Adaptive Scheduling of Robots in the Mixed Flow Workshop of Industrial Internet of Things

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***Abstract*—With the deep integration of industrial Internet of Things technology and artificial intelligence technology, the material robot has been widely used in the Internet of Things workshop. In view of many complex factors such as real-time dynamic change and uncertain condition in workshop, this paper proposes to realize workshop adaptive scheduling decision with component layer construction and SPMCTS search method with real-time state as the root node. This method transforms the robot scheduling problem into a Markov decision process and describes a detailed representation of workshop states, actions, rewards, and strategies. In the real-time scheduling process, the search method is based on the artifact component layer construction, and only considers the state relationship between two adjacent groups, so as to simplify the calculation difficulty. In the subtree search, SPMCTS is applied to search the real-time state as the root node, and the extension method and shear method are applied to conduct strategy exploration and information accumulation, so that the deeper the real-time state node in the subtree, the more the optimal strategy can be obtained quickly and accurately. Finally, the effectiveness and superiority of the proposed method are verified by real case simulation analysis.**

Keywords*—Industrial Internet of Things; mixed flow workshop; robot; Markov decision-making process; SPMCTS

I. INTRODUCTION

In this paper, the performance detection of the robot in the modern factory needs to be optimized, combined with the design of monitoring software, the diversified communication mode; under the premise of data transmission stability, efficient, remote and low-cost transmission wireless network, based on data transmission [1, 2] under TCP / IP communication protocol, remote control terminal design under 3G network, and unified database management. Utilizing optimization algorithms such as genetic algorithms, particle swarm optimization, or simulated annealing to solve complex scheduling problems. These algorithms can be applied to minimize makespan, reduce idle time, and balance workloads in the workshop. Mathematical modeling techniques like queuing theory and Markov chains can also be used to analyze system dynamics and predict performance metrics such as throughput and cycle time. Furthermore, statistical methods such as regression analysis and hypothesis testing can help evaluate the impact of scheduling strategies on productivity and efficiency. The current stage of Internet of Things (IoT) application, both domestically and internationally, is in the developmental phase. However, the establishment of an IoT framework based on the robot testing system remains imperfect. In this context, a more economical and effective approach is required for robot testing. Utilizing high-precision sensors, employing digital output data acquisition methods, and leveraging Ethernet transmission can effectively capture measurement results. This facilitates the enhancement of robot performance parameters, particularly in modern factories where simultaneous multi-station measurements are common. Establishing a multi-node base station within a regional wireless network enables data transmission to a centralized database server terminal, facilitating remote detection and data analysis, which holds significant importance. IIoT enables seamless connectivity between devices, machines, and systems, facilitating efficient communication and coordination in dynamic manufacturing environments. By leveraging IIoT technologies, such as sensor networks and cloud computing, the proposed method can gather real-time production data, optimize scheduling decisions, and dynamically adjust to changing operational conditions. This integration of IIoT enhances agility, flexibility, and responsiveness in robot scheduling, ultimately improving productivity and competitiveness in industrial settings. Robot parameters including current, tracking error, torque, speed for mostly need technicians' site real-time acquisition, and in the environment of the Internet of things, using the 3G network and network operators, remote monitoring robot, to real-time understand the running condition of the robot, alarm, etc., improve the safety and efficiency of field operation. Connecting everything to the same network through a communication device. This is our most basic definition of the Internet of Things. The Internet of Things is a relatively broad concept, its related technologies are more comprehensive, the most typical is the radio frequency technology, it is the characteristics of the initial Internet of things, other there are sensing technology, electronic technology, communication technology and so on. At first, the application of RF technology was more mainly in the food transportation industry, but the inclusiveness and scalability of its technology are also applicable to the industrial field. More and more products are using connected to their enterprise networks for [3, 4], especially in the robotics industry. The concept of "the Internet of Things" was established in 2005, organized by the ITU, at the Information Society Summit held in Tunisia. ITU detailed the features of the Internet of Things, introduced the design technology, and analyzed the market opportunities and pressure challenges as shown in Fig. 1. Integrating deep learning algorithms for intelligent scheduling, leveraging big data analytics to optimize production efficiency, designing smart sensors for real-time monitoring and feedback, researching machine learning models to streamline workflows, and developing intelligent control systems to enhance autonomous decision-making. These works can be scientifically validated through empirical research, simulation modeling, and case studies to demonstrate their effectiveness in improving production efficiency, reducing costs, and optimizing resource utilization.

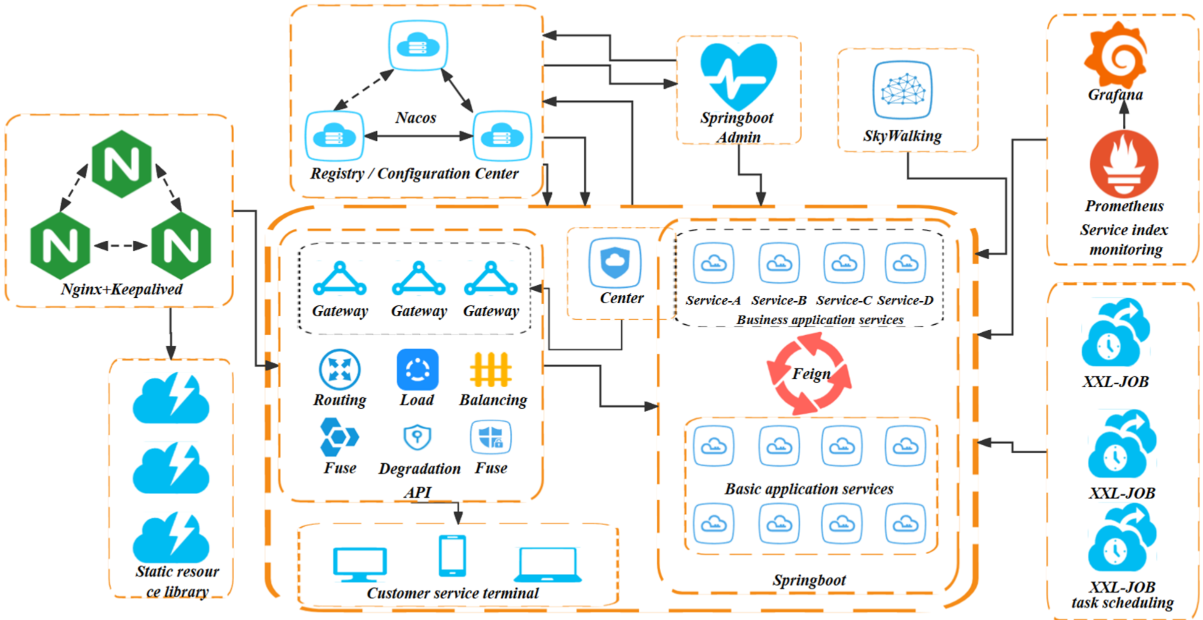

Fig. 1. Communication technology diagram.

In the field of communication and even the whole field of information technology, the of Things has become an inevitable development trend, not only affecting the field of communication, but even the whole field of information technology. Each figure should be accompanied by concise yet informative captions to provide context and aid comprehension. Additionally, ensuring consistency in design elements, such as color schemes and labeling conventions, contributes to the overall clarity and professionalism of the figures. By improving the quality of figures and providing clear explanations, readers can better grasp the complexities of the proposed methodologies and results. In terms of promoting social progress, the Internet of Things industry has promoted industrial upgrading. With Japan, South Korea, the United States, the European Union and other developed countries and regions, they have been at the forefront of the world of Internet of Things research. Japan's Internet of Things technology has been able to respond to disasters, apply in security management, public services and other fields, and advocate mobile payment [5, 6] in large-scale commercial use. In South Korea, cloud computing is an important platform for massive information processing of the Internet of Things, and its technology development has greatly promoted the development space of the Internet of Things. In terms of Internet of Things research, the United States has a great advantage, and many universities and research institutes have done a lot of research on wireless sensor networks. The current research method was chosen for its ability to address the dynamic scheduling challenges posed by IIoT-enabled mixed flow workshops. Unlike traditional methods, which often rely on static scheduling approaches, the proposed method leverages real-time data from interconnected devices to adaptively allocate tasks among robots. This real-time adaptability is crucial for optimizing production efficiency, minimizing downtime, and responding to changing manufacturing demands swiftly. By comparing with traditional methods, the superiority of the proposed approach in terms of flexibility, responsiveness, and overall operational performance can be clearly demonstrated. The current paper lacks a coherent introduction that clearly outlines the purpose, scope, and significance of the research. To enhance the quality of the paper, the authors should provide a concise overview of the problem addressed, the methodology employed, and the primary contributions of the study. Specifically, in the context of adaptive scheduling of robots in the mixed flow workshop of the industrial Internet of Things (IIoT), the introduction should emphasize the critical need for efficient scheduling methods to optimize production processes and resource allocation in dynamic manufacturing environments. Furthermore, it should highlight the importance of integrating IIoT technologies with industrial robotics to enable real-time monitoring, data analytics, and adaptive decision-making, thereby enhancing productivity and efficiency. Over the past ten years, it has made great progress in wireless intelligent sensor network communication technology, micro sensor and many other Internet of Thing's technologies, and has certain technological advantages. The Internet of Things technology has received more and more attention in China. Some major domestic engineering enterprises and scientific research institutions have participated in the research and development of the "monitoring system", on behalf of Xugong Machinery Group, Sany Heavy Industry and Tiangong Machinery Research Institute. At present, the monitoring system has been partially completed for the field operation equipment, and intelligent transformation. The next step will be a simulation demonstration for the practical application of the project that need to be monitored. The motivation behind the proposed work lies in addressing the evolving needs of modern manufacturing facilitated by the Industrial Internet of Things (IIoT). Research gaps exist in the realm of adaptive scheduling for robots in mixed flow workshops, where traditional static methods fall short in meeting dynamic production demands. The objective is to develop a robust scheduling framework that harnesses IIoT capabilities to optimize task allocation, minimize delays, and enhance overall productivity. This research aims to bridge the gap between traditional scheduling methods and the requirements of agile, IIoT-driven manufacturing environments, ultimately improving operational efficiency and competitiveness. However, the development technology of domestic monitoring system is not mature, and there are still the following problems: single function: the research of the system is still in the exploration stage, the product function is not perfect, the remote communication function cannot be realized, the real-time is not high, low efficiency is poor, cannot meet the higher requirements of system design. Due to the limitations of the communication equipment, the data acquisition device in the system saves the collected data to the built-in or external expansion memory of the micro controller, which requires additional configuration of terminals for docking analysis. This brings great inconvenience to debugging and maintenance, and the storage equipment capacity is limited, and also costs a lot of maintenance costs, the security and reliability of the system remains to be discussed. And the content of the relevant technical field, the country has not made the relevant standards. The development situation of foreign countries, take the “remote service” proposed by ABB as an example [7, 8]. The concept was proposed for the robot to alarm to its own failure.During the simulation phase of the research work, the authors may have made assumptions regarding the deterministic nature of robot motion and ignored sensor errors, environmental changes, and fault conditions. These assumptions could lead to deviations between simulation results and real-world scenarios, affecting the credibility and practicality of the study. Therefore, the critique should involve a thorough analysis of the rationale behind these assumptions, their impact on research findings, and suggestions for potential improvements to enhance the accuracy and fidelity of the simulation.

II. Repeated Positioning Accuracy Test System for Industrial Robot

A. System Architecture

The repeated positioning accuracy of the robot refers to the ability of the robot to repeatedly reach the specified command or teaching position. The results are affected by the control system, surrounding environment, transient corresponding conditions of the system, wear of parts, etc. The numerical measurement is helpful to optimize the structure and control mode of the robot and improve the operation ability of the robot. In the manufacturing and production of industrial robots, it is necessary to detect the repeated positioning accuracy of finished robots. At present, most laser tracking instrument is used for detection. The laser tracking instrument has high measurement accuracy and many measurement functions. However, in the measurement process, the tester needs to track the operation in real time and record the measurement data in real time, and the end needs the robot to accurately [9, 10] with the tracking instrument. The final measurement data needs to be processed by the tester, so only the robot can be tested at a single station. The equipment cost of laser tracker is high, and a certain software service fees paid every year. The equipment is only suitable for the research and development of industrial robot, and is not suitable for the testing application of industrial robot mass production. In view of the above problems, this paper proposes a test system with low cost, simple operation, simultaneous MultiTaction measurement, and certain data processing system.

The industrial robot repeated positioning accuracy test system is mainly composed of the test system mainly composed of detection device, data acquisition device and data processing terminal. The detection device measures the spatial position of the robot end with the displacement laser sensor; the data acquisition device connects the controller and the sensor in serial port and preliminarily processes the data. Fig. 2 shows that the standard protocol based on OPC communication transmits the data to the terminal through the wireless device, generates the data report, displays the real-time curve of measurement, obtains the final measurement value, and completes the whole monitoring process [11, 12].

The detection device is composed of three laser sensors fixed on the mounting bracket. The three coordinates of x, y and z in the simulation space are used as the reference coordinate system to determine the end position of the robot. The acquisition signal is transmitted to the small controller by the control unit through the interface of the RS232. There are relevant touch screen devices and wireless devices at the test site, which can receive and view data remotely. The final data terminal processes the data, displays and analyzes the data, and equipped with relevant output equipment to save the final result. The measurement method adopts the traditional measurement method, which teaches the robot to reach the specified position in the space, and lets the robot run the command position repeatedly, measures the position value of each time, and makes relevant records and processing. The final collected data is remotely transmitted to the terminal server through the wireless device, and the data is viewed on the display screen to observe the real-time images. The detection part of the system adopts the contactless measurement method, so the laser sensor is used to measure the end position of the robot. The principle of triangulation is the basic principle of the laser sensor. The detection head emits the visible red laser to the surface of the measured object [13, 14], the sensor will receive the laser reflected by the object, and the internal CMOS signal amplifier will process the reflected light. When the target object changes, the position of the light presented on the CMOS moves. The amount of change of the target is determined by detecting the light position. At the same time, the control unit will calculate the beam position of the original, and output the corresponding value randomly. The sensor of this system has a resolution of 1 μ m and a repetition rate of 2 μ m. The fixed displacement sensor device is an adjustable bracket. The adjustable bracket can adjust the height position in the sensor space. The bottom of the bracket is equipped with universal ball and adjustable foot cup, which is easy to move the whole bracket and fix the bracket position, so as to measure the repeated positioning accuracy of the robot moving to different points in the space. The sensor is mounted on the bracket, so that the projected light is vertical to each other in space, which can be compared to the three-dimensional coordinate system of space. When measuring, by controlling the position of the robot to reach the axis of the sensor. In addition, to ensure that the laser can be projected at the end of the robot, rectangular block loads are installed at the end of the robot. This kind of load has three different vertical sides, which can ensure that the laser can illuminate vertically. Table I shows that Key Considerations for Adaptive Scheduling in IIoT Robotics. However, the laser accuracy of the sensor will show different changes due to the influence of different irradiation surfaces, so the ceramic measuring sheet [15, 16] is installed on the load surface to ensure that the accuracy of the sensor reaches the best state during measurement.

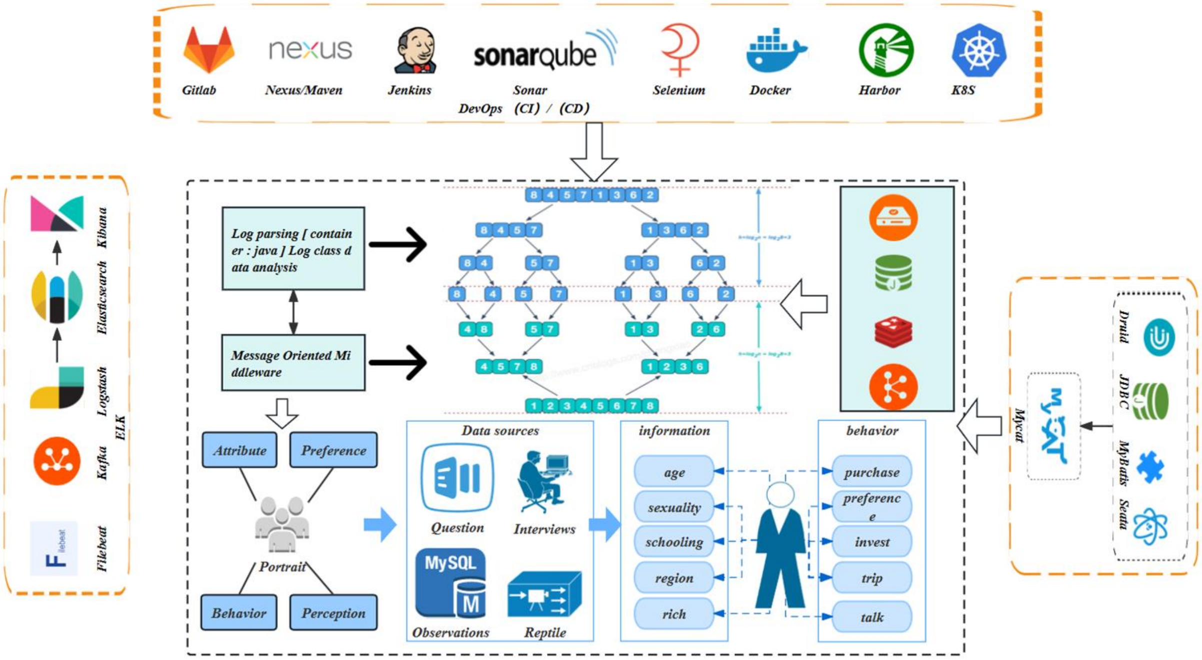

Fig. 2. OPC Communication diagram.

TABLE I. KEY CONSIDERATIONS FOR ADAPTIVE SCHEDULING IN IIOT ROBOTICS

Challenges	Description	Solutions	Benefits	Implementation
Dynamic Workload Variation	Variations in task demands require adaptive scheduling algorithms.	Dynamic task allocation algorithms.	Optimized resource utilization.	Real-time monitoring and adjustment.
Real-time Data Processing	Quick processing of sensor data and task updates is crucial for efficient scheduling.	Edge computing and real-time analytics.	Reduced latency and faster decision-making.	Integration of AI algorithms for predictive analytics.
Interoperability of IoT Devices	Compatibility issues between different IoT devices and platforms.	Standardization of communication protocols.	Seamless data exchange between devices.	Integration of IoT middleware solutions.
Optimization of Energy Consumption	Efficient scheduling to minimize energy consumption and operational costs.	Energy-aware scheduling algorithms.	Reduced energy bills and environmental impact.	Integration of smart energy management systems.
Integration with Existing Systems	Integration challenges with legacy systems and equipment.	Middleware solutions for legacy system integration.	Improved system interoperability.	Retrofitting and API development for legacy system compatibility.

B. Architecture Design

This system uses the B & R X20 series compact small controller. The task cycle of X20 can reach 200us, the instruction cycle can reach 0.01us, and X20 can be installed on the commonly used guide rail, which is fully distributed I / O. The corresponding communication interface for the data collection of the system is RS232 serial communication. RS232 communication is suitable for communication in the range of 0-20000 bit/s. RS232 standard was originally developed by remote optical communication connecting data terminal device DTE and data communication device DCE. At present, the connection between the computer and the terminal, peripherals and other devices is more widely used. The serial communication mode of RS232 is separating the system from the traditional sensor detection data. The traditional sensor data collection is mostly output by 0-5V or 4 - 20 mA. In the process of processing the simulated signal, there are calculation errors and acquisition efficiency, and the accuracy of the data is not high. The sensors of this system adopt the Keens L series, adopt the pioneering series networking mode, and the three-coordinate data can be output by its equipped DL-RS1A communication unit. It sends instructions to the communication unit through an external device, and the communication unit automatically returns the response value. The connection between the controller and the communication unit belongs to the connection of two DTE devices. Instead of providing any hardware handshake signal connection but using the software to control the communication data flow. The wiring diagram is shown in the following figure: The transmission communication specification is 115200 bit/s, the data length is 8bit, no parity bit, and the stop bit length is 1bit. The instruction code is the transmission code based on ASC code, which includes reading instructions, writing instructions and reading and writing instructions. Currently, the data collection frequency is 50Hz. Add the required sending instruction to the data collection program, red the corresponding string data, and convert the final data. The system filters the median value average of the collected data, which is a common digital filtering method. This method is suitable for filtering the signal with random interference, and the fluctuation interference caused by accidental factors can be effectively overcome to eliminate the sampling value deviation caused by it. The specific treatment method is as follows (such as x direction), the median average filtering method, as the name suggests, is the "median filter method" + "arithmetic average filtering" method, Take N points in a sampling period, remove the minimum and maximum points, and calculate the average [17, 18] for the remaining N-2 data, and the result is used as the effective date of one collection.

III. Factory Wireless Monitoring System for Industrial Robot Debugging Station

A. System Architecture

The design of the system follows the principles: complete functions, stable performance, low cost. Considering field implementation and subsequent maintenance efforts, the system needs good scalability and portability. The following are detailed requirements: according to the actual needs and technical conditions, according to the site environment, the design of the system needs to meet the actual production requirements. It is then initialized on the following basis:

Its residual values were then calculated, using each individual Loss function of the sample as the residual value of Equation (1):

$$r_{mi} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right] \tag{1}$$

It was then fitted to a CART regression tree to obtain the set of leaf points. Then update the forecast results as Equation (2):

$$f_m(x) = f_m - 1(x) + \sum_{j=1}^{J} \varphi_{mj} \times I \tag{2}$$

Finally, we get the model of GBDT as Equation (3):

$$f = f_M(x) = \sum_{m-1}^{M} \sum_{i-1}^{J} \varphi_{mj} \times I \tag{3}$$

On the basis of ensuring the satisfying function, the cost is minimized. High reliability and safety are the important basic conditions of the system. Data collection and storage, the stability and safety of the equipment, as shown in Fig. 3, all require the good safety and reliability guarantee of the system. The system needs to support multiple interfaces for the docking of different devices to maximize compatibility. The design idea of redundancy and the added [19, 20] of new concepts and new functions require the system to have rich scalability. Improve the level of supervision and comprehensive management.

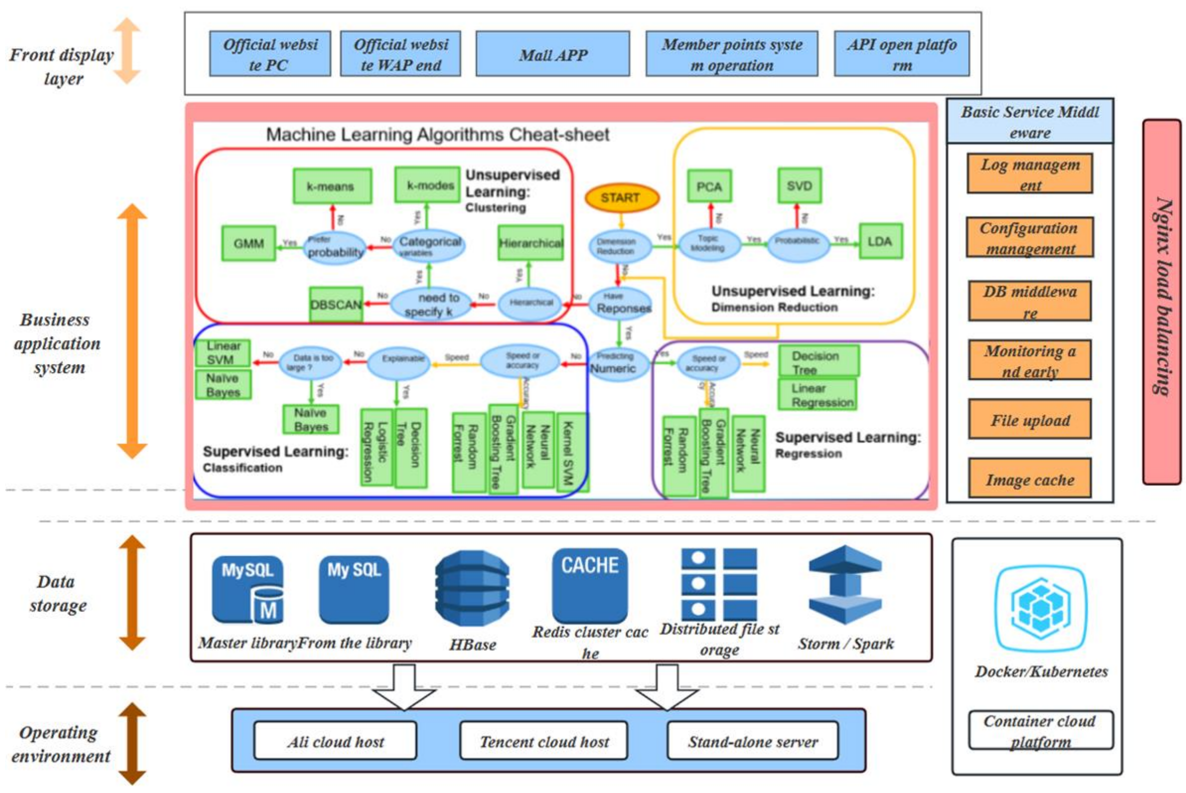

Fig. 3. Redundancy design diagram.

The Pearson's correlation coefficient between two variables is defined as the quotient of the covariance and standard deviation between two variables，Equation (4) display it:

$$\partial_{x,y} = \frac{cov(x,y)}{\chi_x \chi_y} = \frac{E[(x-\delta x)(y-\delta y)]}{\chi_x \chi_y} \tag{4}$$

The above Equation (5) defines the overall correlation coefficient, and the Greek lower case letter symbol is commonly used as the representative symbol. To estimate the covariance and standard deviation of the sample, Pearson correlation coefficient, common English small letters represent:

$$F = \frac{\sum_{j=1}^{m}(xi-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{j=1}^{m}(xi-\bar{x})^2}\sqrt{\sum_{j=1}^{m}(y_i-\bar{y})^2}} \tag{5}$$

The F letter can also be estimated by the standard score mean of the letter sample point to obtain an expression equivalent to the above Equation (6):

$$F = \frac{1}{m-1}\sum_{i-1}^{m}\left(\frac{xi-\bar{x}}{\chi_x}\right)\left(\frac{yi-\bar{y}}{\chi_y}\right) \tag{6}$$

In order to improve the efficiency and accuracy of the equipment control, the system should have sufficient supervision capacity. The background terminal can accept the production information [21, 22] in time, and can make a judgment in the first time, effectively reducing the complex problems on the site. On the basis of ensuring the normal production of the robot, it can predict the production problems of the new plant and give solutions in time. On the basis of reducing the equipment loss, reduce the maintenance cost to optimize the management. One of the core technologies of the Internet of Things is the radio frequency technology, and the most common application of the Internet of Things is to put the RF label on the product, combined with the Internet technology, to retrieve and save the product information. At present, radio frequency technology has been widely used in the modern manufacturing industry, and industrial robots are naturally essential.

We can do the statistics according to the following Equation (7):

$$t = \frac{d-\alpha_0}{s_d / \sqrt{n}} \tag{7}$$

And we award the following Equation (8) as the average of the paired sample difference:

$$d = \frac{\sum_{i=1}^{n} di}{n}, i = 1 \ldots n \tag{8}$$

We can know that the following Equation (9) is the standard deviation of the sample difference value:

$$sd = \sqrt{\frac{\sum_{i1}^{n}(di-d)^2}{n-1}} \tag{9}$$

Radio frequency technology is RFID, a non-contact automatic identification technology. The scanning device scans the product corresponding label [23, 24] by transmitting a wireless carrier signal to activate the label information. The label will return the corresponding carrier information and transmit it to the reader, and the final identifier sends the decoded information to the command detection device. RFID is the expansion and application of wireless technology, data collection breaks through certain limitations, on the basis of improving the data transmission speed, increase the transmission flexibility. The monitoring system design is based on the previous repeated positioning accuracy test system, which optimizes and expands the collected data transmission mode. Based on the requirements of factory multi-station testing and the situation that measured data can be returned at the same time, wireless transmission is more convenient and the cost is relatively low. The EPA client is installed at each test station to upload the collected data as the base station, while the server terminal in the main control room is equipped with wireless AP as the main station, so that a wireless network covering the entire factory can be established. Through this network, the measurement data can be monitored remotely in real time to improve the efficiency of data collection and analysis, which is conducive to the real-time analysis of the online state of the robot. According to the network structure, the system can be divided into three layers. To monitor the operation status of the robot in real time, it is necessary to equip PLC equipment at the debugging station of the robot to carry out the relevant data acquisition work [25, 26], and this equipment constitute the data acquisition layer. The collected data is uploaded to the background terminal through the WLAN network covering the factory, and is uniformly stored and managed logarithmically. This is the data processing layer. Finally, the processed data analysis disk will form the decision and solution to each operation terminal, so as to effectively monitor and manage the sound field and working conditions on the site. This is the data application layer.

B. System Function Realization

The system data acquisition device is still implemented by X20 series controllers, and X20 can also be used as a PLC device for field data collection. Here is mainly to explain the selection of wireless equipment. The wireless communication equipment of this system mainly uses phoenix WLAN5100, EPA and other wireless equipment WLAN5100 is phoenix based on industrial WLAN network design, aiming to make the production and logistics process more efficient and reliable. Its design is simple, reliable, safe and fast, and it is suitable for mobile communication automation and production system. Data mining is to extract potentially useful information from the data. To this end, we write computer programs that screen useful regularities or patterns in the database to enable our implementation methods. If you can find some obvious patterns and summarize them, it is very useful to predict future data. In the real world, data is actually incomplete: some are tampered with, others are lost. Everything we observe is not entirely precise: there are exceptions to any rule, and there are instances that do not conform to any one rule. The algorithm must be sufficiently robust to cope with imperfect data and can extract useful regularities [27, 28]. In recent years, the database has expanded rapidly, such as recording the customers' choice of commodity behavior as the database, which is bringing data mining to the preface of commercial application technology. It is estimated that the growth of data in the world will double every 20 months. Although it is difficult to really verify this number in the sense of quantity, but we can qualitatively increase my growth rate. The world is becoming more and more colorful, and people are immersed in these massive data, and the vision of insight into the patterns that constitute the data is placed on the data mining. Data mining is one of the most advanced research contents of database system and intelligent technology in recent years. The potential value of mining and learning data from the large amount of data and the discovery application rules are our simple definitions of data mining. The process consists of the following steps: data cleaning; data integration; data selection; data transformation and data mining.

The calculation formulas for the final model are Equation (10):

$$G(x)=\sum_{i=1}^{m}\alpha_i G_i(x) \tag{10}$$

Then we set the maximum number of cycles to kmax, and we evaluated the training results of the learner Ck by Equation (11):

$$Q_{k+1}(j)\rightarrow\frac{Q_k(j)}{Z_k}\times\begin{Bmatrix} e^{-\alpha k} \\ e^{\alpha k} \end{Bmatrix} \tag{11}$$

Then the weight is shown in Equation (12)

$$\alpha_i=\frac{1}{2}\times log\frac{1-e_i}{e_i} \tag{12}$$

Data mining technology has different categories according to the type of mining database, mining knowledge type, adopted mining technology and application occasions. Usually, according to the different knowledge types of mining, data mining can be divided into the following categories: association analysis, classification, prediction, sequence analysis, cluster analysis, and isolated point analysis. A very important research content in the field of data mining is data classification. According to the collected data, it finds models that can distinguish and describe different concepts or data, and classify them one by one according to objective attributes and marginal conditions. Decision trees, Bayesian methods, neural networks, genetic algorithms and instance inference are all common methods used for data classification. The wireless LAN module in the 510x series shown in Fig. 4 can provide maximum reliability, data throughput and coverage. WLAN5100 Combining the 802.11n-based standard industrial technology and the modern multi-input and multi-output antenna technology, [29, 30]. The three-antenna MiMo technology significantly increases the stability, speed, and range of wireless communication. The special function module of WLAN510x is that it can be configured quickly and easily.

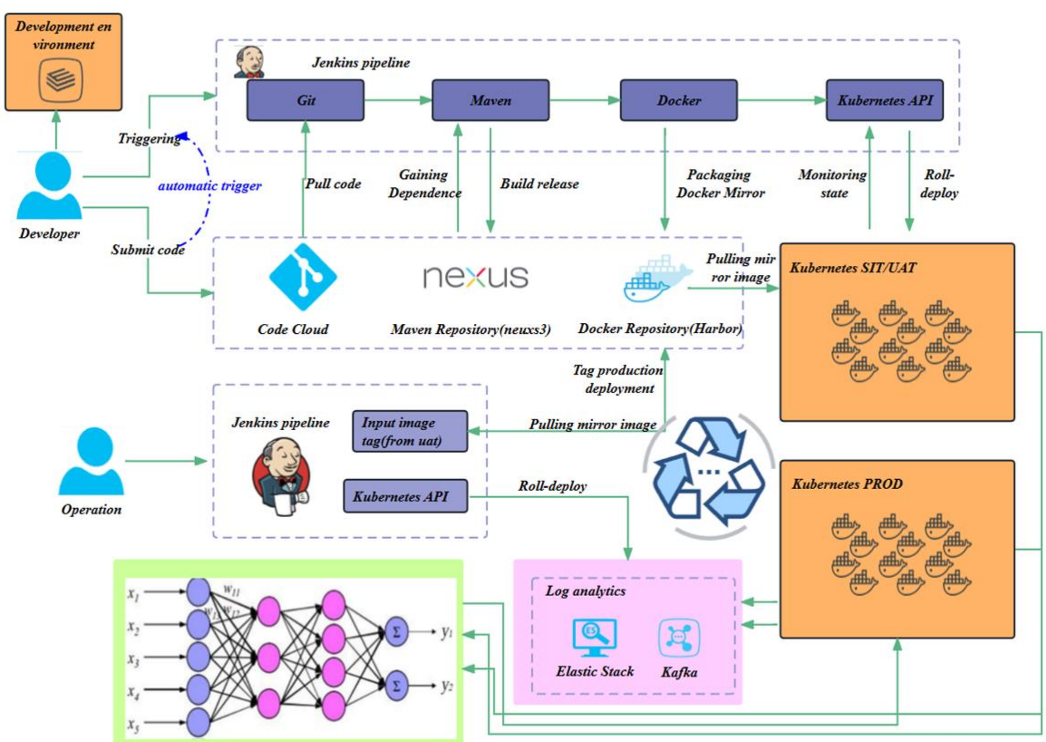

Fig. 4. Wireless LAN module diagram.

Its configuration with WLAN access points is automatically distributed to all other access points for the WLAN networks using the cluster management function. Tap the button, the WLAN client can or can easily integrate into the WLAN network without configuration due to WPS. Similarly, the proposed method enables the creation of fault tree models to analyze various common faults in industrial robots. This facilitates fault diagnosis by service engineers with extensive experience in robot after-sales service and maintenance. By establishing a fault diagnosis system based on fault tree analysis and expanding it to an expert diagnosis system, the method enhances fault detection and resolution efficiency. Additionally, the Ethernet Port Adapter (EPA) serves as a high-performance industrial wireless LAN device, facilitating network connections for various industrial equipment and wireless LAN interfaces, including personal computers, mobile devices, barcode scanners, and RFID readers.

C. *Industrial Robot Remote Service Platform and Monitoring System*

The design of the system is the combination of remote management and data collection and analysis, auxiliary industrial robot equipment, achieve more intelligent, more efficient when the robot to produce a lot of real-time data collection, unified storage management, and can through comparative analysis of operational data, auxiliary engineer judge equipment status, on the other hand using the data mining algorithm, realize the robot equipment fault prediction such as intelligent maintenance. The system comprises three main components: hardware data collector, server-side program with database, and web page front-end program. A communication interface for robot remote service platform and a protocol called Robot Data Acquisition and Remote-Control Protocol (RDCRCP) based on TCP/IP communication protocol are designed. RDCRCP specifies communication parameters, data structure, and message definition, facilitating data interaction. Stable customer-server communication is ensured by establishing long TCP connections for data interaction between devices. The robot master control serves as the server side, while the SegBox data acquisition device acts as the client side, initiating TCP connections and conducting one-to-one request-response interactions. If the client still does not receive the response after waiting for T seconds, the SegBox should resend the message immediately. If the SegBox is still not responded after N-1 consecutive transmission, the transmission request is stopped. When there is no data interaction on the TCP channel, the client will continuously send the link detection package to the robot at every time C to ensure the continuous connection of the communication. If the response message is not sent after the waiting time exceeds T second, the link detection package will be sent again immediately. The TCP connection will break after more than N-1 times of the non-response.

IV. Experimental Analysis

SPT, LPT and SLACK are introduced here to compare with the proposed method mentioned in this paper, processing 500 randomly generated tasks in the same environment and comparing them comprehensively by completion time and delay rate. The workshop parameters of 10 randomly generated cases were optimized by each method, and then the average value was taken for comparison. See Fig. 5 for the schematic diagram of the multi-robot scheduling method. We can intuitively see the comparison results of the five methods under the two indexes of completion time and delay rate. Compared with SPT, LPT and SLACK rules, the SPMCTS algorithm decreased by 28.3%, 27.8% and 31.4%, and 70.4% and 42.9%, respectively, while the delay time decreased by 16.7% and 9.9%, and 38.5% and 22% compared with AHP and RLVNS and 22%, respectively. It can be seen that the single SPT, SPT and SLACK rule scheduling can respond quickly, but its adaptability is poor and the scheduling quality is difficult to guarantee, and the information network is established by applying the SPMCTS algorithm to search and selecting the optimal scheduling strategy to adapt to the current state of multiple rules, so as to get better solution quality.

The system software can be divided into two parts, namely the SPMCTS program developed using python on the TensorFlow platform and the simulation program developed with analog software on the Siemens Tecnomatix platform. The entire simulation program is divided into the following sub-modules: equipment management, task management, state management, communication module and scheduling instruction module. In the production process of simulated workshop, the equipment management module is responsible for the information management of processing equipment, robots and various sensors in the workshop; the task management module is responsible for the management of all artifacts; the key information processing module is to process the real-time equipment and artifact information sent from the equipment management and task management module. Fig. 6 and sends the extracted key information to the communication module. he communication module is to establish a communication network between the SPMCTS program and the simulation program to transmit the state information and the scheduling instruction information in real time. The SPMCTS optimization policy optimizes the dispatching policy according to the current state and sends the dispatching policy to the scheduling instruction module. Finally, the scheduling instruction module performs the scheduling tasks according to the policy coordination rules and the robot.

The quality of SPMCTS solution is better than multi-rule combination AHP method and reinforcement learning RLVNS method, we can see that compared with multi-rule combination AHP method, SPMCTS algorithm is more adaptable; however, RLVNS method only considers the neighborhood search learning of the first process. Fig. 7 cannot distinguish the information difference in work piece scheduling between processes, which has obvious limitations. Therefore, the simulation results verify the effectiveness and superiority of applying SPMCTS for multi-robot scheduling in the mixed-flow workshop under the industrial Internet of Things.

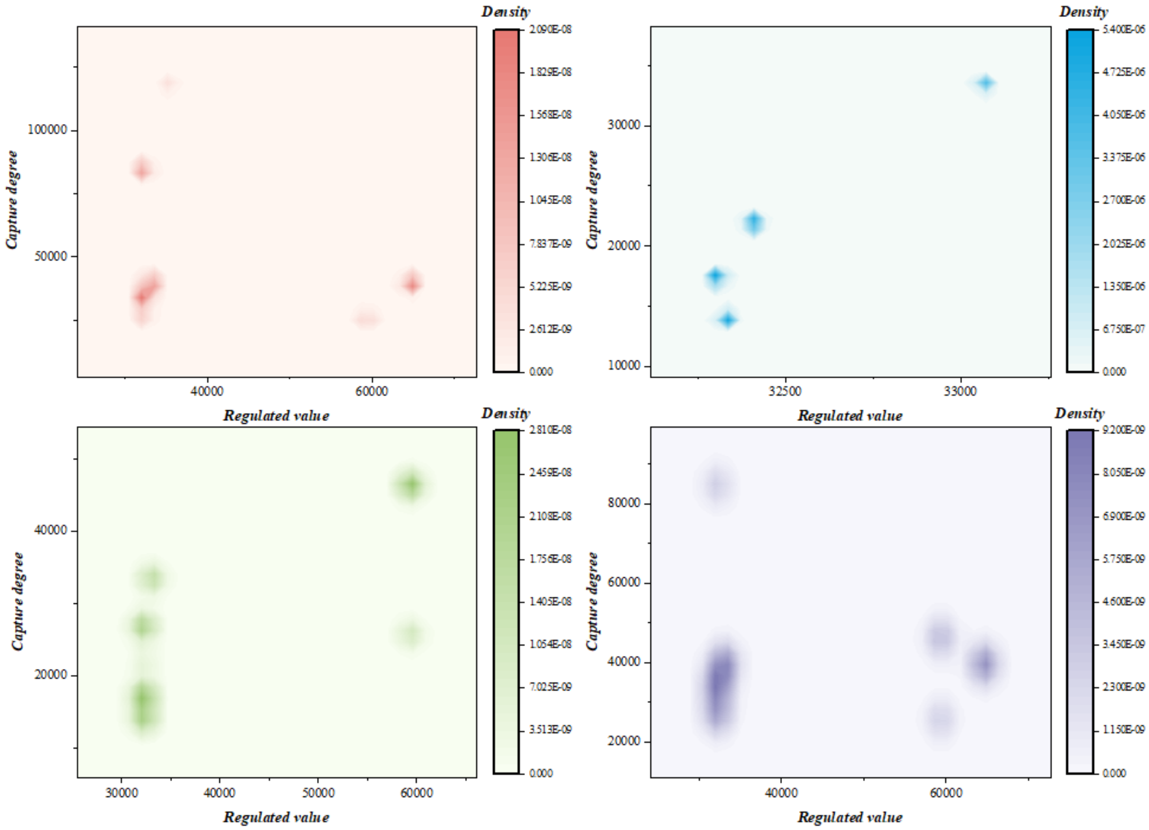

Fig. 5. Indicator results diagram.

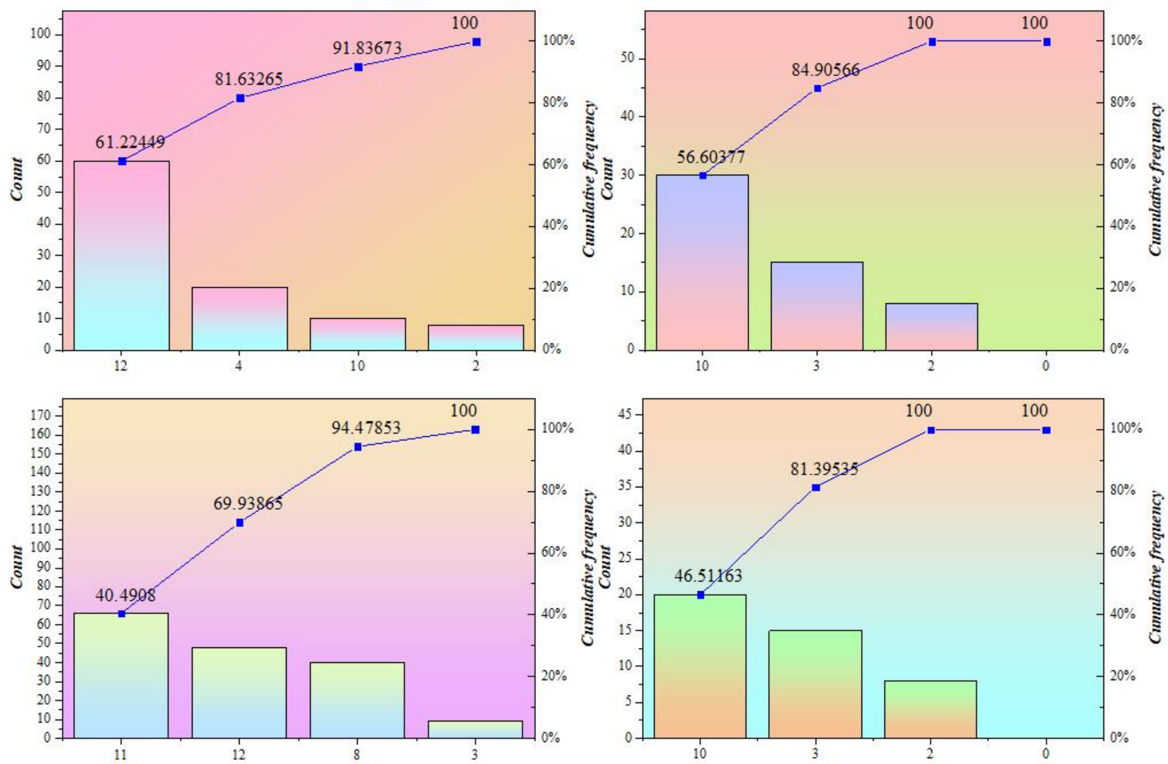

Fig. 6. Strategy optimization diagram.

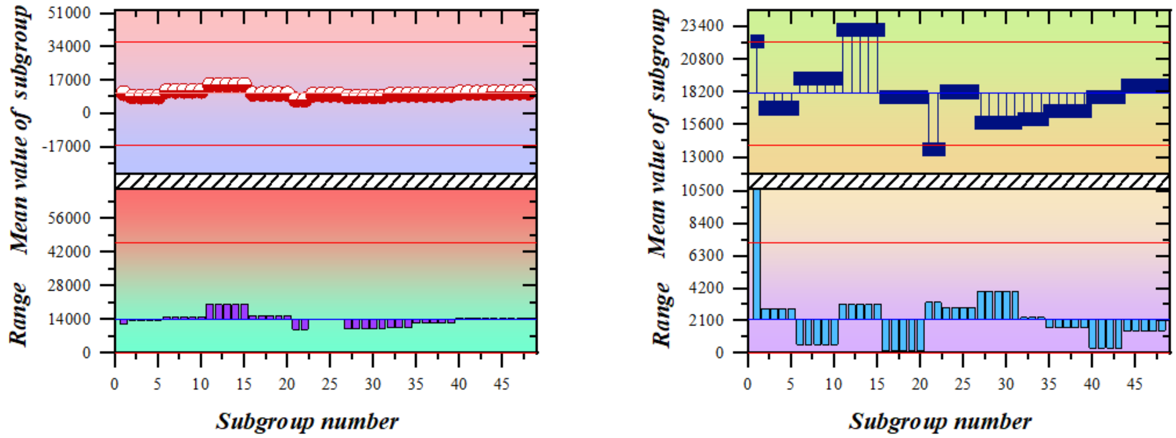

Fig. 7. The Optimization results diagram.

V. Conclusion

This paper introduces three systems: the repeated positioning accuracy test system of industrial robots, the factory wireless monitoring system of industrial robot debugging stations, and the remote service platform and monitoring system of industrial robots. The repeated positioning accuracy test system relies on high-precision laser sensors for real-time spatial position measurement. It enhances traditional analog data transmission by adopting RS32 digital transmission for improved stability and accuracy. Additionally, it integrates wireless equipment transmission to data processing terminal equipment, facilitating data analysis and monitoring. The data terminal has a built-in repeated accuracy algorithm, and designs the relevant monitoring screen and data storage, to ensure that the test results are justified.

The factory wireless monitoring system of the industrial robot debugging station is mainly aimed at the monitoring scheme of the industrial robot production site.For instance, highlight how the proposed scheduling algorithm significantly reduced production downtime by optimizing task allocation among robots. Discuss how the integration of IIoT technologies facilitated real-time monitoring and adaptive decision-making, leading to improved operational efficiency. Acknowledge limitations such as the complexity of real-world industrial environments and the need for further refinement of the scheduling algorithm. Finally, recommend future studies focusing on enhancing algorithm robustness, exploring dynamic scheduling strategies, and investigating the integration of AI for predictive maintenance in IIoT-enabled manufacturing settings. In addition to the current advancements, future research directions in the field of adaptive scheduling for industrial robots could explore the integration of artificial intelligence techniques for more intelligent decision-making processes. Moreover, the development of predictive maintenance algorithms could enhance equipment reliability and minimize downtime. Furthermore, investigating the integration of advanced communication protocols and edge computing technologies could optimize real-time data processing and improve system efficiency.

Acknowledgment

Jiangsu Provincial Department of Education “2023 Field Engineer Project”, 2023 Jiangsu Province Higher Education Reform Research Project.

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