International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 892-901

https://doi.org/10.70517/ijhsa46482

Research on the design and application of mechatronic intelligent manufacturing system based on the optimization of metal material properties

Yang Lu[1,*]
[1] Intelligent Manufacturing School, Taizhou Polytechnic College, Taizhou, Jiangsu, 225300, China
Corresponding authors: (e-mail: 20066954@163.com).

Abstract Under the background of Industry 4.0, intelligent manufacturing technology has become the core driving force to enhance the competitiveness of manufacturing industry. Aiming at the problems of low control accuracy and low resource utilization of traditional manufacturing systems in metal material processing, this paper designs an intelligent manufacturing system based on mechatronics technology. The research adopts digital intelligent control algorithm combined with PID control structure and state space equation to establish the system mathematical model, realizes the organic integration of enterprise layer, management layer, operation layer, control layer and field layer through the design of layered architecture, and constructs active real-time production plan management system. The performance test results show that the average memory occupancy rate of the system is 15.205% when processing 2,000 products, which is 12.702% and 18.054% lower than that of the system based on digital twin and cloud computing, respectively; the real-time data acquisition in the functional test is 2.5 seconds, and the accuracy rate of fault diagnosis reaches 98.8%. The study shows that the intelligent manufacturing system based on mechatronics technology is better than the traditional system in terms of resource occupation, processing efficiency and stability, and provides an effective solution for intelligent processing of metal materials.

Index Terms Mechatronics technology, intelligent manufacturing system, digital intelligent control algorithm, metal materials, performance optimization, layered architecture design

I. Introduction

Machinery manufacturing industry, as one of the basic industries of national industry, has undergone profound changes in recent years driven by information technology and intelligent technology [1]. The traditional way of machinery manufacturing has been difficult to meet the market's increasing demand for product quality and production efficiency, intelligent manufacturing technology came into being, and gradually became the transformation direction of the industry [2], [3]. Mechatronics technology, on the other hand, significantly improves the functionality and flexibility of the equipment by organically combining mechanical, electronic, information and control technologies, and provides solid technical support for the intelligence of the manufacturing system [4]-[6].

Mechatronics system, usually defined as a complex system that integrates multiple disciplines such as mechanical technology, electronic technology, automatic control technology and information technology [7]. Its core concept is to integrate and apply technologies from different disciplines in a unified system to achieve effective control of physical and information flows [8], [9]. In the field of industrial manufacturing, mechatronics systems are widely used in the design and manufacture of CNC machine tools, industrial robots, automated production lines, and other equipment, and these applications not only significantly improve the production efficiency and product quality, but also greatly reduce the production cost and human resource dependence [10]-[13]. At the same time, with the help of intelligent technology based on data analysis, predictive modeling and autonomous learning algorithms, the manufacturing system is endowed with the ability of “sensing-learning-adapting”, so that it can independently adjust the parameters, optimize the production efficiency and reduce the waste of energy in the process of metal product production [14]-[17].

The technical route of this research adopts the method of combining theoretical analysis and experimental verification, firstly, the functional requirements of the intelligent manufacturing system are determined through demand analysis, and then the digital intelligent control algorithm and system architecture are designed based on the mechatronics technology to construct the intelligent manufacturing system that contains core functional modules such as visual inspection, predictive maintenance, production plan management, and so on. In the process of system realization, a five-layer architecture model is established by adopting the layered design concept, and the feasibility and effectiveness of the system are verified through mathematical modeling and simulation technology.

Finally, the practical application effect of the system is comprehensively verified through multi-dimensional evaluation methods such as load test, functional test and performance test.

II. Demand analysis for smart manufacturing systems

II. A. Visual inspection and defect recognition

In the field of manufacturing, vision inspection and defect recognition technology is developing rapidly. These technologies utilize the principles of image processing and machine vision to efficiently and accurately identify defects on the surface or inside the product without human intervention, thus ensuring product quality. With the application of deep learning technology, the recognition ability of the vision inspection system has been greatly improved, not only to detect small defects, but also to operate stably in complex industrial environments. For example, in the electronics manufacturing industry, the vision inspection system can recognize tiny cracks and solder joints on printed circuit boards to ensure the functionality and safety of electronic products. With the enhancement of computing power and optimization of algorithms, vision inspection technology has also made significant progress in improving detection speed and accuracy. By processing a large amount of image data in real time, the inspection results can be fed back quickly, which greatly improves the working efficiency of the production line. In the automobile manufacturing industry, vision inspection technology is widely used in body coating quality inspection, can accurately identify the uneven thickness of the coating, color difference abnormality and other problems.

II. B. Predictive maintenance and troubleshooting

Predictive maintenance and fault diagnosis technology plays a crucial role in modern manufacturing. Relying on big data analysis and machine learning algorithms, it can accurately predict potential equipment failures, so as to take maintenance measures in advance to avoid production interruptions and economic losses. The application of this technology has changed the traditional passive maintenance mode, adopting a more proactive maintenance strategy, effectively extending the service life of equipment and improving productivity. For example, in heavy industry, by monitoring parameters such as vibration, temperature and sound, predictive maintenance systems can identify abnormalities in equipment operation in real time and intervene before problems worsen. As technology continues to advance, the predictive accuracy and responsiveness of troubleshooting systems have improved dramatically. These systems are able to analyze historical and real-time data, use complex algorithmic models to predict equipment failures, and even automatically adjust production parameters to adapt to the real-time state of the equipment to ensure the continuous operation of the production line. In the automotive industry, predictive maintenance and troubleshooting technologies are used to monitor the performance of key components such as engines and transmissions to prevent breakdowns and ensure driving safety.

III. Optimization of numerical control algorithms based on mechatronics technology

III. A. Digital Intelligent Control Algorithm

Digital intelligent control algorithm is one of the key components of the digital intelligent control system of mechatronics based on digital modeling, and its design and optimization directly affect the performance and stability of the system. This study focuses on the characteristics and needs of mechatronics systems and proposes an innovative digital intelligent control algorithm aimed at realizing the intelligent monitoring and control of mechatronics systems. The specific form of the algorithm is:

$$u(t)=K_p\cdot e(t)+K_i\cdot\int_0^t e(\tau)d\tau+K_d\cdot\frac{de(t)}{dt} \tag{1}$$

where, $u(t)$ denotes the control input of the system; $e(t)$ denotes the error signal of the system; and K_p, K_i and K_d denote the proportional, integral and differential coefficients respectively, which are used to regulate the magnitude and rate of change of the control input.

The algorithm adopts the classical PID control structure to realize the precise control and stable operation of the electromechanical system by comprehensively adjusting the proportional, integral and differential of the error signal. In addition, in order to realize the real-time monitoring and response of the system, the state-space equation is introduced for describing the evolution law of the system state, and the related calculation formula is:

$$x(t)=x(t-\Delta t)+\Delta t\cdot f(x(t),u(t)) \tag{2}$$

where, $x(t)$ denotes the state vector of the system at moment t; $f(x(t),u(t))$ denotes the state transfer function of the system. By numerically solving the state space equations, the state information of the system at different time points can be obtained, thus realizing real-time monitoring and tracking of the system state.

In the process of system design and optimization, the performance indexes in optimal control theory are adopted, such as the performance function $J(u)$ of the system:

$$J(u)=\frac{1}{2}\int_0^T\left[x^TQx+u^TRu\right]dt \tag{3}$$

The $J(u)$ function integrates the weighted sum of squares of the system's state variables x and the control inputs u over a period of time, and by adjusting the values of the weighting matrices Q and R, flexible regulation and optimization of the system's performance can be achieved [18].

III. B. Digital Modeling Methods and Techniques

Digital modeling methods and techniques play an important role in the design and implementation of mechatronic digital intelligent control systems. This study proposes a digital modeling methodology that integrates mathematical modeling, simulation and optimization techniques, aiming to achieve accurate description and simulation of the electromechanical system, so as to provide support and guarantee for the digital intelligent control of the system.

First, the mathematical modeling method is used to model the electromechanical system. Mathematical modeling is the process of abstracting the physical characteristics and movement laws of electromechanical systems into mathematical models, and through the analysis and abstraction of the structure and parameters of electromechanical systems, mathematical equations are established to describe the dynamic behavior and state changes of the system. Among them, the commonly used mathematical models include differential equations, integral equations, difference equations and so on. For example, for the mathematical modeling of an electric motor, the dynamic equations can be used to describe the relationship between the electromagnetic torque and rotational speed of the motor, i.e:

$$T_e=K_T\cdot I_a \tag{4}$$

$$J\cdot\frac{d\omega}{dt}=T_e-T_l \tag{5}$$

where, T_e denotes the electromagnetic torque of the motor; K_T denotes the torque constant of the motor; I_a denotes the current of the motor; J denotes the rotational inertia of the motor; ω denotes the rotational speed of the motor; and T_l denotes the load torque.

Secondly, simulation technology is used to simulate and analyze the established mathematical model. Simulation is the use of computers to simulate the operation process and performance performance of electromechanical systems, through the simulation and analysis of the system, it can quickly evaluate the design scheme and performance index of the system, discover potential problems and optimize them. Simulation software such as MATLAB/Simulink is used to simulate and analyze the rotational speed response of the motor to verify the accuracy and reliability of the mathematical model.

Finally, optimization techniques are used to optimize the simulation results. Optimization refers to finding the optimal system parameters and control strategies according to the design objectives and constraints of the system, so that the performance index of the system reaches the best state. Commonly used optimization methods include genetic algorithm, particle swarm algorithm, simulated annealing algorithm and so on. For example, in the motor control system, genetic algorithms can be used to optimize the control parameters, so that the speed control accuracy and response speed of the motor are optimized [19].

III. C. Digital Modeling and Implementation of Control System Functions

Digital modeling and the realization of control system functions are key aspects in the study of mechatronic digital intelligent control systems based on digital modeling, which involves transforming detailed mathematical models into actual functions that can accurately control mechatronic systems. Through advanced modeling languages and simulation tools, such as MATLAB/Simulink, LabVIEW, etc., researchers are able to create complex mechatronic system models and simulate the system response in virtual environments, thus predicting the system performance before physical realization. These digital models not only include traditional dynamics and electrical characteristics, but also integrate elements such as sensor data, actuator behavior, and control strategies to ensure the comprehensiveness and practicality of the models. The core of realizing the control system functions lies in transforming these models into practical and executable control algorithms, which requires special software to convert the simulation model code into the code in the embedded system. The final realization of the system function also depends on efficient system integration and debugging.

During the integration process, control algorithms, electromechanical components, sensors and communication protocols must work seamlessly together to achieve the intended control accuracy and response speed. Commissioning involves careful calibration and performance evaluation of the system to ensure that each component meets the design requirements. During this phase, real-time monitoring and data analysis tools play an important role in helping engineers monitor real-time data about system operation and adjust parameters to optimize system performance. The realization of digital modeling and control system functions not only improves the design efficiency and operation efficiency of mechatronic systems, but also significantly improves the reliability and maintainability of the system, providing solid technical support for the future development of mechatronic systems. The continuous progress in this research field indicates that the application of mechatronics technology in the field of intelligent manufacturing and automation will be more and more promising.

IV. Smart manufacturing system design and implementation

IV. A. System architecture design

System architecture design is the cornerstone of building an intelligent manufacturing system based on mechatronics technology. It involves the planning of the entire production system from data flow to control logic. In the architectural design, it is necessary to ensure the efficient synergy between the components, as well as the adaptability and scalability of the system to external changes. Intelligent architecture design based on the concept of layered design realizes the effective integration and optimization of manufacturing resources. For example, the physical equipment at the bottom layer communicates with the decision analysis module at the upper layer through sensors in real time, and the data processing layer analyzes and processes the collected information to provide a basis for the intelligent decision-making at the upper layer. The system architecture design is shown in Figure 1. This hierarchical design not only improves the stability and efficiency of the system operation, but also facilitates the maintenance and upgrading in the later stage [20].

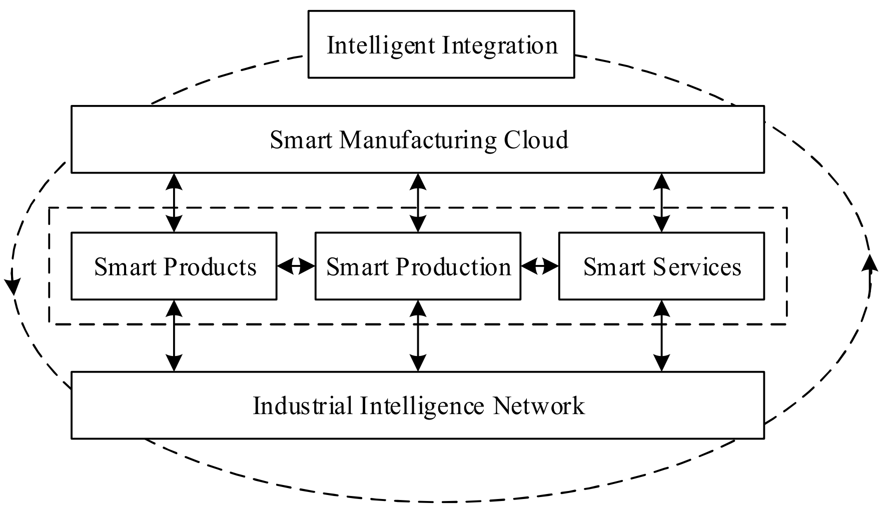

Figure 1: System architecture design

IV. B. Intelligent Manufacturing System Hierarchy Design

According to the above intelligent manufacturing system hierarchical demand requirements analysis, based on the reference system, combined with a company's existing manufacturing and management system, designed a company's intelligent manufacturing system hierarchical model, the hierarchy is designed to be divided into the enterprise layer, management layer, operating layer, control layer and the field layer; where the enterprise layer and the management layer contains the analysis and decision-making support layer, the operating layer contains the data storage layer, and the field layer contains the data acquisition layer as shown in Figure 2. The field layer contains the data acquisition layer as shown in Figure 2.

(1) Enterprise layer

The enterprise layer is the highest level in the company's intelligent manufacturing system hierarchy model. In addition to the analysis and decision support layer, this layer also integrates the product design system, product lifecycle system; through the PLM, MES and ERP systems for the company to realize the full digital definition. And through the Internet of Things (IoT) technology through all the layers of the intelligent manufacturing system, even if the bottom module is abnormal, it will be the first time to feedback to the top layer, greatly accelerating the response speed. Effectively improve production and management efficiency.

(2) Management

Management is mainly responsible for the production plan in the implementation of the main functional departments and daily management, and accept the production plan implementation status of each production link, product quality status, logistics status, equipment status, personnel status, environmental and resource conditions of the feedback information, and make reasonable real-time adjustments. And for the enterprise level decision-making and analysis to provide appropriate support.

(3) Operation layer

The operation layer plays the role of the top and the bottom. Through the process control system and data acquisition system in the integrated automation system, the production process of each production function department is controlled and process information and data are recorded. For the later process analysis to provide important data support.

(4) Control layer

The control layer is mainly based on the CPS network method, through the TIA technology to integrate the field production equipment to physically create the underlying industrial network. Realize all the equipment on site access to the same platform for control, under the same platform can fully grasp the state of each production element, do a good job of production balance and other work.

(5) Field Layer

Field layer through the industrial control system, distributed I / O, process instrumentation and analysis system and industrial identification system to receive instructions from the upper level, the operation of the equipment; and on-site emergencies occurring in a timely manner feedback, and record information and data to facilitate high-level modules to make the appropriate adjustments and responses, so that the production of the product can be carried out smoothly.

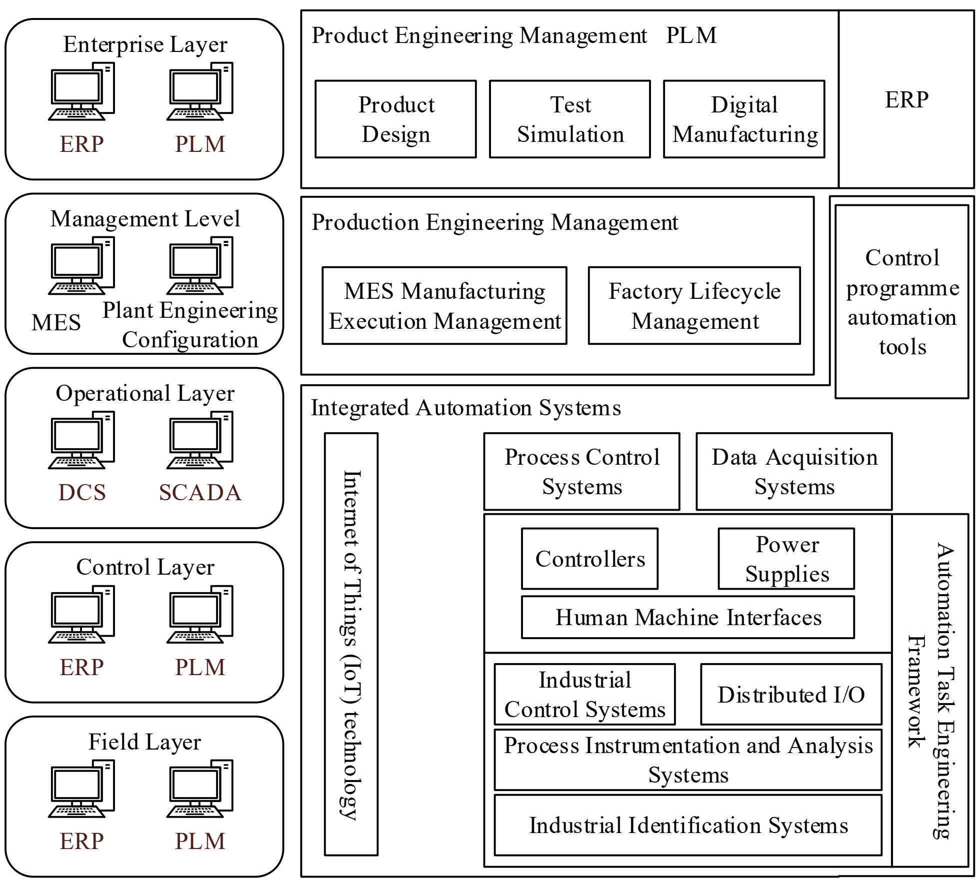

Figure 2: Company intelligent manufacturing system hierarchy model

IV. C. Intelligent production plan management

Active real-time production planning management system is mainly composed of four parts, namely, production planning intelligence module, task allocation intelligence module, production resource intelligence module and arbitration module, active real-time production planning management system framework shown in Figure 3. A company's active real-time production planning management system is based on ERP system development of a system, this system is not only the company's original independent operation of the production planning management of each workshop integrated into a unified platform, to achieve the product-oriented production planning management. Moreover, if a certain product part needs to be produced across factories, the production plan can also be coordinated under the same platform. This system also opens up the external upstream and downstream interfaces, which can speed up the response speed to the production plan changes or emergencies occurring in suppliers or customers, making the product-oriented production planning more reasonable, efficient and economical.

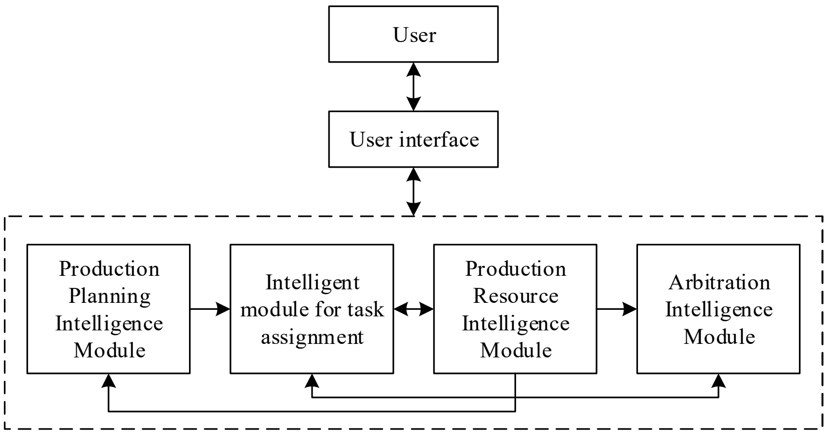

Figure 3: real-time production planning management system framework

V. System application performance testing

V. A. System Test Environment Setup

In order to ensure that the designed intelligent manufacturing system has good performance in the production of actual workpieces and products, it is necessary to test the system under normal operating conditions. The equipment in the system is mainly numerical control and acquisition equipment, the numerical control equipment includes lathe, robot arm and controller, etc., and the acquisition equipment includes temperature and vibration sensors, concentrator and chassis. Install the execution file on the PC, complete the parameter configuration, including the service address and port settings. After successful function debugging, the products are manufactured and processed.

V. B. System test results

V. B. 1) Load testing

The index selected for this performance test is the memory utilization rate. In the system program, the processing time and process steps of the products are set respectively, and the number of manufactured products is set to be 2,000, 6,000 and 12,000 respectively, and the problems of program delay and application failure are prevented in the continuous production of the products. The performance comparison results of the intelligent manufacturing system in different operation scenarios are shown in Table 1. Under the test condition of continuously processing 2000 pieces of products, the average memory occupancy rate of the mechatronics-based intelligent manufacturing system is 15.205%, which is 12.702% and 18.054% lower than that of the digital twin-based and cloud computing-based intelligent manufacturing systems.

Table 1: The memory occupancy rate of 2000 products

Test times	Intelligent manufacturing system based on electromechanical integration/%	Intelligent manufacturing system based on digital twin/%	Intelligent manufacturing system based on cloud computing/%
1	18.22	25.08	34.22
2	16.78	26.77	35.98
3	12.67	24.59	30.78

4	15.89	22.39	28.69
5	9.86	28.56	35.86
6	15.52	30.25	33.23
7	16.69	31.69	33.94
8	18.78	26.78	30.63
9	13.36	28.39	36.78
10	14.28	34.57	32.48

The memory occupancy of processing 6000 products is shown in Table 2. Under the test condition of continuously processing 6000 products, the average memory occupancy of the intelligent manufacturing system based on mechatronics technology is 22.82%, which is 18.03% and 13.535% lower than that of the digital twin-based and cloud computing-based intelligent manufacturing systems.

Table 2: The memory occupancy rate of 6000 products

Test times/times	Intelligent manufacturing system based on electromechanical integration/%	Intelligent manufacturing system based on digital twin/%	Intelligent manufacturing system based on cloud computing/%
1	22.15	36.45	2.68
2	21.69	38.59	40.25
3	20.58	40.78	40.12
4	20.00	40.48	38.78
5	18.49	43.59	41.97
6	26.36	45.89	42.87
7	25.63	36.79	40.58
8	28.46	38.59	40.16
9	24.89	45.06	37.39
10	19.95	42.28	38.75

The memory occupancy of processing 12,000 products is shown in Table 3. Under the test condition of continuously processing 12,000 products, the average memory occupancy of the intelligent manufacturing system based on mechatronics technology is 36.872%, which is 18.994% and 14.308% lower than that of the digital twin-based and cloud computing-based intelligent manufacturing systems.

Table 3: The memory occupancy rate of 12000 products

Test times/times	Intelligent manufacturing system based on electromechanical integration/%	Intelligent manufacturing system based on digital twin/%	Intelligent manufacturing system based on cloud computing/%
1	32.46	55.28	52.48
2	36.69	56.68	50.18
3	35.63	52.38	50.69
4	38.97	55.67	48.97
5	38.04	58.34	52.78
6	37.89	59.26	52.39
7	33.46	54.68	46.69
8	35.10	55.46	52.78
9	40.36	56.03	53.28
10	40.12	54.88	51.56

On this basis, the intelligent manufacturing systems under different running times are tested, and the overall memory occupancy rate changes are shown in Fig. 4. The memory utilization rate of the intelligent manufacturing system in operation is below 80%, and the above three intelligent manufacturing systems do not exceed 70%, which is in line with the passing standard under normal operation conditions. The highest memory occupancy rate of the intelligent manufacturing system based on mechatronics technology designed in this paper is about 45%, while the highest is about 67% and 62% for the intelligent manufacturing system based on digital twin and based on cloud computing, therefore, the intelligent manufacturing system based on mechatronics technology has better performance, and occupies fewer computer resources to complete the product manufacturing process, and to complete the automated transportation of the workpieces and the operations such as warehousing and realize the Intelligent manufacturing.

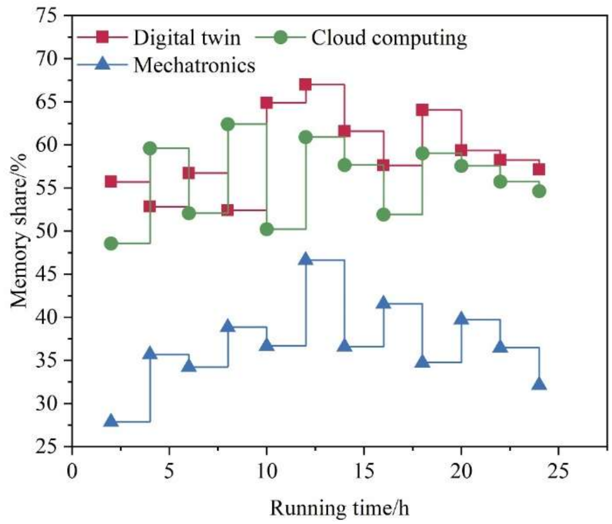

Figure 4: Memory occupancy rate changes

V. B. 2) Functional testing

In order to ensure the accurate execution of the functions of the mechatronics system, this paper designs a detailed functional test program, constructs a test environment that simulates the industrial site, and is equipped with standard test equipment and loads. The test results are shown in Table 4. The test process includes the data acquisition function where sensors deployed in different locations collect data and upload them to the cloud in real time to verify data integrity and real-time performance. Remote monitoring function controls the equipment remotely from the mobile terminal to observe the response speed and operation accuracy. Resource scheduling function adjusts the allocation of system resources according to a preset strategy to record scheduling efficiency and system stability. Fault diagnosis function simulates common fault situations to test the sensitivity of the system's self-diagnosis and alarm mechanism. All the tests are carried out under controlled conditions, specific indicators, such as response time, data loss rate, etc. have reached the expected goal, the functional test results show that the system performance is good.

Table 4: functional test results table

Functional module	Test index	Target value	Measured value	Results
Data acquisition	Data integrity	100	100	Pass
	Real time(s)	≤3	2.5	Pass
Remote monitoring	Response time(s)	≤3	2.4	Pass
Resource scheduling	Dispatching efficiency (%)	≥96	96.8	Pass
Fault diagnosis	Diagnostic accuracy (%)	≥90	98.8	Pass

V. B. 3) Performance testing

The performance test results are shown in Table 5, focusing on evaluating the stability and efficiency of the system under high load conditions, and its test environment simulates the data traffic and complex task scenarios during peak hours, thus ensuring that the test conditions are close to real applications. Tests include system concurrent processing capacity, data processing delay, resource utilization and long-time operation stability. The testing procedure involves gradually increasing the system load until it reaches the design limit, and recording the changes in various performance indicators. The test results show that even under high load, the system can still maintain efficient and stable operation, with low data processing delay, reasonable resource utilization and no abnormal interruptions, which proves that the performance of the system in this paper meets the design expectations.

Table 5: Performance test results table

Performance indicator	Target value	Measured value	Results
Concurrent processing capability (Request/s)	≥500	524	Pass
Data processing latency (ms)	≤50	36	Pass
The cpsa occupancy rate is at (%)	≤70	64%	Pass
Memory occupancy rate (%)	≤80	78%	Pass
Operational stability (h)	≥75	No interrupt operation 75	Pass

VI. Conclusion

In this study, through the comprehensive design and test verification of the intelligent manufacturing system based on mechatronics technology, the system shows significant advantages in several key performance indicators. The load test results show that under the condition of continuously processing 6000 products, the average memory occupancy rate of the system is only 22.82%, which is 18.03% and 13.535% lower than that of similar systems based on digital twin and cloud computing, respectively, reflecting excellent resource utilization efficiency. Functional tests verify the reliability of the system modules, in which the response time for remote monitoring reaches 2.4 seconds and the resource scheduling efficiency is as high as 96.8%, which both meet the real-time requirements of industrial applications. The performance test further confirms the stability of the system, with a concurrent processing capacity of 524 requests per second and a data processing delay of only 36 milliseconds, which fully meets the application requirements of high-load industrial environments. The designed five-layer architecture model effectively integrates the functions from the enterprise layer to the field layer, realizing the intelligent management of the whole process from data collection to decision analysis. The application of digital intelligent control algorithms significantly improves the control accuracy and stability of the system, providing a reliable guarantee for the precision machining of metal materials. The study provides a complete technical solution for the application of intelligent manufacturing technology in the field of metal material processing, and is of great practical guidance significance for promoting the digital transformation of manufacturing industry.

References

[1] Chen, Y. (2017). Integrated and intelligent manufacturing: Perspectives and enablers. Engineering, 3(5), 588-595.
[2] Liang, S., Rajora, M., Liu, X., Yue, C., Zou, P., & Wang, L. (2018). Intelligent manufacturing systems: A review. International Journal of Mechanical Engineering and Robotics Research, 7(3), 324-330.
[3] Barari, A., de Sales Guerra Tsuzuki, M., Cohen, Y., & Macchi, M. (2021). Intelligent manufacturing systems towards industry 4.0 era. Journal of Intelligent Manufacturing, 32, 1793-1796.
[4] Ryalat, M., Franco, E., Elmoaqet, H., Almtireen, N., & Al-Refai, G. (2024). The integration of advanced mechatronic systems into industry 4.0 for smart manufacturing. Sustainability, 16(19), 8504.
[5] Kuru, K., & Yetgin, H. (2019). Transformation to advanced mechatronics systems within new industrial revolution: A novel framework in automation of everything (AoE). IEEE Access, 7, 41395-41415.
[6] Chen, X. (2023). Application of intelligent control in mechatronics system. Engineering Advances, 3(2).
[7] Gheorghe, G. (2019, July). Concepts and mechatronics and cyber-mixmechatronics constructions, integrated in COBOT type technology platform for intelligent industry (4.0). In International Conference of Mechatronics and Cyber-Mixmechatronics (pp. 281-300). Cham: Springer International Publishing.
[8] Liagkou, V., Stylios, C., Pappa, L., & Petunin, A. (2021). Challenges and opportunities in industry 4.0 for mechatronics, artificial intelligence and cybernetics. Electronics, 10(16), 2001.
[9] Zaitceva, I., & Andrievsky, B. (2022). Methods of intelligent control in mechatronics and robotic engineering: A survey. Electronics, 11(15), 2443.
[10] Lin, S., Jia, L., Wang, Y., & Zhang, H. (2020). A new function-topology-based method for assessing passive safety of mechatronics systems. IEEE Access, 8, 9312-9324.
[11] Zheng, S., Wang, S., Chen, X., Xie, Y., Shi, P., & Jiang, Z. (2023). Logic-based switching finite-time stabilization with applications in mechatronic systems. International Journal of Robust and Nonlinear Control, 33(5), 3064-3085.
[12] Mule, S., Hehenberger, P., Plateaux, R., Penas, O., Patalano, S., & Vitolo, F. (2021). An approach and an illustrative case study for a hybrid development process in mechatronic system design. International Journal of Product Lifecycle Management, 13(3), 265-289.
[13] Mohebbi, A., Achiche, S., & Baron, L. (2020). A fuzzy-based framework to support multicriteria design of mechatronic systems. Journal of Computational Design and Engineering, 7(6), 816-829.
[14] Li, J., & Liu, L. (2021, July). Conceptual Design of Mechatronics System Based on Intelligent Control. In Journal of Physics: Conference Series (Vol. 1982, No. 1, p. 012113). IOP Publishing.
[15] Guo, K. (2022). Special Issue on Application of Artificial Intelligence in Mechatronics. Applied Sciences, 13(1), 158.
[16] Ambadekar, P. K., Ambadekar, S., Choudhari, C. M., Patil, S. A., & Gawande, S. H. (2025). Artificial intelligence and its relevance in mechanical engineering from Industry 4.0 perspective. Australian Journal of Mechanical Engineering, 23(1), 110-130.
[17] Orlowska-Kowalska, T., & Wolkiewicz, M. (2022). Fault Diagnosis and Prognosis of Mechatronic Systems Using Artificial Intelligence and Estimation Theory. Electronics, 11(21), 3528.

[18] Yang Zhang,Zhang Yang,Chang Jianghua,Fan Dong & Tian Hongliang. (2020). Research on Intelligent Control Algorithm for Automatic Drilling of Vehicle-mounted Rig. Journal of Physics: Conference Series,1650(3),032037-.

[19] Xining Li,Shiqi Song & Yuzhi Liu. (2025). Deformation control of piezoelectric intelligent curved shell structure with multiple actuators based on neural network optimized by genetic algorithm. Measurement,242(PC),115967-115967.

[20] Tien-I Liu & Chong Oh. (2005). An artificial intelligence approach for the design andmanufacturing of micro electro mechanical systems. International Journal of Knowledge-based and Intelligent EngineeringSystems,9(2),159-171.