization between the digital twin model and the actual shop floor equipment. In the final step, utilize the constructed digital twin model to develop various application scenarios, such as equipment status monitoring, production process simulation, and fault diagnosis. Through the digital twin model, achieve comprehensive monitoring and intelligent control of the shop floor production process, thereby enhancing production efficiency and quality. The principle of this step is shown in figure 2.

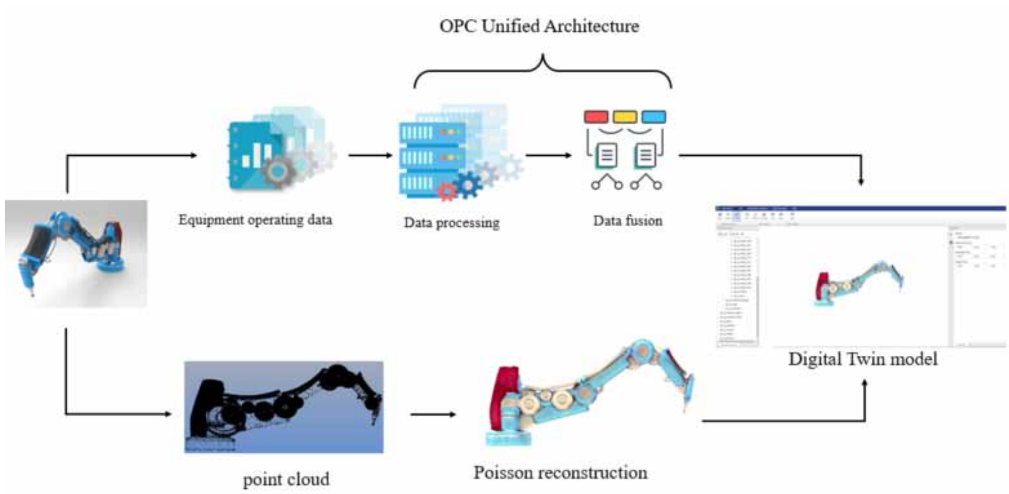
Real-Time Monitoring of Shop Floor Status Based on Digital Twins

This section describes the mapping algorithms for mapping the binary state, enumerated state, and numeric variable state of devices within the smart factory from the physical world to the digital twin model, respectively.

1. Binary states involve devices with Boolean indicator values that can only be true or false. The mapping algorithm for binary states can be expressed by the following equation:

$$BiIND = \left\{ IND\#\ Val_{IND}\left[n\right] \in \left\{True, False\right\}, \forall n \in \left[0, SampleN\right]\right\} \tag{3}$$

Figure 2. The principle of digital twin modeling by using OPC UA and point cloud fitting



In this equation, $BiIND$ represents the set of Boolean indicators and $Val_{IND}[n]$ is an indicative value of the $BiIND$ is at the sample time n, and the $SampleN$ is the total number of sampling points of $BiIND$. The indicated value can only be true or false.

2. Enumerating states involves devices with enumerable indication values, and all possible values form a finite set of states. The mapping algorithm can be expressed in the following equation:

$$EnumIND = \left\{IND\#\ Val_{IND}\left[n\right] \in StatusSet_{IND} = \left\{s_1, s_2, \ldots, s_{m_{IND}}\right\}, \forall n \in \left[0, SampleN\right]\right\} \quad (4)$$

In this equation, $EnumIND$ represents the set of enumerable indicators, $Val_{IND}[n]$ is the indicated value of the $EnumIND$ is at sample time *n*, and $StatusSet_{IND}$ is the finite set of all possible states of the $EnumIDN$. The indicated values can have states different from the finite set.

3. Numerical variable states involve devices with numerical indicator values, such as a robotic arm with rotatable joints. The mapping algorithm can be expressed in the following equation:

$$NumIND = \left\{IND = f\left(Val_{IND}\left[n\right]\right)Val_{IND}\left[n\right] \in Values_{IND}, \forall n \in \left[0, SampleN\right]\right\} \quad (5)$$

In this formulation, $NumIND$ denotes the set of numerical indicators, $f\left(\cdot\right)$ denotes the mapping method of the *j*th $NumIND$, and $Values_{IND}$ is the data range in the physical device side. The mapping algorithm maps the data on the physical device side to the $NumIND$ values on the digital twin side.

For the data obtained after mapping, in order to prevent anomalies in the data collected by the IoT subsystem from the physical world, this system has devised anomaly detection algorithms. These algorithms are employed to analyze and identify abnormal samples from the input time-series data originating from the physical world. In the presence of abnormal samples, the system will choose to either eliminate or re-sample the data.

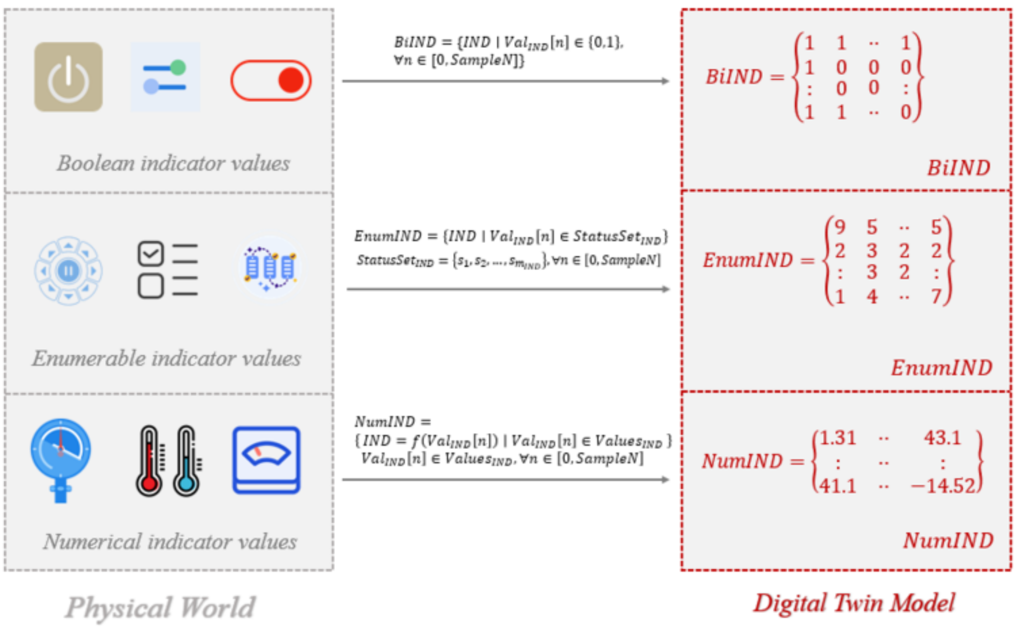
The whole mapping relationship from the physical world to the DT model is shown in Figure 3.

Production Process Automation Based on DT and DQN Algorithms

This smart factory uses a deep-Q-network (DQN) algorithm for production process decision optimization in the MES system, which is based on the principle of training an agent to make near-optimal production decisions in real time. Incorporating the DQN algorithm for production process scheduling in smart factories brings numerous advantages. Firstly, the DQN algorithm enables intelligent scheduling in complex and dynamic production environments through the learning and optimization of decision-making strategies. Secondly, the DQN algorithm can dynamically adapt to changes in production, enhancing the flexibility and adaptability of the manufacturing process by continuously learning and optimizing, thereby more effectively addressing uncertainties and fluctuations in production. Additionally, the DQN algorithm maximizes production efficiency by optimizing resource utilization and task allocation, leading to reduced production costs and improved output quality.

The DQN algorithm is a deep reinforcement learning (RL) algorithm (Pengcheng et al., 2022) that uses a neural network called Q-network to approximate the optimal action-value function

Figure 3. The mapping relationship from the physical world to the DT model



$Q(s,a)$. s represents the current state of the factory and a represents the action to be taken. This system s is set as an N-tuple: s = {workshop 1 production rate, workshop 2 production rate, workshop 3 production rate...workshop N production rate}. And a represents the action to be taken, and the set of actions is $A \in$ {workshop 1 increase production rate by 1 unit, workshop 1 decrease production rate by 1 unit, workshop 2 increase production rate by 1 unit, workshop 2 decrease production rate by 1 unit, workshop N increases production rate by 1 unit, workshop N decreases production rate by 1 unit}.

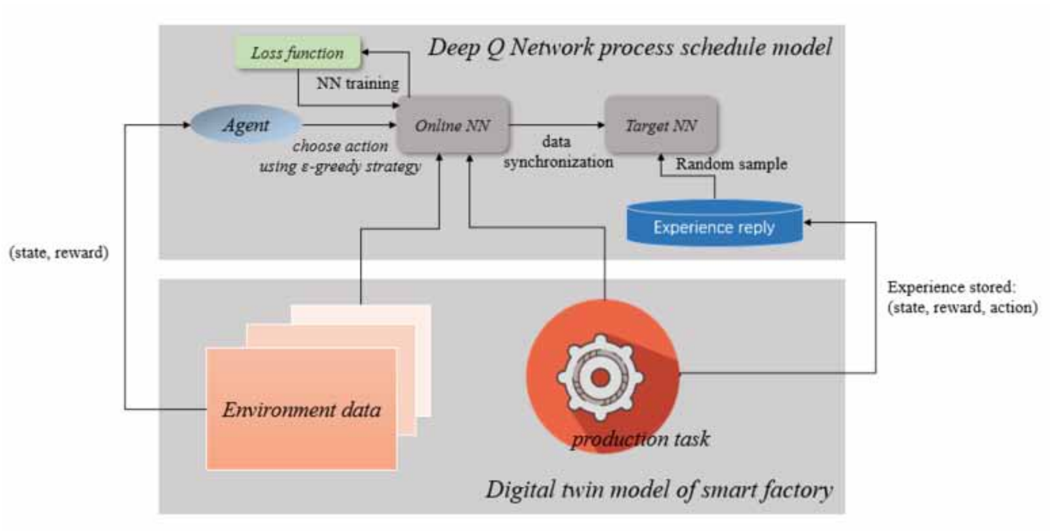
The DQN algorithm uses two key strategies to improve performance: experience replay and fixed parameters. Experience replay involves storing past experiences in replay memory, which is then used to randomly sample and train the Q network. This helps to break the correlation between successive experiences and improves the stability of learning. Fixed parameters are used to categorize the Q network into two versions: the online Q network and the target Q network. The online network is used to select actions in the current time step, while the target network provides target values for training. The parameters of the target network are regularly updated using the parameters of the online network.

In summary, the fundamental process of the DQN algorithm is as follows: (1) Define the state space of the problem s, representing the different states observed by the algorithm during the learning and decision-making process. (2) Action selection: Choose an action a based on the current state using a specified policy. (3) Execute action and observe reward r: Execute the selected action and observe the reward returned by the environment, along with the new state $next\_s$. This process simulates the interaction between the agent and the environment. (4) Experience replay: Store the executed actions and observed results in an experience replay buffer. (5) Target value computation: Utilize a neural network to approximate the Q-value function (action-value function) and calculate the Q-values for each possible action in the current state. This Q-value represents the long-term return of choosing a particular action. (6) Optimization based on the loss function: Define a loss function that measures the disparity between the model's predicted Q-values and the target Q-values. Update the parameters of the neural network through an optimization algorithm, gradually aligning the predicted Q-values with the target Q-values. (7) Iterate the aforementioned learning process, continually updating the parameters of the neural network to enhance the model's decision-making performance in the environment.

In this smart factory decision-making algorithm for production process automation, the DQN algorithm is combined with a digital twin (DT) to build a DQN production process optimizer. This optimizer uses the DT as input data to the algorithm to provide real-time information about the equipment. After the optimizer retrieves the necessary input data from the DT, real-time interaction between the optimizer and the DT is achieved, and the optimizer subsequently trains its internal deep neural network based on the retrieved input data.

The principle of this algorithm is shown in Figure 4.

Figure 4. The principle of the DQN process optimum algorithm



The production process optimization algorithm based on DT and DQN algorithms is represented in the form of pseudo-code as shown in Algorithm 1.

Algorithm 1. Process of a single DQN model training with DT data input

```
# Initialize parameters
env = Digital_Twin_Input()
agent = DQNAgent(state_size, action_size)
# Training DQN using Digital Twin data
Initialize num_episode
for episode in range(num_episodes):
    s = env.reset()
    total_reward = 0
    while  (Loss()> m)
        # Choose action using ε -greedy strategy
        a = agent.act(s)
```

```
        # Execute action, observe next state, reward, and done
flag
        next_s, reward, done = env.step(a)
        next_s = np.reshape(next_s, [1, s_size])
        # Train DQN model using experience replay
        agent.train(s, a, reward, next_s, done)
        # Update state and total reward
        s = next_s
total_reward += reward
    end while
end for
```

EXPERIMENT

Experimental Design

We conducted a simulation experiment for the automated optimization of intelligent manufacturing processes utilizing the Deep Q Network (DQN) model from deep reinforcement learning. The objective of the experiment was to validate the capability of the DQN model for performing intelligent production decision tasks within a smart factory environment, aiming to maximize production efficiency and resource utilization. Data were extracted from a running digital twin model of an electric car automated manufacturing plant, constituting a dataset encompassing products, equipment, and manufacturing processes within the smart factory. This dataset provided a realistic and highly simulated environment for the DQN model to learn and optimize intelligent decision-making.

In the experiment, Network Architecture Search (NAS) techniques were employed to optimize the Deep Q Network model. This involved tuning the network architecture, hyperparameters such as learning rate, discount factor, and experience replay buffer size, ensuring stable convergence during training, and enhancing the model's learning capabilities in complex decision environments.

It is noteworthy that, to ensure the accuracy and authenticity of the data from the digital twin factory, the collection of factory environment data was aligned with the real-time scenarios in the digital twin model. Additionally, the experiment paid special attention to the generalization ability of the DQN model in complex shop floor environments, ensuring superior performance when scheduling various production stages.

To validate the performance of the model, this study conducted a comparative analysis by examining 10 baseline models for intelligent manufacturing task scheduling, drawn from literature over the past three years.

Model #1 (Mzili et al., 2023): Proposed a spotted hyena optimization algorithm in order to identify and implement optimal schedules for jobs in a flow shop environment.

Model #2 (Qiu et al., 2023): Proposed an improved memory algorithm (MA) which combines a genetic algorithm (GA) with educational operators to solve integrated production scheduling decision problems.

Model #3 (Azevedo et al., 2023): Developed a multi-objective optimization model for improving production scheduling performance metrics to help managers make decisions related to job scheduling.

Model #4 (Fontes et al., 2023): Considered the minimization of two optional performance metrics, duration and exit time, and the optimal solution of the model is solved by the Mixed Integer Linear Programming (MILP) algorithm.

Model #5 (Bamoumen et al., 2023): Proposed an algorithm that combines the MILP algorithm and an algorithm similar to the Greedy Randomized Adaptive Search Procedure (GRASP) to solve the problem of automated scheduling of production processes.
Model #6 (Chen & Liu, 2023b): Combined discrete-time simulation methods to establish a delivery date change response model and constructed dynamic scheduling rules using gene expression programming (GEP) algorithms to realize dynamic production planning.
Model #7 (Tang et al., 2023): Proposed a heuristic algorithm based on learning mechanisms and ant colony optimization for solving the collaborative scheduling problem.
Model #8 (Kang et al., 2023): Proposed a multi-strategy individual adaptive mutation difference evolutionary algorithm (MSIADE) for this production scheduling problem.
Model #9 (Saqlain et al., 2023): Proposed a flexible job scheduling algorithm based on Monte Carlo tree search for scheduling highly complex jobs in a real-time job environment.
Model #10 (Wang et al., 2023): Proposed a hybrid genetic algorithm based on variable neighborhood search (GAVNS) for solving the production scheduling problem.

Literature #1, 2, 6, 7, 8, 10 are strategies based on genetic algorithms, literature 3, 4, 5 are strategies based on optimization methods, and literature 9 is a strategy based on solution space search.

This study inputs production demands and resource consumption data from smart factories into these models. Multiple models are employed to provide production planning schemes for various shop floors within the factory during a specific period. Subsequently, diverse evaluation metrics are utilized to compare the planning results of multiple schemes. Performance metrics included production efficiency per unit time, resource utilization rate, energy consumption during manufacturing (RMB), raw material consumption during manufacturing (RMB), and total daily downtime (hours). Through these metrics, we will assess the application potential and optimization effects of the DQN model in real factory environments.

Dataset

The dataset used in this experiment is derived from a recently established smart electric vehicle manufacturing plant. This newly constructed facility serves as a rich source of data, encompassing various workshops within the factory. The dataset includes detailed information on production tasks, equipment statuses, and process parameters, among other aspects. The real-time data stream from sensors deployed throughout the factory provides insights into factors such as temperature, humidity, and equipment states, as well as detailed information on production efficiency and output. This comprehensive dataset from the entire factory ensures robust testing of the proposed algorithms in a realistic and dynamic production environment.

The reason for not adopting public datasets is that intelligent manufacturing tasks often occur in a specific environment, facing a particular production task and a set of specific production equipment.

Table 1. Attributes of the experimental dataset extracted from the smart manufacturing generation environment

Attribution name	Attribution value
Number of workshops	5
Number of equipment	30
Number of products	15
Data generation time	2023.1.1 ~ 2023.1.31
Data set size	20.1G
Number of data samples	9522

For such algorithms, generalization ability and robustness are not the primary considerations; stability of the algorithm and enhancement of actual production capabilities are the most crucial factors to be considered. Therefore, algorithm optimization for intelligent manufacturing tasks must directly use real data from the production environment so that the trained model can achieve optimal performance in actual production scenarios.

COMPARISON STUDY

Comparison of This Paper's Method With Baseline Models

As we can see from the experimental results, the DQN model, combined with digital twin technology, comprehensively considers the complex correlations in the actual production process, making the model more intelligent and adaptable. As a result, it achieves superior performance in production scheduling.

From the experimental results, there are several reasons why the proposed DQN model outperforms these 10 baseline models in production scheduling.

First, compared to optimization models #3, 4, 5, the DQN model utilizes deep reinforcement learning technology, enabling real-time and automated production task scheduling in complex manufacturing environments and adapting flexibly to evolving production demands. The comparison results of production efficiency per unit time and total daily downtime show this advantage in Figure 5.

Second, in contrast to evolutionary computation-based models #1, 2, 6, 7, 8 and 10, the DQN model demonstrates superior generalization capabilities, accommodating variations in different workshops and production stages, thereby enhancing its applicability in real factory settings. The comparison results of energy and raw material consumption during manufacturing show this advantage in Figure 6.

Table 2. Comparison results with ten baseline models

Model	Production efficiency per unit time	Resource utilization rate(%)	Energy consumption during manufacturing(RMB)	Raw material consumption during manufacturing(RMB)	Total daily downtime(h)
Mode1 #1 (Mzili et al., 2023)	89%	75%	12.52K	344.34K	1.04
Mode1 #2 (Qiu et al., 2023)	63%	70%	18.24K	315.62K	0.75
Mode1 #3 (Azevedo et al., 2023)	96%	64%	12.76K	301.46K	0.26
Mode1 #4 (Fontes et al., 2023)	70%	64%	15.53K	291.51K	0.92
Mode1 #5 (Bamoumen et al., 2023)	74%	65%	19.92K	310.42K	1.06
Mode1 #6 (Chen & Liu, 2023b)	67%	81%	14.67K	291.53K	1.04
Mode1 #7 (Tang et al., 2023)	70%	83%	19.12K	295.62K	0.67
Mode1 #8 (Kang et al., 2023)	59%	78%	15.51K	285.93K	0.49
Mode1 #9 (Saqlain et al., 2023)	80%	90%	13.54K	272.34K	0.42
Mode1 #10 (Wang et al., 2023)	71%	83%	15.22K	289.23K	0.39
Our Model	100%	95%	11.12K	242.14K	0.13

Figure 5. The comparison results of production efficiency per unit time and total daily downtime

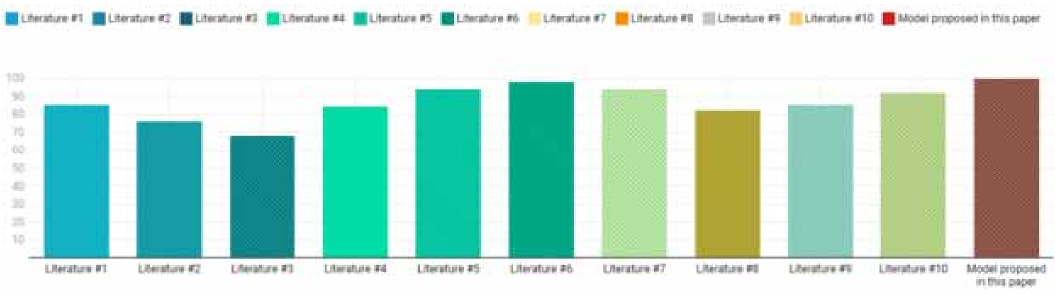
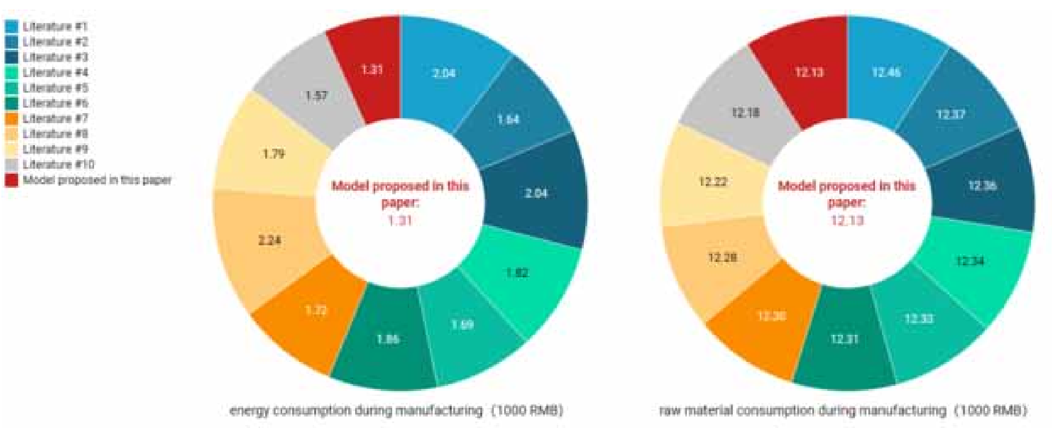


Figure 6. The comparison results of energy and raw material consumption during manufacturing



Additionally, compared to model #9, the DQN's feature learning based on deep learning facilitates more effective planning and decision-making for complex production tasks, improving the overall performance of the model. The comparison results of the resource utilization rate show this advantage in Figure 7.

Finally, with the integration of digital twin technology, the DQN model comprehensively considers intricate correlations in actual production processes, enhancing its intelligence and adaptability, resulting in superior performance in production scheduling.

Comparison of Model Scheduling Performance in the Final Assembly Workshop

We conducted a production data analysis in the final assembly workshop of the factory, and the experimental results unequivocally demonstrate the superior performance of our proposed DQN production automation scheduling model compared to other models. Through real-time scheduling of production tasks, the DQN model effectively enhanced assembly efficiency and optimized resource utilization. The experimental results are shown in Table 3.

The results' differences between models in the final assembly workshop are shown graphically in Figures 8a-8e.

As a key workshop in the assembly line of a smart factory, the optimization of production process scheduling is especially critical in the process of efficiently assembling pre-produced parts into a complete vehicle. From the collected experimental result data, the DQN-based production process

Figure 7. The comparison results of resource utilization rate

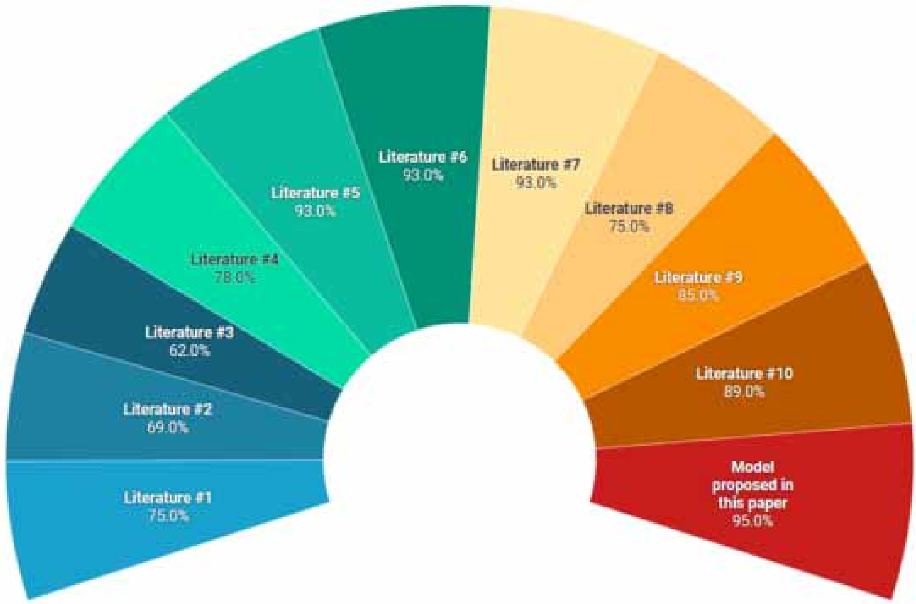


Table 3. Comparison results in final assembly workshop

Model	Production efficiency per unit time	Resource utilization rate(%)	Energy consumption during manufacturing(1000 RMB)	Raw material consumption during manufacturing(1000 RMB)	Total daily downtime(h)
Mode1 #1 (Mzili et al., 2023)	85%	75%	2.04	12.46	0.01
Mode1 #2 (Qiu et al., 2023)	76%	69%	1.64	12.37	0.02
Mode1 #3 (Azevedo et al., 2023)	68%	62%	2.04	12.36	0.03
Mode1 #4 (Fontes et al., 2023)	84%	78%	1.82	12.34	0.02
Mode1 #5 (Bamoumen et al., 2023)	94%	93%	1.69	12.33	0.01
Mode1 #6 (Chen & Liu, 2023b)	98%	93%	1.86	12.31	0.04
Mode1 #7 (Tang et al., 2023)	94%	93%	1.72	12.30	0.02
Mode1 #8 (Kang et al., 2023)	82%	75%	2.24	12.28	0.07
Mode1 #9 (Saqlain et al., 2023)	85%	85%	1.79	12.22	0.03
Mode1 #10 (Wang et al., 2023)	92%	89%	1.57	12.18	0.02
Our Model	100%	95%	1.31	12.13	0.01

Figure 8a. Comparison of production efficiency per unit time

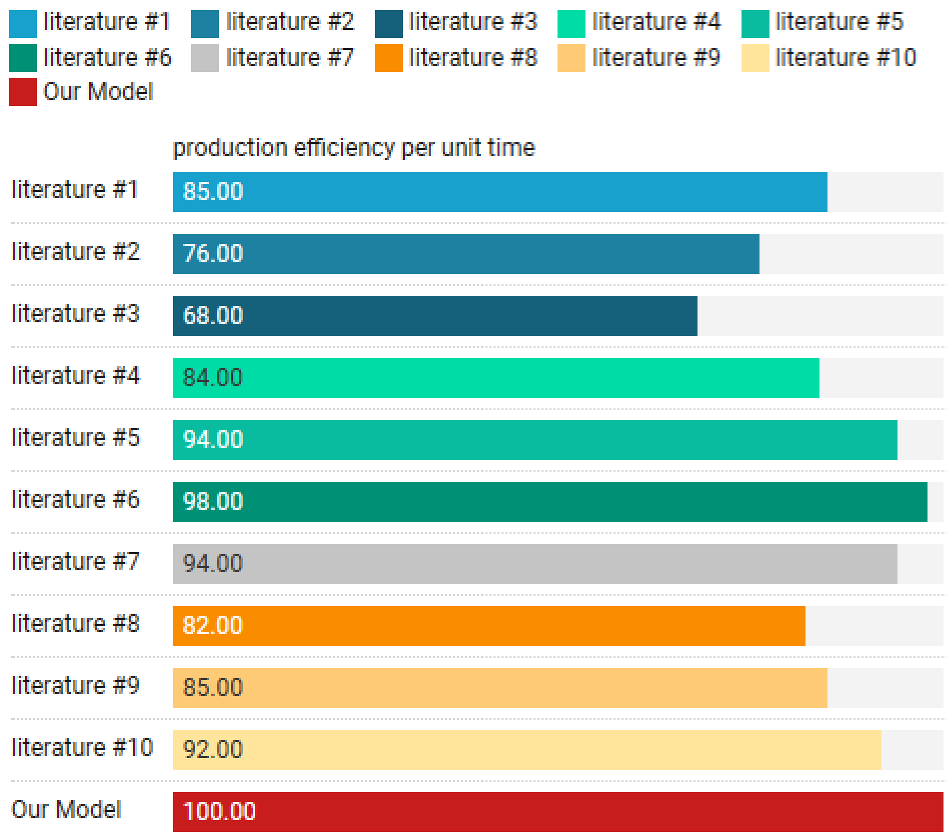


Figure 8b. Comparison of resource utilization rate

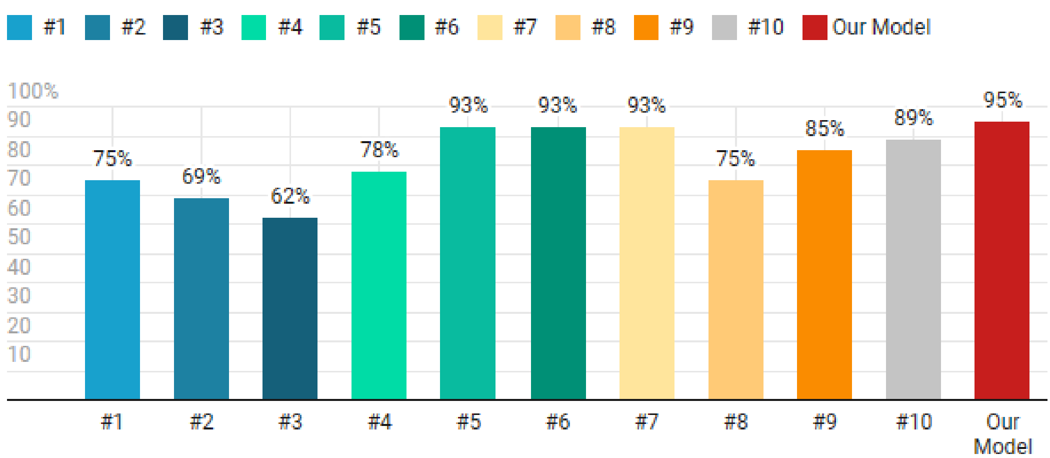


Figure 8c. Comparison of energy consumption during manufacturing

Figure 8d. Comparison of raw material consumption during manufacturing

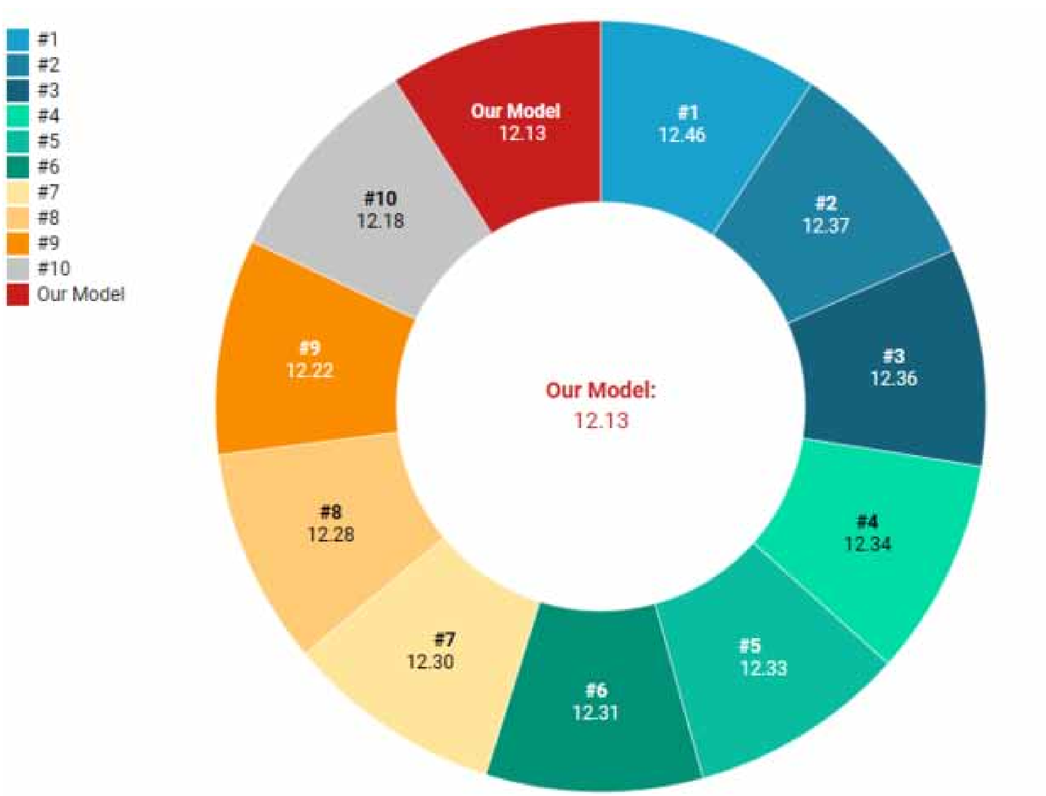
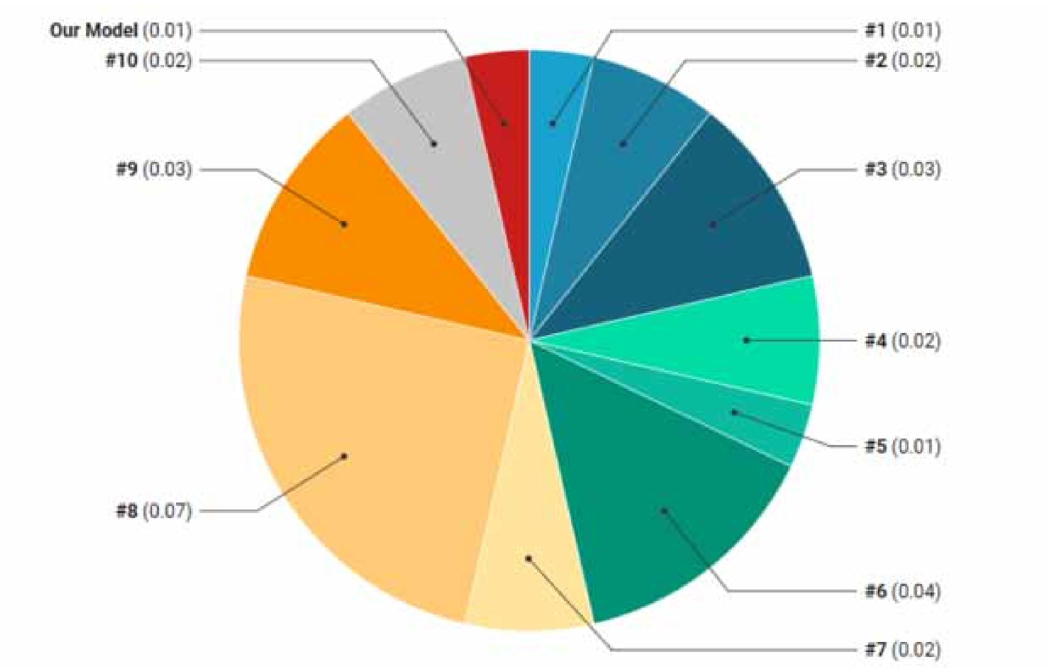


Figure 8e. Comparison of total daily downtime



automation scheduling model makes the smart factory in the final assembly shop have multiple evaluation indexes with multiple advantages compared with the 10 baseline models.

Case Study

To validate the impact of the DQN algorithm on the production capacity improvement of the smart factory, a case study was conducted to compare the manufacturing of electric vehicles in the factory before the system went live with the situation after the system went live. The productivity changes of the smart factory before and after the system went live are shown in Table 4.

A graphical representation of the changes before and after the system go-live is shown in Figure 9.

Table 4. The productivity changes of the smart factory before and after the system go-live

Time	Production efficiency per unit time	Resource utilization rate(%)	Energy consumption during manufacturing(RMB)	Raw material consumption during manufacturing(RMB)	Total daily downtime(h)
Before	32%	54%	19.56K	311.31K	1.32
After	100%	95%	11.12K	242.14K	0.13

Figure 9. Graphical representation of the changes before and after the system go-live

After implementing intelligent production scheduling algorithms based on deep learning and digital twin in the smart electric vehicle factory, there has been a significant improvement in factory production efficiency. Possible reasons for this improvement include, firstly, the application of deep learning technology, which enhances the algorithm's ability to understand and learn from the complex production environment, improving its capacity to handle large-scale data and complex external factors. This aids the model in more accurately predicting key information, such as production demands and equipment status changes, facilitating more intelligent and real-time production task scheduling. Secondly, the introduction of digital twin technology provides a virtual simulation environment based on the actual factory, modeling the real production processes through digital twin models, thereby increasing the practicality of the algorithm.

From Figure 9, it can be observed that, following the implementation of the DQN model for factory production process scheduling, there is a notable reduction in the daily downtime of the system. The emergence of this phenomenon can be attributed to the real-time adaptability of the DQN model. With the dynamic changes in the production environment, the model can swiftly adjust the scheduling scheme, mitigating issues that static scheduling, traditionally employed, is unable to flexibly address. Consequently, this capability reduces the probability of equipment downtime.

Additionally, algorithms based on deep learning and digital twin can comprehensively consider the complex correlations between various production processes, including collaborative operations among devices and the impacts between different manufacturing processes. This comprehensive consideration makes the algorithm more intelligent, allowing it to make more precise and rational scheduling decisions, thereby maximizing production efficiency.

CONCLUSION

Study Conclusion

This study aims to address challenges in optimizing the production process of a smart factory. The research proposes resolving issues related to process automation in intelligent manufacturing by introducing smart algorithms and digital twin technology. The primary approach involves leveraging deep reinforcement learning techniques, specifically an enhanced Deep Q Network (DQN) model, to achieve real-time and automated scheduling of production tasks within the factory. The research seeks to enhance algorithmic performance and overcome limitations by introducing innovative methods and making full use of the advantages offered by smart algorithms and digital twin technology. The goal is to improve production efficiency and resource utilization in the electric vehicle industry. The effectiveness of the proposed methods is briefly demonstrated through a simulation experiment and a case study.

In addition, although this study does not improve the DQN algorithm, the combination of the digital twin model and the relational mapping algorithm from the physical world to the DT model proposed in this study can be seen as an improvement to the DQN model as a solution to the task of automated scheduling of the production process in an electric vehicle smart factory.

Outlook

It can be anticipated that the integration of solutions incorporating digital twins and DQN models will contribute to elevated levels of automation, enhanced flexibility in production scheduling, and more sustainable operational models in the construction and operation of smart factories. This integration is expected to further propel the digital transformation and intelligent development of the manufacturing industry.

Currently, there is room for improvement in the performance of our algorithm, especially in real-time and distributed scheduling. To address this deficiency, we plan to design and introduce more optimized artificial intelligence algorithms. This will involve in-depth research into scheduling algorithms to enhance their efficiency and accuracy. Additionally, we will explore more flexible distributed scheduling methods to adapt to complex production environments.

Another notable deficiency is the lack of robustness in anomaly monitoring in the smart factory. Despite significant advancements in enhancing the level of automation in the system, there is still room for improvement in anomaly monitoring and automatic recovery capabilities. To address this issue, we plan to strengthen the design of the anomaly monitoring system and introduce more intelligent and sensitive monitoring technologies. Simultaneously, we will focus on improving the system's automatic recovery capabilities in response to anomalies, aiming to minimize the need for manual intervention. This improvement will contribute to enhancing the stability and reliability of the system.

Although the current production of electric vehicles has achieved a high level of automation, there are still some stages that require manual intervention. To further reduce human intervention in the system, we plan to explore more automation and intelligent solutions. This includes conducting in-depth research on stages that currently involve manual intervention to identify potential automated alternatives. By incorporating more advanced machine learning and automation technologies, we aim to achieve a greater degree of autonomy in the electric vehicle production process, ultimately enhancing overall production efficiency.

This study aims to optimize the production processes in smart factories through the integration of intelligent algorithms and digital twin technology. By enhancing the Deep Q Network (DQN) model within the framework of improved deep reinforcement learning, the research focuses on real-time and automated scheduling of production tasks within the factory, aiming to enhance production efficiency and resource utilization. The study proposes improvement strategies in terms of optimizing algorithm performance, strengthening anomaly monitoring and automatic recovery capabilities, as well as reducing manual interventions. In summary, this research endeavors to provide a novel algorithm and presents an effective technological application for the field of intelligent manufacturing, contributing positively to the development of more intelligent and efficient production processes in the electric vehicle industry.

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DATA AVAILABILITY

The data used to support the findings of this study are included within the article.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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AUTHOR NOTE

We have no known conflict of interest to disclose.

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