

Research Article

Research on Modeling and Scheduling Methods of an Intelligent Manufacturing System Based on Deep Learning

Xiaoyi Lan¹ and Hua Chen² 

¹School of Economic Management, Xi'an Technological University, Xi'an 710021, China

²School of Mechatronic Engineering, Xi'an Technological University, Xi'an 710021, China

Correspondence should be addressed to Hua Chen; chenhua2035@126.com

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Under the background of intelligent manufacturing, the modeling and scheduling of an intelligent manufacturing system driven by big data have attracted increasing attention from all walks of life. Deep learning can find more hidden knowledge in the process of feature extraction of the hierarchical structure and has good data adaptability in domain adaptation. From the perspective of the manufacturing system, intelligent scheduling is irreplaceable in intelligent production when the manufacturing quantity of workpieces is small or products are constantly changing. This paper expounds the outstanding advantages of deep learning in intelligent manufacturing system modeling, which provides an effective way and powerful tool for intelligent manufacturing system design, performance analysis, and running status monitoring and provides a clear direction for selecting, designing, or implementing the deep learning architecture in the field of intelligent manufacturing system modeling and scheduling. The scheduling of the intelligent manufacturing system should integrate intelligent scheduling of part processing and intelligent planning of product assembly, which is suitable for intelligent scheduling of any kind and quantity of products and resources.

1. Introduction

Over the years, people have conducted extensive research on the application technology of artificial intelligence in a manufacturing system. As a result, a variety of expert systems and knowledge-based systems for specific fields have been developed, forming a series of “intelligent arc islands” [1]. With the deepening of research, people gradually realize that the future manufacturing automation should be intelligent integration and the further improvement of manufacturing automation depends on the self-organization ability of the whole manufacturing system [2]. The intelligent manufacturing system can be regarded as a complex system composed of various intelligent subsystems or intelligent nodes. Each subsystem completes the distributed collaborative solution on the basis of material, energy, and information exchange and converts manufacturing system resources into products [3]. The purpose of the intelligent manufacturing system is to simulate the skills and expert knowledge of the manufacturing technology by integrating knowledge engineering and

manufacturing software system, robot vision, and robot control, so that intelligent machines can produce without manual intervention [4]. The purpose of intelligent scheduling is to complete the production tasks of production processing and machine assembly on the premise of meeting various constraints of the manufacturing system. In the process of intelligent production, due to the frequent changes of production objectives, such as the acceleration of product upgrading, the intelligent manufacturing system can also be adjusted according to the new production tasks to ensure that the machine can complete the production tasks with high utilization [5].

The purpose of the intelligent manufacturing system is to turn human intellectual activities into intelligent activities of manufacturing machines. The physical basis of the intelligent manufacturing system is an intelligent machine, which includes intelligent machining machine tools with various programs, tool and material conveying devices, detection and test devices, assembly devices, etc. [6]. Intelligent automation of product processing and manufacturing has

become the main direction today. It is particularly important to make job shop scheduling intelligent, which is an urgent need for the survival and development of enterprises [7]. In the intelligent manufacturing process, production is fully automated and unmanned. Once unreasonable processing process arrangement occurs, the machine may collide and cause safety accidents [8]. From the perspective of the manufacturing system, intelligent scheduling is irreplaceable in intelligent production when the number of workpieces is small or the products are changing [9]. The intelligent dispatching system is an important part of IMS. Intelligent scheduling should be a scheduling technology that comprehensively studies the intelligent scheduling of part processing and intelligent planning of product assembly from the overall index. It must be highly universal, intelligent, and flexible [10]. This paper expounds the outstanding advantages of deep learning [11–14] in intelligent manufacturing system modeling [15], provides an effective way and powerful tool for intelligent manufacturing system design, performance analysis, and operation state monitoring, and provides a clear direction for intelligent manufacturing system modeling and scheduling field selection, design, or implementation of deep learning architecture.

IMS refers to a highly flexible and integrated method to simulate the intelligent activities of human experts in the manufacturing process through computers in all links of the manufacturing process, that is, to analyze, judge, reason, conceive, and make decisions on intelligent problems in manufacturing [16]. With the emergence of new manufacturing modes such as computer-integrated manufacturing, flexible manufacturing system, fine production, and virtual manufacturing, it has indeed brought great convenience to enterprises in terms of manufacturing cost and product quality assurance [17]. Intelligent scheduling is the key to ensure the efficient, reliable, and safe production of the intelligent manufacturing system, so the research on intelligent scheduling has very important practical significance. The planning, design, scheduling, control, operation status monitoring, intelligent manufacturing system modeling, system maintenance, and performance analysis of the intelligent manufacturing system must be supported by corresponding models [18]. Deep learning is also called the deep neural network (DNN). It adopts the hierarchical structure of multiple neural layers and extracts information from input data through layer-by-layer processing. This “deep” layer structure allows it to learn the representation of complex raw data with multiple levels of abstraction. From the original input, DNN automatically discovers complex structures in large datasets and learns useful features layer by layer. DNN has been widely used in visual recognition and language understanding because of the characteristics of feature learning, and this feature learning ability has become its key advantage [19]. The neural network [20–22] architecture aims at modeling the high-level representation of data and classifying or predicting patterns by stacking multilayer information processing modules in the hierarchy [23]. The intelligent machining unit is an important intelligent node of the intelligent manufacturing system. In-depth research on modeling and scheduling of the intelligent manufacturing system based

on the deep learning neural network can improve the intelligence level of the intelligent machining unit.

2. Related Work

In recent years, artificial intelligence algorithms [24–26] have gradually entered the stage of solving industrial manufacturing scheduling problems. Literature [27] proposes a simple optimization algorithm based on pareto by constructing a mathematical model of multiobjective flexible industrial manufacturing scheduling based on parallel machines. Literature [28] established a new hybrid genetic algorithm, which solved the problems of premature, slow searching speed and poor convergence effect on the manufacturing scheduling problem of operation industry. Literature [29] starts from the perspective of multivariety and small-batch production, adopts standard datasets to prove and solve the manufacturing scheduling of the flexible operation industry, considers the factors such as the maximum completion time, machine load rate, and total load rate as multiple scheduling objectives, and uses the method of analysis and deconstruction to verify the effectiveness and practicability of the algorithm. Literature [30] solves the flowshop problem of two machines, in which the optimization object is the minimum processing time and the dynamic programming algorithm is mainly used. Literature [31] conducted a detailed study on the flow line problem from three aspects of system modeling, solution method, and algorithm performance evaluation in 2020 and proposed the use of the Lagrangian algorithm to solve the static scheduling problem of flow line operations. Literature [32] used the branch and bound method to solve the multimachine flowshop-type problem.

Traditional scheduling methods can still achieve satisfactory results for simple and small-scale scheduling problems, but it is difficult to solve the actual scheduling problems that are more complex, large scale, and difficult to model with ordinary methods. Literature [33] puts forward an encoding method based on EDD-LPT when using genetic algorithms to solve scheduling problems to solve various unexpected situations encountered during scheduling, combining various real examples of manufacturing in the remanufacturing workshop, and constructing. Many different scheduling models have been developed to provide theoretical and technical guarantees. Literature [34] puts forward the concept of autonomous and open-system machine tools in the future environment and believes that in the future advanced manufacturing system, processing machine tools should be autonomous and open. As an experimental prototype, they developed an intelligent machine tool based on a vertical machining center. Literature [35] proposed a method of controlling system beacons to avoid system deadlock, but when manufacturing system considerations gradually become more complex, deep learning models will explode and bring huge trouble to beacon control. Literature [36] proposes to avoid the deadlock of the system by controlling the strict minimum beacon of the system, that is, to maintain the activity of the system by adding a controller to each minimum beacon. This article combines deep learning to

optimize the modeling and scheduling of intelligent manufacturing systems, provides an effective way for the design, performance analysis, and monitoring of operating conditions of intelligent manufacturing systems, and selects, designs, or implements deep learning architectures for intelligent manufacturing system modeling and scheduling.

3. Materials and Methods

3.1. Structural Model. The intelligent manufacturing system is a digital, networked, and intelligent manufacturing based on ubiquitous state awareness in virtual reality. In the process of product design, it involves the knowledge or professional knowledge of various fields related to the product and also involves the comprehensive processing and utilization of these multifield knowledge, experience, and data. There are many difficulties in the process of transforming the applicability of scientific and technological achievements in manufacturing small and microenterprises. From the perspective of system modeling, the manufacturing system is divided into resource elements and process elements and resource elements are divided into equipment resource elements and information resource elements. The former includes various machine tools and tools, while the latter includes various CAD, CAPP, and other software that provide accompanying information such as design data, process flow, and machining data for process elements [37]. As one of the intelligent nodes of the intelligent manufacturing system, the intelligent processing unit is also composed of many intelligent nodes. It includes the flexible manufacturing system, flexible assembly system, intelligent fault detection system, and human experts. The structural model of the manufacturing system mainly describes the attributes, quantities, and interrelationships of equipment resource elements and process elements.

Figure 1 shows the mode structure of a completely distributed intelligent manufacturing system, which is composed of many relatively autonomous self-agents connected by a system bus. Self-agents, which are relatively autonomous, are connected to the communication network in the form of intelligent nodes and accomplish tasks together through the collaboration and cooperation of all nodes. In implementation, modules with strong cohesion and low coupling with other tasks can be separated to form collaborative tasks. This can reduce the boundary constraints and facilitate the early start of the next task. In the process of project execution, the workflow provides a process monitoring tool, which is convenient for managers at all levels to know the work progress and status. This can relatively reduce the difficulty of the task and speed up the completion of the task. The collaborative design system for concurrent engineering should provide enough facilities to form a collaborative environment, so that collaborative participants can use the facilities in the environment to describe collaborative requirements. Because the concurrent design of concurrent engineering is divided into intergroup and intragroup collaboration, the work of members in the group is closely related and collaboration generally requires synchronization. However, the design work between groups may need to be

coordinated at intervals, so the collaboration can be carried out asynchronously. Intelligent nodes can include any form of intelligent units, and other intelligent nodes can be connected to the system bus, such as intelligent CAPP (computer-aided process planning) nodes and intelligent CAD (computer-aided design) nodes. Each intelligent node is an independent self-agent.

The system organization mode of the intelligent processing unit is a distributed mode, which adopts the centralized control and scheduling mode in its local implementation, and is managed by a core node, which is responsible for the dynamic allocation of tasks and resources, coordinates the competition and cooperation among other nodes through global planning, and acts as an arbitrator to resolve conflicts. Other nodes apply for tasks from core nodes in a certain way according to their own capabilities. The nodes receiving tasks can complete tasks independently, and at the same time, they can request cooperation from other nodes through core nodes. Under the macrocontrol of core nodes, they can establish temporary cooperative relations with other cooperative nodes to complete tasks together.

3.2. Behavior Model. With the development of information technology and manufacturing technology, the complexity of products is increasing, the amount of information to be processed in product manufacturing is increasing, and the division of social specialties is becoming more and more detailed, which makes the cooperation between enterprises increasingly close. Multilevel supplier collaboration aims at the realization process of complex products, major equipment, or large-scale projects, and with the help of various information and management technologies and means, enterprise resources distributed in different spaces and times and belonging to different partners are quickly and effectively organized into a unified organism. In the manufacturing process of complex products, from the initial conceptual design to the mass production of products, suppliers are involved and undertake the development and production tasks of important parts. In the allocation process, the priority of task allocation between internal and external resources is considered based on the allocation strategy and the optimal supplier of the product collaborative development chain is selected by integrating the factors of task influence and supplier influence.

The intelligent manufacturing system is a very complex large-scale system, which is a multifactor, high-order, and nonlinear system, and the traditional modeling method is very difficult. It is characterized by discreteness, difficulty in on-line detection, uncertainty of the process model, rapidity of process, and instability of processing multilevel information feedback [38]. The intelligent modeling method can be realized by fuzzy mathematics, neural network, and other methods. Scheduling problem is actually a constrained optimization problem. In the past research on scheduling methods, the assumption of constraints was often limited to resource constraints. The change of the manufacturing process state is determined by the change of the resource element and process element state. Equipment resource elements have three valid states: idle state, busy state, and

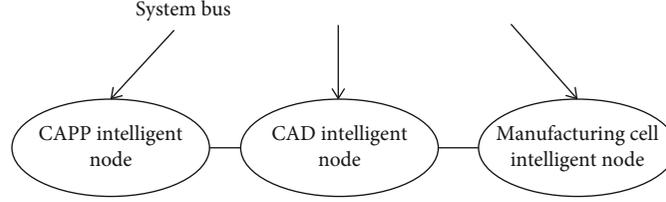


FIGURE 1: Distributed intelligent manufacturing system structure.

fault state. Process elements show different states according to their different processing stages.

Artificial intelligence technology can very accurately monitor the stability of electronic information systems during information transmission to ensure the safety and accuracy of information input or output. Only in this way can information processing be carried out better and a good auxiliary role be played for the implementation of the intelligent manufacturing system. Using the existing technology to establish an artificial intelligence manufacturing environment, the intelligent design operation process is shown in Figure 2.

Generally speaking, the parts in the machining process can be in different stages such as clamping, machining, transportation, cleaning, and measurement. Each process may go through the processes of waiting, loading, processing, unloading, finishing, etc. However, due to the different process routes of the parts, the change paths between these states are also different. The scheduling of intelligent processing units in the intelligent manufacturing system should integrate intelligent scheduling of part processing and intelligent planning of product assembly, which is suitable for intelligent scheduling of any kind and quantity of products and resources. This method can automatically make intelligent decisions according to product requirements and system resources, so as to maximize the autonomy of intelligent processing units.

3.3. Control Decision Model. Because the utilization of equipment resources by various activities in the manufacturing process is random in time and the processing tasks are also dynamic, there is competition in the utilization of equipment resource elements and choice in process elements. This needs to be solved by system scheduling, and the scheduling must establish the control decision model of the system. For the intelligent scheduling of intelligent processing units, besides the system resource constraints, the priority order constraints of each working procedure and the priority order constraints of part completion should also be considered [39]. These priority constraints are provided by the assembly planning system of the flexible assembly system and meet the requirements of optimal assembly. The distributed networked IMS prototype system is the comprehensive embodiment of the research achievements of this project in the basic theory and technology of intelligent manufacturing. The basic idea is to start from the essential characteristics of the intelligent manufacturing system and, in the distributed manufacturing network environment, according to the basic idea of distributed integration, apply the theory and method of the multiagent system in distributed artificial intelligence, and focus on the flexible and intelligent integration of the

manufacturing unit and network-based manufacturing system. The structure of the deep neural network in this article is shown in Figure 3.

The determination of the weight of each index in the technical analysis of intelligent manufacturing is a very important step in the calculation process of the technical evaluation index. Since the weights of each process in the entire intelligent manufacturing process are not the same, it is necessary to use the analytic hierarchy process to determine the specific weights, in which each index is calculated as follows:

(1) Disassembly index

$$\lambda_1 = \frac{m_{\text{ideal}} \times t_{\text{ideal diss}}}{t_{\text{actual diss}}}, \quad (1)$$

where m_{ideal} is the ideal number of parts, $t_{\text{ideal diss}}$ is the ideal disassembly time, and $t_{\text{actual diss}}$ is the actual disassembly time

(2) Cleaning index

$$\lambda_2 = \frac{m_{\text{ideal}} \times 1}{l_{\text{cleaning}}}, \quad (2)$$

where l_{cleaning} is the cleaning score and $m_{\text{ideal}} \times 1$ is the ideal cleaning score. There are four main cleaning methods: blowing, wiping, baking, and washing. When different cleaning methods are used, the cleaning scores are 1, 3, 3, and 6, respectively

(3) Check index

$$\lambda_3 = \frac{m_{\text{ideal insp}}}{m - m_{\text{replaced}}}, \quad (3)$$

where $m_{\text{ideal insp}}$ is the ideal number of inspections, m is the number of parts, and m_{replaced} is the number of replacements

(4) Detection index

$$\lambda_4 = \frac{m_{\text{test}} \times t_{\text{ideal test}}}{t_{\text{actual test}}}, \quad (4)$$

where m_{test} is the number of parts to be inspected, $t_{\text{ideal test}}$ is the ideal inspection time, and $t_{\text{actual test}}$ is the actual inspection time

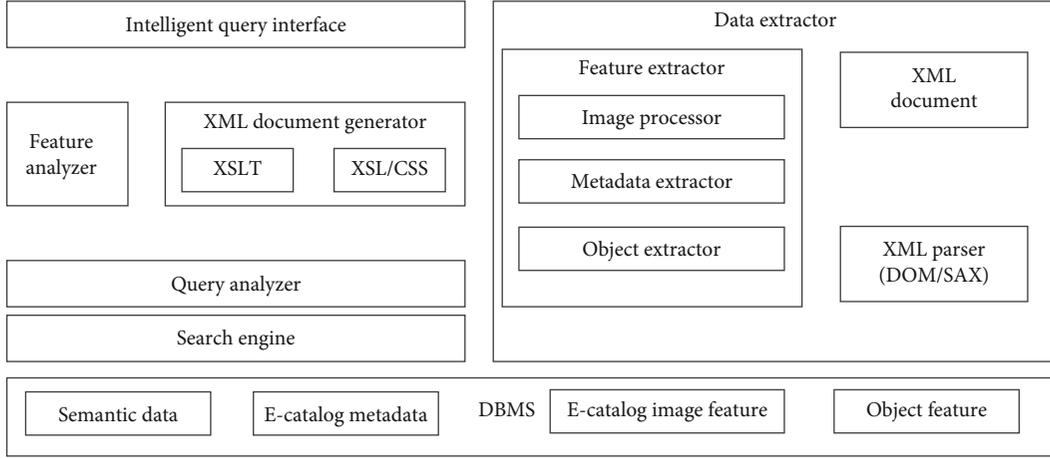


FIGURE 2: Manufacturing intelligent design operation process.

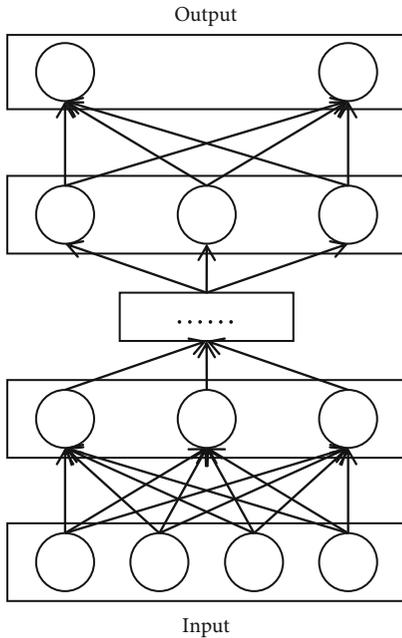


FIGURE 3: Deep neural network learning model.

(5) Assembly index

$$\lambda_5 = \frac{m_{ideal} \times t_{idealass}}{t_{actualass}}, \quad (5)$$

where m_{ideal} is the ideal number of parts, $t_{idealass}$ is the ideal assembly time, and $t_{actualass}$ is the actual assembly time. After determining the calculation of each index, the technical evaluation index λ_T can be further calculated:

$$\lambda_T = \left(\sum_j \frac{W_j}{\lambda_j} \right)^{-1}, \quad (6)$$

where $j = 1, 2, \dots, 5$, λ_j is the aforementioned 5 indexes, and W_j is the weight of the 5 indexes. The range of the calculated

λ_T is $[0, 1]$. When $\lambda_T > 0.5$, it shows that it is suitable for intelligent manufacturing from a technical point of view.

The scheduling method of the intelligent processing unit should be based on the overall index and comprehensively study the scheduling technology integrating intelligent scheduling of part processing and intelligent planning of product assembly. It must be highly universal, intelligent, and flexible. Each activity first requests the response of the process element server and then requests the response of the corresponding resource server according to the attributes of the selected parts.

4. Scheduling Analysis of the Intelligent Manufacturing System Based on Deep Learning

4.1. Reconfiguration and Optimization of Cell Resources in Intelligent Manufacturing. The purpose of data acquisition is to collect relevant data such as vibration, acoustic emission, current, velocity, temperature, and other signals from various sensor sources deployed on the equipment system. Data processing mainly includes data cleaning and other strategies for preprocessing. Through the signal processing technology and dimension reduction strategy, fault sensitive features are extracted and selected from the original signals and data fusion is carried out on multisensor signals. The purpose of intelligent manufacturing system modeling is to extract the production factors in the system and express their relationship reasonably, which can be used to analyze the performance or existing problems of the system. The complexity of the complex system lies in its complex structure, many variables, strong coupling among system variables, high nonlinearity, time delay, and time variability. There are many objects to realize health management, and the status signals containing health information are complex and diverse, as well as dynamic, static, continuous, and discrete, which usually requires a combination of modeling and forecasting techniques of intelligent manufacturing systems.

In engineering design, not only rich professional knowledge and basic design data but also practical experience and knowledge of experts are needed. Through the analysis and prediction of data, the traditional way of operation judgment

based on intuition and fuzzy judgment will be gradually replaced. The relationship between the number of nodes and processing time is shown in Figure 4.

Assume the intelligent processing unit shown in Figure 1 as follows: there are n parts; the i th part has n_i processes; there are m -type resources, and the number of s th-type resources is r_s ; the completion time of each part has priority constraints. The completion time of each part has priority constraints; the total completion time of all parts of the system is required to be the shortest, and the completion time of each part is recorded as x_i .

For the convenience of description, the following symbols are introduced: n is the number of parts; n_i is the number of processes of the part; m is the number of resource types; r_s is the number of resources of each type; R_i is the process pair $[j, l]$ set of the i th part p . Among them, process j has priority over process l ; Q_i is the process pair $[j, l]$ set of the i th part p_i , where processes j, l have no priority constraint relationship; I_i is the process set that can be arranged for the first time; N_{sq} is the use of the q th process set of s resources; P is the set of parts with priority completion time constraints; t_{il} is the processing time of process l of the i th part p_i ; x_{ij} is the completion time of process j of the i th part p_i . The completion time is the last process of each part in the scheduling sequence. $i = 1, 2, \dots, n$; $j = 1, 2, \dots, n_i$. x_{ij} should satisfy the following inequalities:

$$\begin{aligned}
x_{ij} - x_{il} + t_{il} &\leq 0, & \text{for all } [j, l] \in R_i, \\
x_{ij} - x_{il} + t_{il} &\leq 0 \text{ or } x_{il} - x_{ij} + t_{ij} \leq 0, & \text{for all } [j, l] \in Q_i, \\
x_{ij} - x_{il} + t_{ij} &\leq 0 \text{ or } x_{ij} - x_{il} + t_{il} \leq 0, & \text{for all } [j, l] \in N_{sq}, \\
x_{ij} - x_{il} + t_{il} &\leq 0, & \text{for all } [j, l] \in R_i, \\
x_k - x_i &\leq 0, & \text{for all } [K, j] \in P, \\
t_{ij} - x_{ij} &\leq 0, & i = 1, 2, \dots, n; j = 1, 2, \dots, m.
\end{aligned} \tag{7}$$

In the given neural network model, if it represents a neuron, the energy function of the network is

$$\begin{aligned}
E = & \sum_{i=1}^n x_i + \sum_{i=1}^n \sum_j \sum_l H_1 \cdot F_1(x_{ij} - x_{il} + t_{il}) \\
& + \sum_{i=1}^n \sum_j \sum_l H_2 \cdot [\min(F_1(x_{ij} - x_{jl} + t_{jl}), F_1(x_{jl} - x_{ij} + t_{ij}))] \\
& + \sum_{s=1}^m \sum_{q=1}^{r_s} \sum_j \sum_l H_3 \cdot [\min(F_1(x_{ij} - x_{il} + t_{jl}), F_1(x_{jl} - x_{ij} + t_{ij}))] \\
& + \sum_k \sum_i H_4 \cdot F_1(x_k - x_i) + \sum_{i=1}^n \sum_{j=1}^{n_i} H_5 \cdot F_1(t_{ij} - x_{ij}).
\end{aligned} \tag{8}$$

Among them, $F_1(\cdot)$ is the penalty function; H_1, H_2, H_3, H_4, H_5 is a sufficiently large normal number. Deep neural networks can converge to a stable state, which corresponds

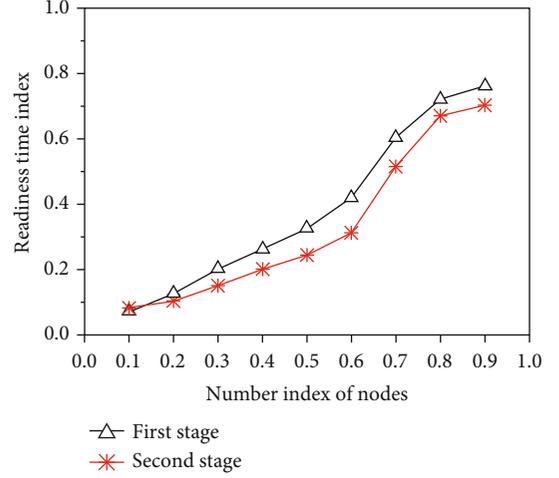


FIGURE 4: Number of nodes and processing time.

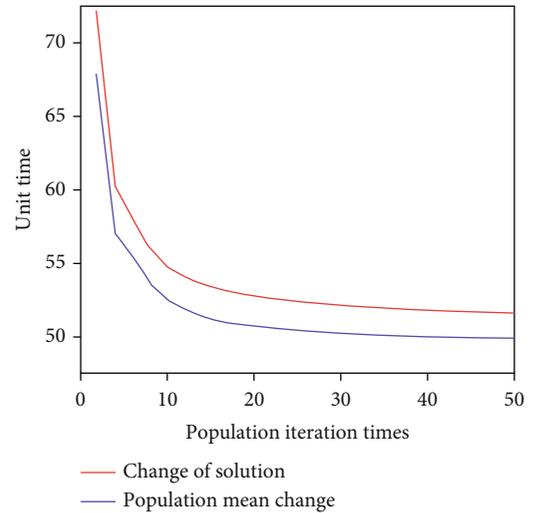


FIGURE 5: The population mean and the change of the optimal solution.

to an optimal solution of the problem. The population mean and the optimal solution changes are shown in Figure 5.

The main task of scheduling is to allocate the limited resources of the system reasonably and optimize some performance indexes. These resources can be machine tools, tools, fixtures, etc. System equipment status data is precious wealth, which contains abundant health information, and is the cornerstone of the data-driven intelligent manufacturing system modeling and prediction technology. Too many sensors will cause extra burden to health management objects, and too many sensor data will also cause data redundancy, which will bring difficulties to feature extraction and fault analysis.

4.2. Dynamic Characteristics of NC Machine Tools in the Intelligent Manufacturing System. Because of the complexity and uncertainty of the actual system, it is difficult to find a clear mathematical model. The method based on the failure physical model depends on the failure physics of the key components of the system, such as wear, fatigue, and aging.

TABLE 1: Characteristic value corresponding to each characteristic.

Features	A1	A2	A3	A4	A5	A6	A7	A8	A9
Characteristic value	75.5	88.7	87.8	95.6	74.5	76.8	87.3	92.3	75.4

The failure physics of different components has different failure processes and laws. It is costly and time-consuming to master the wear, fatigue, and aging process laws of key components. The performance of various intelligent devices in the intelligent manufacturing system plays an important role in the normal operation of the intelligent manufacturing system. With the improvement of automation, informationization, and intelligence of the machining system, the dynamic characteristics of modern CNC machine tools are also required to be improved accordingly. Whether the knowledge-driven method can model and predict an efficient intelligent manufacturing system depends on whether there is a complete expert system knowledge base, and it is difficult to deal with new faults without matching related rules. In the process of running, the expert system cannot get new knowledge from reasoning examples and it is very difficult to solve some novel faults and some marginal problems of the system design.

The configuration of components and the selection of performance parameters of CNC machine tools will directly affect the dynamic characteristics of the system. For the whole computer control system, starting with the electromechanical system composed of a servomotor and mechanical device, the mathematical model is established by using the laws of the mechanical system and electrical system. The transfer function of the mechanical system is

$$G_1(s) = \frac{C(s)}{\theta_m(s)} = \frac{L}{2\pi} nK_s \frac{1}{J_e s^2 + B_e s + K_s} = \frac{K_0 \omega_n^2}{s^2 + 2\xi \omega_n^2 + \omega_n^2}, \quad (9)$$

where:

$$\begin{aligned} K_0 &= \frac{Ln}{2\pi}, \\ \omega_n &= \sqrt{\frac{K_s}{J_e}}, \\ \xi &= \frac{B_e}{2} \sqrt{\frac{1}{J_e K_s}}. \end{aligned} \quad (10)$$

The transfer function of the electrical system is

$$\begin{aligned} G_2(s) &= \frac{\theta_m(s)}{V_a(s)} \\ &= \frac{K_l/R_a}{(T_e s + 1)[(J_1 + J_m)s^2 + B_m s + K_m(1-n)] + K_e K_l s/R_a}, \end{aligned} \quad (11)$$

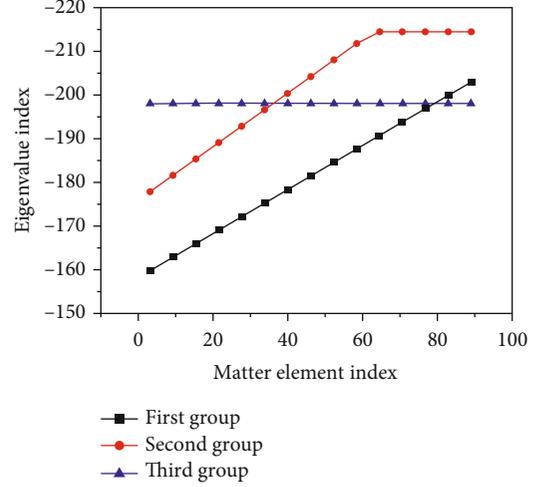


FIGURE 6: Relationship between eigenvalues and matter element.

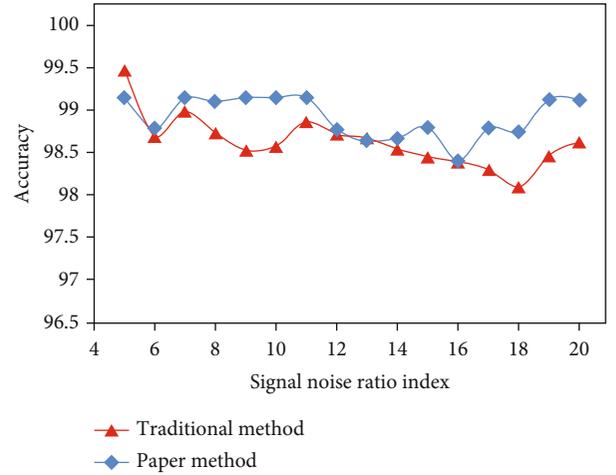


FIGURE 7: Modeling effectiveness of different methods.

where

$$T_e = \frac{L_a}{R_a}. \quad (12)$$

For matter elements, A is the evaluation characteristic, that is, the index. Some eigenvalues can be calculated by the system, and the corresponding eigenvalue of each feature is shown in Table 1. Figure 6 is the relationship between eigenvalues and matter elements in three groups of experimental data.

System modeling and simulation is an important means to analyze and design the system. It can easily put forward measures to improve the existing system and predict its dynamic performance and modify its parameters before

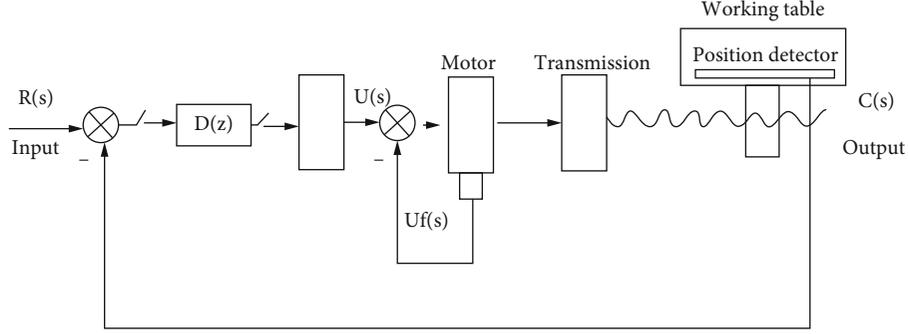


FIGURE 8: CNC machine tool closed-loop control system.

the system is established, so as to achieve the optimal design effect. The modeling effectiveness of different methods is shown in Figure 7.

In addition to the electromechanical control system of the CNC machine tool closed-loop control system, there is also a digital computer $D(z)$ that completes digital signal processing, a sampler that completes analog-to-digital signal conversion, and a zero-order holder that completes digital-to-analog signal conversion. So the structure of the whole system is shown in Figure 8.

In which,

$$G(s) = \frac{K_v G_1(s) G_2(s)}{1 + K_v K_f S G_2(s)}. \quad (13)$$

$G(s)$ is the transfer function of the controlled object.

Ignoring the effect of the interference signal $n(t)$, that is, $N(S) = 0$, the output response $C_R(Z)$ of the system to the input $R(Z)$ can be obtained:

$$C_R(z) = \frac{D(z)G'(z)}{1 + D(z)G'(z)}R(z), \quad (14)$$

where

$$G'(z) = Z \left[\frac{1 - e^{-Ts}}{s} G(s) \right]. \quad (15)$$

Equipment status data contains abundant information on the equipment status, including the relationship between equipment components and random errors, which can truly describe the system performance. In practical engineering, it is uneconomical or even impossible to obtain mathematical models and it is difficult to express expert knowledge and experience effectively. In this case, data-based technology is more used. By comparing the scheduling results of the general modeling method and deep neural network, as shown in Figure 9. It can be seen that the modeling and scheduling effect of the intelligent manufacturing system based on the deep neural network is better than that of general modeling methods.

The intelligent manufacturing system must realize typical intelligent signs of state perception, real-time analysis, independent decision making, and precise execution and real-

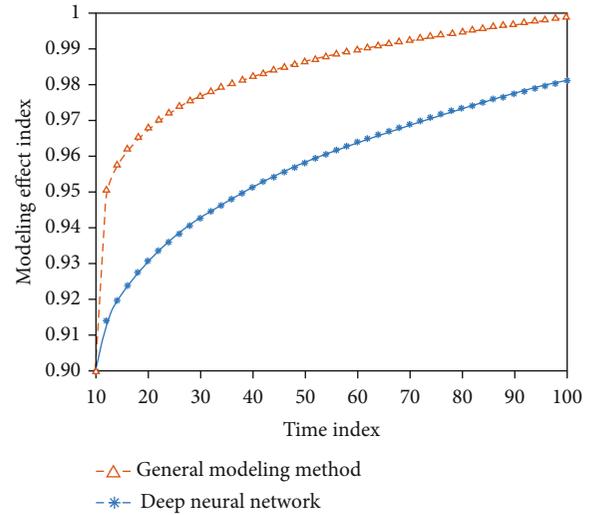


FIGURE 9: Comparison of the deep neural network and the general modeling method.

ize visual monitoring [40, 41] of the product manufacturing process. For modeling and simulation of a computer control system, the general method is to establish a mathematical model describing the movement of the system according to the dynamic relationship among various physical quantities in the system, then to model the mathematical model twice and turn it into a simulation model, and to finally send the simulation model to a computer for the solution. With the improvement of the computer processor performance and the reduction of its cost, artificial intelligence technologies such as the expert system, fuzzy system, and neural network have gradually developed. Based on these technologies, there is an increasing interest in developing artificial intelligence solutions in the field of equipment health management. Compared with the traditional diagnosis method, the diagnosis based on intelligent technology can improve the performance with the least manual help and can be easily expanded and modified and can be adjusted according to the new data.

5. Discussion

Compared with traditional machine learning methods, due to the deep architecture and the learning method of learning useful features layer by layer, the deep learning model can

automatically find the fault mode features contained in large datasets, so as to realize automatic feature learning without a special feature extractor. In some application scenarios, the fault diagnosis and prediction accuracy of the support vector machine and traditional artificial neural network can reach the accuracy equivalent to that of the deep learning model, but in terms of robustness in a noisy environment, the deep learning model is better than the former. The traditional artificial neural network is easy to fall into the trap of gradient explosion and overfitting. The deep learning model can effectively avoid similar problems. However, in terms of computational speed, because the computational complexity of the deep learning model is higher than that of the support vector machine and traditional artificial neural network, the training time is more than that of the latter.

The deep learning model is essentially developed from a traditional neural network. Improve the model generalization ability, strengthen the local feature learning, optimize the model parameters using optimization algorithm, and improve the data preprocessing technology, multimodal data fusion, and mixed integration of multiple models, and other technical routes are continuously integrated into the deep learning framework, which effectively improves the model generalization ability, multimodal data fusion, and mixed integration of multiple models. With the introduction of various technologies, the computational complexity of the model will inevitably increase. How to extend the fault prediction and diagnosis model trained by historical data in order to ensure the accuracy of medium- and long-term fault prediction and diagnosis is a major challenge. In order to improve the generalization ability of the model, the transfer learning technology has been introduced to construct different domain-adaptive deep learning models and simulate different working conditions on the training data as much as possible. However, for practical application, the generalization ability of the model still needs to be strengthened. In general, the training of the deep learning model needs massive data. However, it is not easy to obtain the health information of the actual complex equipment system. Due to historical reasons, there are often few or no sample data, while the running equipment is in normal working state for most of the running time and a small amount of fault sample data can be collected.

6. Conclusions

Under the global market competition environment, manufacturing globalization is an inevitable trend of manufacturing development and it is also an opportunity and challenge faced by Chinese manufacturing enterprises. With the arrival of the customized manufacturing trend, the future development of the manufacturing industry will become more and more intelligent, which puts forward higher and higher requirements for the scheduling of intelligent manufacturing systems. Traditional manual scheduling methods can no longer meet the requirements of intelligent manufacturing systems and complex manufacturing systems. The modern manufacturing industry is facing the requirements of individuation and diversification and the phenomenon of a shorter and shorter product cycle,

which requires the product design and process design to be coordinated. The scheduling of intelligent processing units in the intelligent manufacturing system should integrate intelligent scheduling of part processing and intelligent planning of product assembly, which is suitable for intelligent scheduling of any kind and quantity of products and resources. The foundation of intelligent manufacturing is digital manufacturing. By constructing the digital platform of the intelligent manufacturing system, the digital, networked, and intelligent system architecture operation model of the intelligent manufacturing system is built.

Compared with the traditional diagnosis method, the diagnosis based on intelligent technology can improve the performance with the least manual help and can be easily expanded and modified and can be adjusted according to the new data. In the process of manufacturing system modeling, through the modeling and simulation analysis of basic manufacturing cells, the bottom-up modeling is realized and the basic manufacturing cells are continuously expanded upwards, and finally, the manufacturing system model is established. In the aspect of scheduling algorithm research, the deep neural network proposed in this paper has solved the multiobjective scheduling problem but it needs further research on the determination of the convergence algebra and coding mode. By establishing standardized models for various types of scheduling problems, the research on scheduling algorithms will be more targeted, which will help to speed up the research on intelligent scheduling algorithms.

Data Availability

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

Conflicts of Interest

The authors do not have any possible conflicts of interest.

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