

Automatic Control and Intelligent Management of Mechanical Assembly Process Based on Big Data Technology

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ABSTRACT Mechanical assembly is a core production process in modern manufacturing, but traditional assembly systems often suffer from low efficiency, high labor cost, unstable quality, and weak adaptability due to human operation and fixed control logic. To improve real-time control and intelligent management, this paper investigates the application of big data technology in mechanical assembly processes and designs an automatic control and intelligent management system integrating multisource data acquisition, data cleaning, clustering analysis, association rule mining, and closed-loop control. Sensors, data acquisition cards, and industrial communication devices are used to collect assembly parameters such as displacement, force, pressure, temperature, speed, equipment status, and product quality. K-means clustering is adopted to identify assembly-state categories, while a lightweight improved association rule mining method is used to discover parameter correlations and convert them into real-time control thresholds and actuator commands. The system further includes modules for data integration, real-time monitoring, fault diagnosis, intelligent decision support, and visual management. Experimental comparison with a conventional automated assembly system shows that the proposed system achieves lower failure rates, faster response time, higher product qualification rates, and better fault monitoring accuracy. The minimum response time reaches 510.75 ms, and the maximum qualification rate reaches 99.59%. The results indicate that big-data-driven automatic control, combined with industrial sensing and electromagnetic-compatible signal acquisition, can significantly improve assembly stability, quality consistency, and intelligent manufacturing capability.

INDEX TERMS big data technology, mechanical assembly, automatic control, intelligent management, electromagnetic sensing

I. INTRODUCTION

THE machinery manufacturing industry is a pillar of the national manufacturing sector [1-2]. However, conventional production processes face challenges including high manufacturing costs, low production efficiency, and frequent quality defects caused by human error and limited technical levels, leading to high scrap rates and restricting enterprise development. Therefore, improving the efficiency and quality of machinery manufacturing has become a critical issue. Big data technology has been increasingly applied in mechanical assembly, driving the integration of information technology and advanced manufacturing [3-4]. At present, automatic control technologies have been widely used in mechanical assembly, completing tasks via pre-programmed logic and production efficiency and product stability. Meanwhile, intelligent management systems based on big data enable real-time monitoring, analysis, and optimization of the entire assembly process. With the advancement of big data and the Internet of Things (IoT), multi-source assembly

data can be collected, processed, and utilized in real time, supporting scientific production planning, process optimization, and continuous improvement of efficiency and quality.

This paper focuses on the automatic control and intelligent management of mechanical assembly processes driven by big data technology. By integrating IoT, edge computing, and data mining technologies, this study constructs a closed-loop intelligent assembly system to achieve real-time data-driven control and refined management, ultimately enhancing assembly efficiency and quality.

II. LITERATURE REVIEW

A. APPLICATION OF BIG DATA TECHNOLOGY IN MANUFACTURING

Many scholars have conducted extensive research on the application of big data technology in the manufacturing industry. Raguseo Elisabetta's empirical survey on the adoption of big data technology by enterprises shows that big data technology has significant benefits and risks in the

manufacturing industry. However, it also brings risks such as privacy issues and potential data leakage [5]. Gao Rixiang discussed the application of big data technology in future smart factories. Among them, the manufacturing industry can enhance the level of automation and intelligence through big data technology, better meet customer needs, and realize the autonomous operation and quality control of production lines. In addition, data privacy and network security issues in the application are also pointed out. Therefore, in the construction of smart factories, big data technology must be carefully selected and used to maximize its advantages and minimize potential risks [6]. Huang Yujin identified and analyzed the influencing factors of manufacturing agglomeration in the Beijing-Tianjin-Hebei region based on enterprise big data. The research results show that factors such as market demand, industrial policy, and talent supply have a significant impact on agglomeration. In addition, big data analysis has been proven to be an effective tool for manufacturing decision-making and can provide guidance for industrial planning and policy making in the region. His research emphasizes the importance of using big data technology to drive manufacturing innovation and promote economic growth [7].

Despite progress, existing research lacks systematic and application-oriented designs, and the potential of big data in mechanical assembly has not been fully exploited, limiting its practical effects.

B. AUTOMATION CONTROL OF MECHANICAL ASSEMBLY PROCESS

Mechanical assembly refers to the process of assembling various parts in a certain order and manner to complete a complete mechanical equipment or product. Traditional assembly relies heavily on manual work, resulting in low efficiency and inconsistencies caused by human error. The emergence of mechanical assembly automation control technology has transformed the traditional mechanical assembly method, enabling it to operate efficiently in a digital, automated, and information-based environment. It involves production line automation, intelligent logistics and warehousing, quality control and testing, data analysis and optimization, and many other aspects.

The application of automation technology in mechanical assembly is developing rapidly and attracting much attention. Aliu Albert discusses the application of automated control in developing countries. The research showed that the efficiency and quality of mechanical assembly can be enhanced, and the labor cost and manual variability can be reduced through automatic control technology. However, in applications in developing countries, there are also many technical and management challenges, such as slow technological updates and high equipment maintenance costs. Therefore, when promoting automation control technology, it is necessary to comprehensively consider factors such as technology, management, personnel, and the characteristics of developing countries in order to achieve technologi-

cal transformation and industrial upgrading [8]. Schossig Thomas discussed the importance of modern test automation and control systems for mechanical assembly processes. He could more accurately detect and analyze problems in the mechanical assembly process by introducing new testing techniques and methods, thereby improving production efficiency and quality. simultaneously, the test automation and control system can also provide real-time monitoring and feedback, and adjust and optimize the production process in time to reduce production costs and shorten the time to market. Therefore, the intelligent management of mechanical assembly needs to strengthen the research and application of test automation and control systems to enhance the competitiveness and market share of enterprises [9].

In addition, Cheng Y. introduced the application of wireless communication technology in industrial automation control. During the mechanical assembly process, he utilized ZigBee wireless communication technology to achieve data transmission between machines, as well as remote monitoring and control. Therefore, using wireless communication technology in the automation control of mechanical assembly processes has broad application prospects and important research significance [10]. Ding Shu Yu introduced the application of wireless communication technology in industrial automation control, explored its advantages and limitations in control systems, and proposed an industrial automation control scheme based on ZigBee. As an industrial automation application, the mechanical assembly process can also be automated and controlled using ZigBee wireless communication technology. Therefore, the content of his paper had positive significance for the development of intelligent management of mechanical assembly [11].

Current automatic control systems still struggle with high-precision positioning, dynamic adaptation, and handling complex assembly tasks, calling for data-driven intelligent optimization.

C. INTELLIGENT MANAGEMENT OF MECHANICAL ASSEMBLY PROCESS

Intelligent management can play an important role in the mechanical assembly process. How to apply intelligent management to the mechanical assembly process has become an important research field in the mechanical manufacturing industry. For example, Wang Hua et al. proposed a method for using an intelligent computing system to achieve precise assembly of large laser optical components. His research used a variety of intelligent algorithms, including genetic algorithms, linear programming, and Bayesian networks, to predict, optimize, and control the geometric characteristics of optical components, achieving precise assembly of large laser optical components. This method can avoid human error and machine instability, and can detect and adjust in real time during the assembly process, realizing intelligent management and control of mechanical assembly [12].

Cui Chaofeng introduced the application of engineering intelligent mechanical construction equipment in the

construction of prefabricated building. Mechanical equipment uses an intelligent management system to monitor the assembly process in real time, optimize scheduling, and enhance engineering efficiency and quality. Intelligent management systems can optimize the mechanical assembly process and reduce operational errors and safety hazards, which has broad application prospects and important significance. Therefore, the application of this system can promote the intelligent management and development of mechanical assembly process, and promote the further development of prefabricated building [13]. Li Feng'e introduced the application of intelligent online torque error prevention in assembly line of construction machinery. The online torque error prevention system can achieve intelligent management, and achieve real-time monitoring, data analysis, and intelligent scheduling of mechanical assembly processes through technologies such as sensors, computers, and cloud platforms. Intelligent management can optimize the production efficiency and quality of mechanical assembly line, enhance the efficiency of mechanical assembly and save labor costs. Therefore, the intelligent management of the online torque error prevention system has broad application prospects and important significance in the mechanical assembly process [14]. In the field of mechanical manufacturing, the mechanical assembly process is a very important step and one of the most fundamental production links.

The mechanical assembly process requires the completion of the assembly of parts, usually requiring high precision and technical level. Currently, research has mostly focused on how to enhance the accuracy and technical level of mechanical assembly, and there are still some urgent problems that need to be solved. This paper discusses the application of big data technology in the field of mechanical assembly, and how to achieve automatic control and intelligent management of the mechanical assembly process through big data technology.

III. DESIGN AND IMPLEMENTATION OF AUTOMATION CONTROL SYSTEM FOR MECHANICAL ASSEMBLY PROCESS

A. DATA COLLECTION

Data collection is the foundation of the automatic control model. Multi-source sensors and acquisition devices are deployed to collect real-time data during assembly, including temperature, pressure, position, clamping force, robot running status and speed, machine tool utilization, raw material inventory, and part quality parameters. The design covers sensor selection, layout, and acquisition methods:

1) Sensor selection: Select different sensors according to the physical quantities that need to be measured during the mechanical assembly process to ensure that the collected data can meet the requirements. In the mechanical assembly process, KEYENCE's LJ-G series laser displacement sensor is selected as the detection equipment. This sensor can meet the measurement needs in the mechanical assembly process.

Other commonly used sensors include force sensors, pressure sensors, temperature sensors, speed sensors, etc.

2) Sensor layout: The sensors are arranged according to the parameters and targets that need to be controlled during the mechanical assembly process. In order to control the position of components during mechanical assembly, a laser displacement sensor is installed above the assembly platform to measure the height of the components. At the same time, when selecting the location of the sensor, detailed consideration should be given to factors such as distance, angle, and direction between the sensor and the measured object to ensure that the sensor can accurately collect data from the measured object.

3) Data acquisition method: The data acquisition method includes two methods: analog signal acquisition and digital signal acquisition. In the process of mechanical assembly, this article selects the commonly used data acquisition method - digital signal acquisition. By using NI's NI DAQmx series PCI-6221 data acquisition card and LabVIEW software, the data collected by various sensors is processed and analyzed.

B. DATA CLEANING

1) Data cleansing: In the collected data, there are usually some disordered data and Outlier. Therefore, it is necessary to organize and clean the data to ensure its accuracy and consistency. The collected invalid data are identified and removed, such as missing values, duplicate values and Outlier. The equation is:

$$y_i = \frac{z_i - \alpha}{\beta} \quad (1)$$

After data cleaning and filtering out abnormal data in the data set, the value ranges of different features are mapped to the values of the same scale.

2) Data denoising: Filtering algorithms are used to smooth the data and remove sudden noise interference.

The equation is:

$$M = (H_1 + H_2 + H_3 + \dots + H_n)/n \quad (2)$$

Among them, H_n represents the previous n data. This step can effectively eliminate the noise in the data and obtain a smooth data sequence.

3) Data correction: Adjust the collected data to eliminate systematic errors and measurement deviations.

$$D_c = D_o + F \quad (3)$$

Among them, F is the correction constant.

4) Data normalization: Normalize the data and map it to a suitable range.

$$C_i = \frac{b_i - \min(x)}{\max(x) - \min(x)} \quad (4)$$

Among them, b_i is the original data. This step maps data of different ranges to a unified range.

5) Data verification: This paper uses anomaly detection algorithm to detect outliers in the data to eliminate the interference of abnormal data on subsequent analysis.

$$G = (F - \mu) / \sigma \quad (5)$$

Among them, σ is the standard deviation. Moreover, the data is logically validated to ensure that the relationships and constraints between the data meet expectations.

6) Data completion: For data with missing values, interpolation, regression, or other completion methods are used to fill in the missing values. For damaged or incomplete data, it is repaired and supplemented based on relevant information and knowledge.

C. DATA ANALYSIS AND MODEL ESTABLISHMENT

Data analysis and modeling are the core steps in the design of automation control models for mechanical assembly processes. Through the application of statistical analysis, machine learning and data mining technologies on the collected data, valuable information and patterns can be extracted from them. Based on these data analysis results, a mathematical model of the mechanical assembly process is established to describe the relationships and influencing factors between various stages in the assembly process. The architecture of data analysis and establishment of an automated control model for the mechanical assembly process is shown in Figure 1.

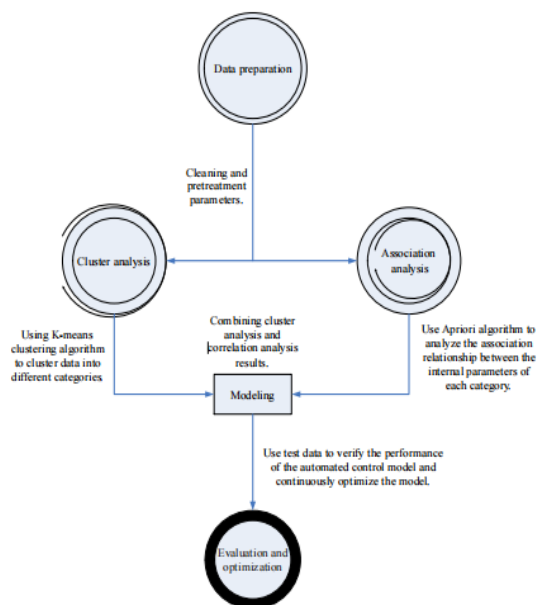


FIGURE 1. Mechanical assembly process architecture diagram

D. CLUSTER ANALYSIS

Cluster analysis plays an important role in automation control models, especially in mechanical assembly processes, as it can enhance the accuracy and efficiency of automation

control models. In the mechanical assembly process, the automated control model can process data in real time and identify assembly patterns through cluster analysis, thereby optimizing assembly sequence and parameters. This method can automatically identify the characteristics of different assembly tasks and dynamically adjust control parameters, thereby improving assembly efficiency and quality. This paper also performs cluster analysis on the collected assembly data.

This paper uses the K-means clustering algorithm to classify the acquisition parameters, and divides the data into K categories by calculating the distance between the sample and the cluster center. The number of clusters is determined based on the silhouette coefficient indicator, and the K value that maximizes the silhouette coefficient is selected to obtain the optimal clustering effect. This method can effectively evaluate the compactness within the cluster and the separation between clusters. K cluster centers are randomly selected in the initialization stage; the distance between each sample and each center is calculated, and the cluster assignment is completed accordingly.

$$\text{Distance}(\mathbf{x}, \mathbf{c}) = \sqrt{(x_1 - c_1)^2 + (x_2 - c_2)^2 + \dots + (x_n - c_n)^2} \quad (6)$$

Where $\mathbf{c}$ is the feature vector and n is the feature dimension. After calculating the distance between the sample and each cluster center, assign it to the class where the nearest cluster center is located.

For each cluster, calculate the average value of all samples and use the average value as the new cluster center. Repeat the above steps until the cluster center no longer changes or reaches the preset stop condition. Through iterative updates, the samples are assigned to the appropriate cluster center, thus achieving cluster analysis.

E. CORRELATION ANALYSIS

Cluster analysis and association analysis are the core methods for constructing the model in this article. Cluster analysis classifies various parameters involved in the mechanical assembly process to achieve the goal of automated control. Correlation analysis aims to achieve process optimization and production efficiency enhancement by analyzing the correlation relationships between various parameters.

This paper designs a lightweight improved association rule mining method oriented to real-time assembly control, which optimizes the core steps of the algorithm while retaining the ability of parameter correlation mining.

The improved method adopts incremental data sliding window sampling to replace global data traversal. Only the latest batch of assembly data in the window is taken as the analysis object, which greatly reduces the amount of calculation and shortens the analysis time. At the same time, the algorithm pre-screens candidate itemsets based on the prior knowledge of mechanical assembly, and directly eliminates the parameter combinations that have no practical control significance, so as to reduce the number of invalid

candidates. On this basis, the support calculation is simplified by using the statistical results of historical frequent items, avoiding repeated distance measurement and sorting, so that the algorithm can run efficiently on the embedded controller with limited computing resources.

In terms of control signal conversion, this paper establishes a mapping model from association rules to robot execution instructions. The frequent itemsets mined by the improved algorithm are no longer used as static analysis results, but are converted into real-time adjustable control thresholds and action sequences. When the system monitors that the assembly parameters match the antecedent of the association rule, it immediately calls the corresponding control strategy and outputs the position, speed or force signal to the actuator. This design realizes the closed-loop drive from data correlation to physical control, and solves the problem that traditional association rule mining is separated from motion control.

Evaluation and screening of association rules: Based on indicators such as support, confidence and enhancement, the association rules are evaluated and screened to select rules with significant association relationships.

Process optimization and production efficiency enhancement: Based on the discovered association rules, optimization is performed by adjusting parameter values, changing processes or adding control measures.

Monitoring and adjustment: Continuously monitor the effectiveness and applicability of association rules, and adjust and enhance them based on real-time data.

F. AUTOMATION CONTROL MODELING

A control model is constructed based on the results of clustering and correlation analysis, and corresponding automation strategies and parameter configurations are formulated for various characteristics. Through the automated control system [15-16], the category to which the current data belongs is automatically determined based on the parameter data collected in real time, and the corresponding control strategy is executed.

Different automated control strategies are formulated according to the characteristics of different categories. And according to the characteristics of different categories, corresponding control parameters are set. For stable assembly processes such as assembly speed and assembly force, fixed control parameters are set; for unstable assembly processes, control parameters are dynamically adjusted according to the parameter data collected in real time to maintain the stability of the assembly. Finally, according to the results of cluster analysis, corresponding control thresholds are set. Different control thresholds are set for different types of assembly processes to determine whether adjustments or interventions are needed. Assembly processes that exceed the control threshold will be subject to additional control or corrective measures.

G. CONTROL STRATEGY DESIGN AND IMPLEMENTATION

In the design of the automatic control model of the mechanical assembly process, the control strategy design is the ultimate goal. By optimizing the data analysis results and the established mathematical model, a suitable control strategy is designed to realize the automatic control and optimization of the assembly process.

Control strategy selection: This paper selects the PID (proportional integral differential) control strategy, which is suitable for assembly processes with high assembly accuracy requirements. For assembly processes with high-speed requirements, an adaptive control strategy is selected.

Control signal generation: In PID control, the proportional, integral and differential terms are calculated based on the assembly error, and the control signal is generated by parameter combination.

Actuator control strategy design: This paper selects the motor as the actuator, and uses position control, force control and speed control methods to control the motor.

Selection of hardware platform: Considering the complexity of the control algorithm, real-time requirements, communication requirements and other factors, this paper selects the embedded controller as the hardware platform, which can provide higher real-time performance and reliability, and is suitable for mechanical assembly processes that require fast response and high-precision control.

IV. DESIGN AND IMPLEMENTATION OF AN INTELLIGENT MANAGEMENT SYSTEM FOR MECHANICAL ASSEMBLY PROCESS

The intelligent management of mechanical assembly process can use advanced technical means, big data technology and intelligent management system to carry out comprehensive and fine management of mechanical assembly process to enhance production efficiency and quality and reduce manual intervention, so as to achieve automatic and intelligent control [17].

A. DATA INTEGRATION AND SHARING MODULE

In the design of intelligent management systems for mechanical assembly processes, data integration and sharing are very important components. By integrating and sharing data from various assembly stages, a unified data platform can be built to achieve data sharing and circulation, thereby improving the visualization, intelligence, and collaboration of the assembly process.

1) **Determining the requirements for data integration and sharing:** Firstly, it is necessary to clarify the data requirements and sharing objectives of each link in the mechanical assembly process. According to the characteristics of the assembly process, the data types that need to be integrated and shared are determined, such as the parameters of assembly parts, assembly process parameters, assembly quality data, etc.

2) Design data integration architecture: Design a suitable data integration architecture according to the needs of data integration and sharing. The data acquisition subsystem is responsible for collecting data from each assembly link; the data processing and storage subsystem is responsible for processing and storing the collected data; and the data sharing and circulation subsystem is responsible for realizing data sharing and circulation between different links.

3) Data collection and processing: The data required by the sensors and other data collection devices are used. The data processing and storage subsystem performs data cleaning, verification and analysis, and stores the processed data in a database or cloud platform.

4) Data sharing and circulation: Through the data sharing and circulation subsystem, data sharing and circulation between different links are achieved. Standardized data formats and interfaces are used, combined with message queues, data buses and other services to achieve cross-system data interoperability and ensure secure and reliable transmission.

5) Build a unified data platform: Establish a centralized big data management platform to achieve unified storage, efficient query, intelligent analysis and visual display of data, and enhance data utilization efficiency. Data analysis and visualization tools are utilized to statistically and analyze data, providing decision support and optimization suggestions.

6) Data security: During the process of data integration and sharing, data security and integrity are guaranteed and privacy protection is strengthened through data encryption, access control, backup and other means.

B. REAL TIME MONITORING AND WARNING MODULE

In the design of the intelligent management system, real-time monitoring and analysis of mechanical assembly data are used to realize abnormality identification and early warning, ensuring the efficiency and stability of the assembly process.

1) Status judgment and anomaly detection: The collected real-time data is stored in a database or cloud platform. The collected data is processed and analyzed in real-time, and based on the processing results of real-time data, it is used for status judgment and anomaly detection. Appropriate thresholds and rules are set, and whether the state of the assembly process is normal is judged according to the changes and trends of real-time monitoring data. If an abnormal situation is found, the corresponding warning mechanism is triggered.

2) Early warning mechanism and notification: According to different situations and the severity of problems during the assembly process, early warnings are classified into severe, moderate, and minor levels. Mild level warnings are notified by sound, while moderate level warnings are notified by sound and light. The severity level warning adopts sound, light, and SMS (short message service) notification methods to achieve timely warning of relevant personnel.

The template for warning information is pre defined and filled in according to the corresponding content of the warning level and problem type. The warning information includes a description of the problem and its possible impact, as well as suggested handling measures.

3) Exception handling and feedback: After the system triggers an alarm, the staff must respond and handle the problem immediately, and enter the processing results into the system. The system automatically records the complete processing process and final results to provide data support for subsequent optimization.

C. FAULT DIAGNOSIS AND OPTIMIZATION MODULE

In the design of intelligent management system for mechanical assembly process, fault diagnosis and optimization are crucial links. Using big data analysis technology, faults in the assembly process can be diagnosed and analyzed, and corresponding optimization suggestions can be put forward, so as to enhance the efficiency and quality of the assembly process.

Fault diagnosis and classification: Based on the collected data, big data analysis technology is used to perform fault diagnosis, automatic identification and classification.

Fault analysis and optimization suggestions: Further analyze the diagnosed faults and put forward corresponding optimization suggestions. Analyze the causes of faults, the scope of impact, solutions and enhancement measures of the assembly process.

Optimization verification and enhancement: collect data in real time for comparative analysis, evaluate the effectiveness and impact of enhancement measures, and adjust enhancement plans in a timely manner to ensure continuous optimization and enhancement of the assembly process.

Data analysis and visualization: Through data analysis and visualization tools, the data of the assembly process is statistically analyzed and visualized. Data dashboards, fault analysis charts, trend analysis charts, etc., are used to help personnel understand and analyze faults and problems during the assembly process, and optimize and enhance them.

D. INTELLIGENT DECISION SUPPORT MODULE

Intelligent decision support is a key task in the design of intelligent management systems for mechanical assembly processes. The intelligent decision support module based on the analysis results of big data can help managers make decisions and schedule the assembly process to optimize resource utilization and enhance production efficiency.

1) Big data technology: Big data technology is used to process data and analyze the use of each area of the production line. Areas with low productivity are identified. The efficiency of robots is calculated and compared. The location and dwell time of deadlocks are analyzed to obtain valuable results. Then, these analysis results are displayed in visual forms such as flow charts and line chart, so that administrators can view and understand them easily.

2) Decision support function: Based on data analysis results, intelligent decision support function is implemented to assist management personnel in making and scheduling assembly processes, determining the priority and sequence of assembly tasks, and conducting reasonable task scheduling and allocation. For example, based on prediction models and inventory levels, recommendations for the optimal time and quantity of parts ordering are provided for management personnel to avoid situations of excessive or insufficient inventory. According to the analysis results of big data, the operation status and life of the equipment are judged to provide equipment maintenance plans and repair suggestions to ensure that the equipment is in good operation. Based on the bottleneck analysis of robot efficiency and production lines, optimization suggestions for task scheduling are provided for managers to enhance production efficiency and reduce downtime. By analyzing the quality data of part installation process, the adjustment suggestions of relevant process parameters are provided to optimize the quality of part assembly and reduce the defective rate. Suggestions for improving production efficiency are provided by analyzing the production situation in various regions, such as adjusting process flow, optimizing layout, etc., to reduce production cycles and increase output. In order to facilitate the understanding and use of decision support functions by management personnel, the intelligent decision support module can provide a visual interface to display data analysis results and decision suggestions, includes dashboards, charts, reports, and more, to help management personnel intuitively understand the assembly process and make corresponding decisions.

In short, intelligent management of mechanical assembly processes is an important means of intelligent transformation in modern manufacturing industry. Through big data technology and intelligent management system, comprehensive and refined management and optimization of mechanical assembly process can be realized, and production efficiency and quality level can be enhanced. Production cost and energy consumption can be reduced, and intelligent transformation and upgrading of manufacturing industry can be promoted.

V. EXPERIMENTAL VERIFICATION AND EVALUATION

The experimental environment mainly includes automatic control and intelligent management system of mechanical assembly process, assembly robot, sensor, workpiece, computer and other equipment. The system adopts intelligent algorithm based on big data, combined with assembly robot and sensor, to realize efficient automatic control and intelligent management of mechanical assembly process. Among them, assembly robot can realize automatic control of mechanical assembly. Sensors are used to monitor key parameters (tightening force, position accuracy, assembly angle) in the mechanical assembly process in real time, and transmit these data to the system, and provide efficient control instructions and management strategies through big

data analysis algorithm. The experimental data are processed and analyzed by computer to obtain the data set of mechanical assembly process system. The data set is divided into training set and test set. 50% is test set and 50% is training set. To ensure the statistical validity of the experimental results, the total sample size of the mechanical assembly process dataset used in this study is 12,000 valid samples, which are randomly divided into a training set and a test set with a ratio of 50%:50%, that is, 6,000 samples for training and 6,000 samples for testing. This sample size is sufficient to avoid overfitting and underfitting in model training and to guarantee the reliability and reproducibility of the failure rate, response time, qualification rate and other performance indicators. Experiments are carried out on training set and test set using traditional automatic assembly system and system method designed in this paper respectively. The obtained data are divided into two groups. The control group is the traditional assembly system, and the experimental group is the system method designed in this paper. The two groups of data are analyzed and compared to evaluate the performance and effect of automatic control and intelligent management system of mechanical assembly process designed based on big data technology.

To ensure the scientificity and comparability of the experiment, the control group in this study is clearly defined as a typical traditional automated assembly system: the system adopts a standard industrial PLC as the main controller, uses classical PID algorithm for closed-loop control of position, speed and force, configures the same model of assembly robot, laser displacement sensor and execution hardware as the experimental group, and completes exactly the same assembly task, assembly path and part type. The control system only runs pre-written fixed logic programs without big data collection, online analysis, dynamic parameter adjustment and real-time decision-making functions. Under the same assembly beat, workpiece specifications and working conditions, the two groups are compared to ensure that the performance differences come from the control and management architecture rather than hardware differences.

A. SYSTEM FAILURE RATE

System failure rate refers to the number of times a system malfunctions per unit time. The system failure rate has many impacts on the automation control and intelligent management system of the mechanical assembly process. Once the system fails, the assembly line or production line may be shut down, which undoubtedly leads to a straight decline in production efficiency, and the controlled links in the assembly process may also suffer unexpected damage, making it difficult to maintain the assembly quality. This undoubtedly increases cost expenditures, as it is inevitable to repair and eliminate faults in order to repair them. This not only increases additional maintenance costs, but also brings about production downtime losses. In addition, production planning has also been hindered, requiring the rearrangement of assembly processes and production pro-

cesses. For critical data, malfunctions may also lead to data loss or inaccuracy, causing difficulties in the management and monitoring of the assembly process. The lower the failure rate of the system, the more stable and reliable the assembly process can be, thus maintaining the continuous improvement of production efficiency and product quality. This paper also conducted a system performance test and recorded the system failure rate per unit time of the control group and the experimental group. The comparison results are shown in Figure 2.

Sub-figure a describes the system failure rate data of the control group and the experimental group using the training set. The average system failure rate of the experimental group is 4.3793%, while the average system failure rate of the control group is 6.6573%. Sub-figure b describes the system failure rate data of the control group and the experimental group using the test set. The average system failure rate of the experimental group is 5.618%, while the average system failure rate of the control group is 6.5807%.

The results showed that the automatic control and intelligent management system of mechanical assembly process based on big data technology designed in this paper run more smoothly.

B. QUALIFICATION RATE

The qualified rate refers to the ratio of the number of qualified products to the total output in the assembly process. Product quality is the core concern of the automation control and intelligent management system of the mechanical assembly process, which directly affects the reputation and market competitiveness of the enterprise. Therefore, high-quality product quality is the core concern of the automation control and intelligent management system of the mechanical assembly process, which directly affects the reputation and market competitiveness of the enterprise, and has an important impact on achieving efficient, stable and sustainable development of the assembly process. Record the qualified rate of the control group and the experimental group. The comparison results are shown in Figure 3 below, where the X-axis represents the control group and the experimental group, and the Y-axis represents their pass rate.

In Figure 3 (a), the qualification rate data of the control group and the experimental group using the training set are described. Among them, the highest qualification rate in the experimental group was 99.59%, while the highest qualification rate in the control group was 94.82%. In Figure 3 (b), the qualification rate data of the control group and the experimental group using the test set are described. Among them, the highest qualification rate in the experimental group was 99.29%, while the highest qualification rate in

the control group was 94.25%. The results indicated that the system designed in this article produced higher quality products.

C. ASSEMBLY COSTS

Product assembly cost refers to the various costs involved in the mechanical assembly process, including labor costs, equipment costs, material costs, etc. Product assembly costs directly affect the automated control and intelligent management system of the mechanical assembly process. By adopting high-precision, high-stability automated equipment and intelligent algorithms, errors and anomalies in the assembly process can be reduced, assembly consistency and quality stability can be enhanced, and equipment failure and repair frequency, maintenance costs, and production downtime losses can be reduced. Taking a manufacturing company as the empirical object, the automated control and intelligent management system for the mechanical assembly process designed in this paper and the traditional automated assembly system were put into use on the company's mechanical assembly production line for one quarter. The assembly costs incurred by the experimental group in each link during the experiment were recorded every month, as shown in Table 1.

TABLE 1. Monthly assembly costs incurred by the experimental group in various aspects during the experimental process

Labor costs (yuan)	Equipment cost (yuan)	Material cost (yuan)	Maintenance costs (yuan)
17713	7085	10628	1521
20789	8315	12473	2152
19771	7809	11862	1478

As shown in Table 1, the lowest monthly total assembly cost for the experimental group was 36947 yuan. Among them, the lowest labor cost was 17713 yuan, and the lowest equipment cost was 7085 yuan. The lowest material cost was 10628 yuan, and the lowest maintenance cost was 1478 yuan. The monthly assembly costs incurred by the control group in various aspects during the experimental process were recorded, as shown in Table 2.

TABLE 2. Monthly assembly costs incurred by the control group in various aspects during the experimental process

Labor costs (yuan)	Equipment cost (yuan)	Material cost (yuan)	Maintenance costs (yuan)
18125	9184	11486	2015
22256	9630	13485	2354
21584	8711	14961	1984

As shown in Table 2, the lowest monthly total assembly cost for the control group was 40810 yuan. Among them, the lowest labor cost was 18125 yuan, and the lowest equipment cost was 8711 yuan. The lowest material cost was 11486 yuan, and the lowest maintenance cost was 1984 yuan. It

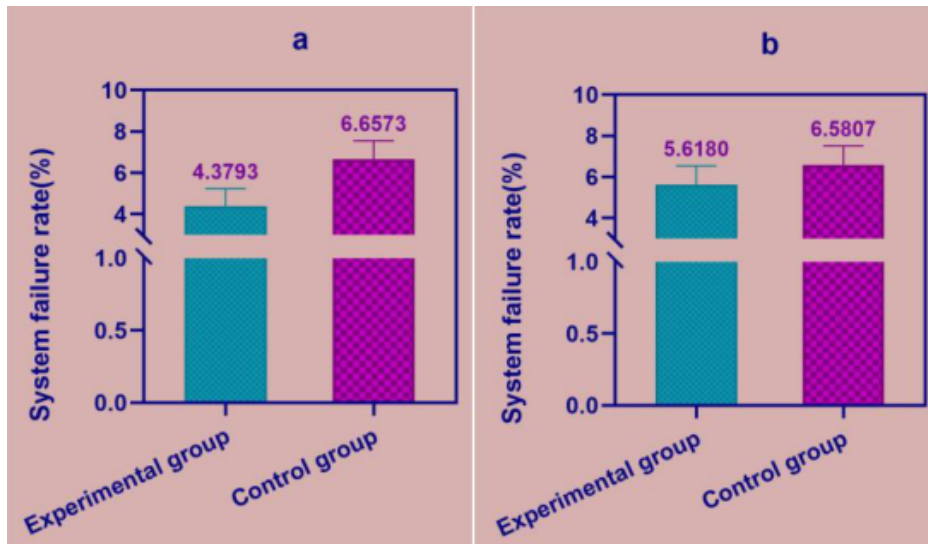


FIGURE 2. System failure rates of the control and experimental groups
Figure2(a): Comparison results on the training set Figure2(b): Comparis on results on the test set

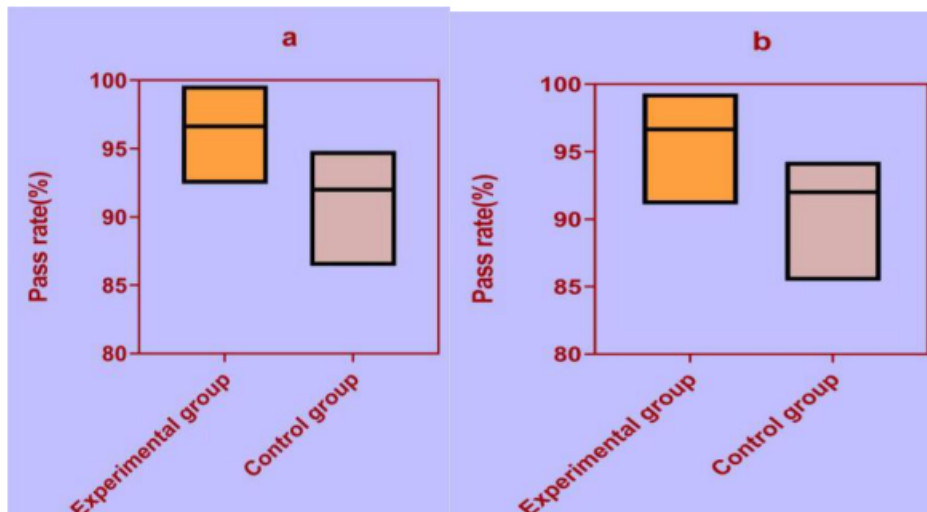


FIGURE 3. Qualification rates of the control and experimental groups

Figure3(a): Qualification rate data of the control group and experimental group using the training set
Figure3(b): Qualification rate data of the control group and experimental group using the test set

can be concluded that the system designed in this article can better reduce assembly costs.

D. MONITORING FAULT ACCURACY

The accuracy of monitoring faults has a significant impact on the automation control and intelligent management system of mechanical assembly processes. The enhancement of accuracy means that possible faults can be more accurately identified and located, and corrective measures can be taken in a timely manner, thereby reducing faults and downtime in production and improving production efficiency and product quality. simultaneously, improving the accuracy of monitoring faults can also help people identify bottlenecks and problem points in assembly, optimize and enhance them in a targeted manner, and enhance the stability and reliability of the entire production line. Various fault cases that occur in the actual system are collected, recorded, and classified according to the type of fault, and a fault sample library

is established to accurately label the samples. The fault samples contain various types of fault situations to cover the various fault conditions that the system may encounter. Common types of faults include circuit faults, mechanical faults, sensor faults, etc. The monitoring accuracy of the experimental group for different types of faults at different times was recorded.

TABLE 3. Monitoring fault accuracy of the experimental group for different types of fault situations

Circuit malfunction (%)	Mechanical failure (%)	Sensor fault (%)	Power failure (%)
94.33	98.55	90.40	95.91
93.12	98.45	94.03	96.11
94.51	99.70	93.78	95.45
93.39	98.03	90.53	95.48
93.89	99.82	90.52	96.12

From the data in Table 3, it can be concluded that the

highest monitoring accuracy of the experimental group for circuit faults is 94.51%, the highest monitoring accuracy for mechanical faults is 99.82%, the highest monitoring accuracy for sensor faults is 94.03%, and the highest monitoring accuracy for power supply faults is 96.12%.

The monitoring accuracy of different types of faults in the control group was recorded.

TABLE 4. Monitoring accuracy of different types of faults in the control group

Circuit malfunction (%)	Mechanical failure (%)	Sensor fault (%)	Power failure (%)
91.31	96.27	90.26	94.37
91.47	97.21	91.54	93.15
91.56	97.63	89.10	94.48
92.41	97.06	92.75	94.08
92.40	96.15	92.46	93.35

From the data in Table 4, the control group had the highest monitoring accuracy of 92.41% for circuit faults and 97.63% for mechanical faults. The highest accuracy rate for monitoring sensor faults was 92.75%, and the highest accuracy rate for monitoring power supply faults was 94.48%. It can be concluded that the system designed in this article has a higher accuracy in monitoring faults.

E. SYSTEM RESPONSE TIME

System response time refers to the processing time of input requests or events in the automated control and intelligent management system of the mechanical assembly process. Fast system response speed can ensure timely control and adjustment, enabling the system to respond to changes and demands in the assembly process in a timely manner, improving production efficiency and product quality. The system response time of the control group and the experimental group was recorded.

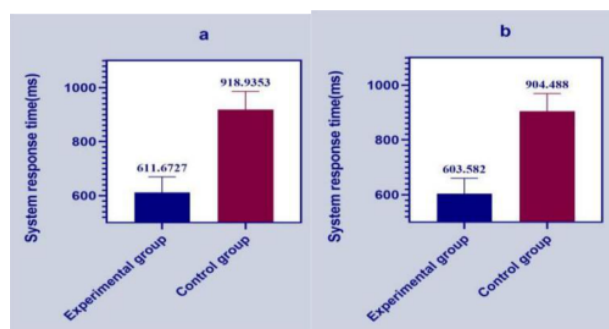


FIGURE 4. Comparison of system response times

Figure4(a): System response time data of the control group and experimental group using the training set

Figure4(b): System response time data of the control group and experimental group using the test set

In Figure 4 (a), the system response time data of the control group and the experimental group using the training set

are described. Among them, the lowest system response time in the experimental group was 530.43ms, while the lowest value in the control group was 822.28ms. In Figure 4 (b), the system response time data of the control group and the experimental group using the test set are described. Among them, the lowest system response time in the experimental group was 510.75ms, while the lowest value in the control group was 807.88ms. The results indicated that the system designed in this article had a faster response speed.

VI. CONCLUSION

Based on big data, this paper designed an automatic control and intelligent management system for mechanical assembly process, and realized efficient automatic control and intelligent management of mechanical assembly process through experiments. After analyzing and processing the experimental data, it was concluded that the system designed in this paper was more effective than the traditional automatic assembly system. The automatic control and intelligent management system of mechanical assembly process based on big data technology can reduce the number of defective products and waste products, and enhance the product qualification rate, assembly quality and speed, etc. By analyzing the data generated during the assembly process, quality issues can be identified during the assembly process. Based on the analysis results, corresponding measures can be taken to adjust and enhance the assembly quality. At the same time, the evaluation of the automation control and intelligent management system for the mechanical assembly process also evaluated the degree of intelligence of the system, providing a reference for further optimization and enhancement. In a word, the automatic control and intelligent management of mechanical assembly process based on big data technology is a new field and has broad prospects for development in the future.

AUTHOR CONTRIBUTIONS

RZ designed the research study. RZ analyzed the data. RZ wrote the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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