

PERCEPTION SYSTEM OF GARMENT MACHINERY PRODUCTION LINE BASED ON THE INTERNET OF THINGS

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Abstract - The vigorous development of the Internet of Things and information technology promotes the transformation of the manufacturing industry from traditional management to intelligent informatization. In order to discuss the intelligent production line monitoring and sensing system, this paper selects the garment mechanical parts processing production line as the object. Firstly, on the production line data collection, the characteristics and existing problems of the garment mechanical parts processing production line are analyzed. Then, the production line's awareness monitoring demand is summarized. Secondly, the production line's data sources and acquisition methods are discussed. Based on the configurable idea, a real-time data acquisition system for the garment mechanical parts processing production line is proposed. In addition, in terms of quality prediction, based on the Back Propagation Neural Network (BPNN), the Multiple Population Genetic Algorithm (MPGA) is introduced to build the MPGA-BPNNNN quality prediction algorithm. Finally, the performance of the system and algorithm is tested based on simulation experiments. The results show that the system's data acquisition and concurrent client pressures are 1.86ms and 650 users, respectively, meeting the requirements. Compared with the traditional BPNN, the MPGA-BPNNNN algorithm has a more accurate prediction result, with a root mean square error of 0.0645, which is also relatively small. The design of a perceptual data acquisition system and the construction of a quality prediction algorithm for garment mechanical parts processing production lines can provide a path for transforming traditional manufacturing production lines into intelligent digital perceptual systems.

Keywords: Clothing machinery parts; Intelligent perception; Data acquisition of numerical control system; Back Propagation Neural Network; Quality prediction.

1. Introduction

The scientific and technological revolution and industrial transformation of the manufacturing industry with information technology as the core promote the integration of manufacturing physics and information systems, as well as the development of Internet of Things (IoT) technology with embedded systems, Radio Frequency Identification (RFID) and wireless sensor network as the core [1]. With the continuous development of these manufacturing technologies and the continuous development of production line operation status monitoring systems, enterprises gradually use advanced production site information management technology to replace the traditional mode. This management method has laid a solid foundation for subsequent improvement of processing efficiency and cost reduction [2]. The transformation of the traditional manufacturing industry into intelligent is an important means for enterprises to achieve rapid development and improve competitiveness. Still, it also brings severe challenges to enterprises with a low level of intelligence. Improving the intelligence

level of manufacturing enterprises is an important issue related to core competitiveness.

Scholars have conducted many related studies on the intelligent transformation of the traditional manufacturing industry. Ghobakhloo (2020) conducted a state-of-the-art and content-driven literature review, consulted a group of experts from academia and industry, and implemented an explanatory structural modeling approach. Eleven factors that determine the implementation of intelligent manufacturing information and digital technologies are identified. The interrelation between these factors is plotted. They found perceived benefits and management support as the two driving factors for implementing IT in intelligent manufacturing. These factors can promote the maturity of manufacturing digital conditions in the era of Industry 4.0 [3]. Wang et al. (2021) conducted a qualitative and quantitative survey of the literature, systematically compared the inherent differences between smart and intelligent manufacturing, and provided a basis for people to understand the meaning of the two. They found that the trend of combining these two terms in Industry

4.0 is gradually increasing [4]. Fragapane et al. (2020) developed and tested an analytical model for throughput analysis. They used the model to reveal the advantageous conditions of flexible production networks based on autonomous mobile robots compared to traditional production lines. The model utilizes multiple crossing points and analyzes flow and loading/unloading stages to avoid congestion. Additionally, it can help decision-makers understand how autonomous mobile robots in process industry production systems can improve manufacturing performance in terms of productivity, flexibility, and cost [5]. These studies put forward suggestions for the intelligent transformation of the traditional manufacturing industry from different aspects. However, the research on the perception system of the production line is still relatively few.

Therefore, this paper takes the parts processing production line of clothing machinery as the object and summarizes the requirements of the perception system for the running state of the parts processing production line of clothing machinery from the characteristics and existing problems of the parts processing. The source of the data collected on the production line is analyzed. The data acquisition method of Siemens' numerical control system is studied. A real-time configurable data acquisition system for the garment machinery parts processing line is proposed. In addition, in terms of quality prediction, a multi-population genetic algorithm is added to the Feedforward Neural Network (FNN). A quality prediction method is constructed based on a multi-population genetic algorithm and FNN. Finally, the effectiveness of the system and algorithm is tested based on simulation experiments. The design of the perception system of garment mechanical parts processing production line based on the IoT can provide some ideas for the perception monitoring system of mechanical parts processing production line.

2. Design of Operation State Perception System for Garment Mechanical Parts Processing Production Line

2.1 Perceived Monitoring Demand Analysis of Garment Mechanical Parts Processing Production Line

With the advancement of information technology and intelligence, the competition in the clothing machinery market is becoming increasingly fierce. The advantages of important parts in this machinery can greatly improve the competitiveness of the whole machinery. Major machinery manufacturers pay more attention to the independent research and development (R&D) and manufacturing capabilities of core products [6]. Garment machinery parts processing has the characteristics of fine structure, great processing difficulty, complex process, and

increasingly high-quality requirements [7]. Additionally, the huge market space and fierce competition put forward stricter requirements for the processing quality and efficiency of parts. However, the modernization level of garment machinery parts processing production line is not high. There are still some problems, such as high consumption of parts processing process management, low degree of informatization in the manufacturing process, insufficient production control capability, great difficulty in process optimization, backward tracking and monitoring means, poor information traceability, etc. [8]. These problems increase the burden on production management personnel, affect the workshop's efficiency, and it isn't easy to optimize the process in time, thus seriously affecting the efficiency of the enterprise.

With the rapid development of IoT technology and its integration with other fields, it is a general trend for manufacturing production lines to be digital and intelligent. Based on the problems existing in the garment machinery parts processing production line, the requirements of the operation status perception system of the garment machinery parts processing production line are analyzed, as shown in Figure 1.

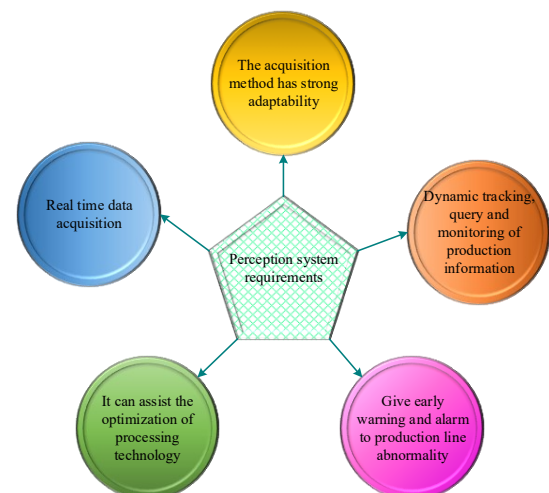


Figure 1: Demand analysis of operation state perception system of garment mechanical parts processing production line

In Figure 1, the demand for the operation state perception system of the garment mechanical parts processing production line is mainly analyzed from five aspects [9]. Firstly, the system can collect real-time data on equipment. The perception of the running state of equipment and the real-time collection of machine tool processing information, including spindle, feed speed, processing power, and processing time, are realized. The realization of online management of a numerically-controlled (NC) machine tool processing program is convenient for production and processing site personnel and

enterprise senior management personnel to master the whole processing process. The ability of digital control in the processing of garment machinery parts has been improved. The potential of machine tools and other equipment can be brought into full play to help the informatization and intelligent process of garment machinery parts processing. Secondly, the system data acquisition method has strong adaptability. Many kinds of equipment are on the garment machinery parts processing production line. The monitoring data sources are complex and diverse, such as different types of CNC systems, data acquisition sensors, etc. There are many types of communication interfaces and diversified communication protocols. It is required that the production line operation state perception has better adaptability and scalability in the data acquisition mode to achieve dynamic adaptation. The third is dynamic tracking, inquiry, and monitoring of production information. In the production process of garment mechanical parts, the production plan formulation, processing task allocation, material flow, and other processes involved will continuously generate a large amount of processing information. Based on on-site data collection of the production line, it is necessary to track and visually query the production plan implementation progress, material distribution progress, and other information in real-time. In addition, it monitors the implementation process of the product processing technology, involving detailed information such as processing technology, current processing operation, current processing equipment, processing personnel, used equipment, and processing time. It also provides functions such as viewing and statistical analysis of historical processing information. Fourthly, it can assist in the optimization of processing technology and processing quality. The garment machinery parts processing production line involves multiple processes. The upstream and downstream process parameters have a coupling relationship and affect the processing accuracy of the parts. Research and establishment of the processing accuracy prediction model play an important role in improving the processing quality of the parts. The processing technology of parts is complex.

The basic data of the workshop, such as equipment, drawings, processing technology, and NC program, are digitally managed. The processing quality data are analyzed to optimize the shortcomings of various processes. Fifthly, it can give early warning and alarm to the abnormalities of the production line. In garment mechanical parts processing, the processing equipment will inevitably have some abnormalities after a long time of work. The cause of abnormal production status is monitored and analyzed to provide an abnormal production alarm. On the one hand, it can reduce unnecessary consumption of processing resources, and on the other hand, it can also ensure the production process's safe and efficient operation.

2.2 Analysis of Data Sources to be Collected in the Production Line

The core of the manufacturing industry is CNC machine tools and other processing equipment, which is also an important support for development [10]. The data collection of CNC machine tools and other equipment is an important link to realizing the digitalization and intelligentization of production lines. For machine tool manufacturers, data acquisition can realize remote monitoring of machine tools to solve problems remotely, such as fault diagnosis and maintenance of machine tools. For manufacturing enterprises, processing data collection helps to monitor and manage the production process, optimize production decisions, and improve production efficiency [11]. The processing machine tools of manufacturing enterprises are often composed of products from different manufacturers. Different machine tools have different information interaction capabilities, leading to the lack of effective data collection methods for production lines composed of diversified CNC machine tools. For perceptual monitoring of garment mechanical parts processing production line, the data sources of perceptual monitoring collection can generally be divided into the following categories, as shown in Figure 2 [12].

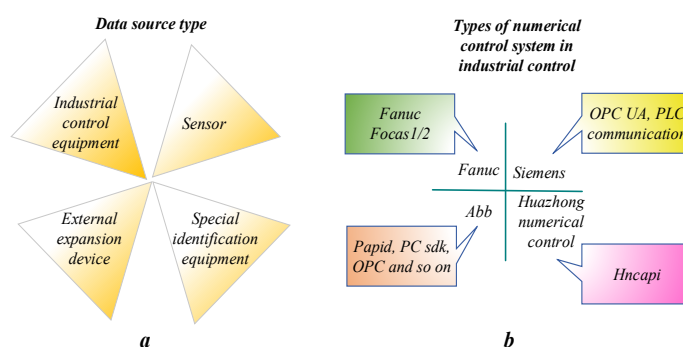


Figure 2: Categories of acquisition data sources (a is the classification of acquisition data sources; b is the classification of NC system communication modes of industrial control equipment)

In Figure 2 (a), the data sources collected by perceptual monitoring mainly come from sensors, external expansion devices, industrial control, and special identification equipment. The sensor is a kind of information monitoring device which can sense external information and convert the information into specific signals that are easier for users to understand according to certain rules. Generally, the type of converted output signals can be divided into voltage, current, resistance, frequency, and other types. According to different application scenarios, there are also different measuring ranges for users to choose reasonably. Communication modules and data acquisition boards are used to expand the communication of traditional equipment. The analog or digital signals measured by the equipment are collected. Serial ports, Universal Serial Bus (USB), or Ethernet are used to transmit information about the running status of traditional equipment. Then, the data is processed and analyzed more deeply in the upper computer. Industrial control equipment includes various numerical control systems, Programmable Logic Controllers (PLC), etc., with good industrial control capability. A CNC system is a machine tool control system with comprehensive control capability, which can deal with various complex processing tasks. Different CNC systems have special communication modes, as shown in Figure 2 (b).

Additionally, their respective data acquisition methods are also different. Siemens CNC system supports PLC communication and collects part of the data of the machine tool by accessing the PLC of the Siemens data system machine tool. It also supports data acquisition via Ethernet. Special identification equipment includes barcode, infrared, image, Radio Frequency Identification (RFID), etc. Among them, RFID establishes the connection between the identification target and the database through wireless communication to realize the fast exchange and storage of non-contact data information. Because of its large amount of information that can be stored and identify multiple targets, it can realize the management of information in relatively complex production environments [13].

2.3 Data Acquisition based on Siemens CNC System

Siemens CNC system has built an Ole for Process Control Unified Architecture (OPC UA) server for process control object linking and embedding. The processing status and alarm information during the machine tool operation will be stored on the server. The OPC UA server has been packaged by Siemens manufacturers and is available for direct use by users. The functional model of OPC UA user client and server is shown in Figure 3 [14].

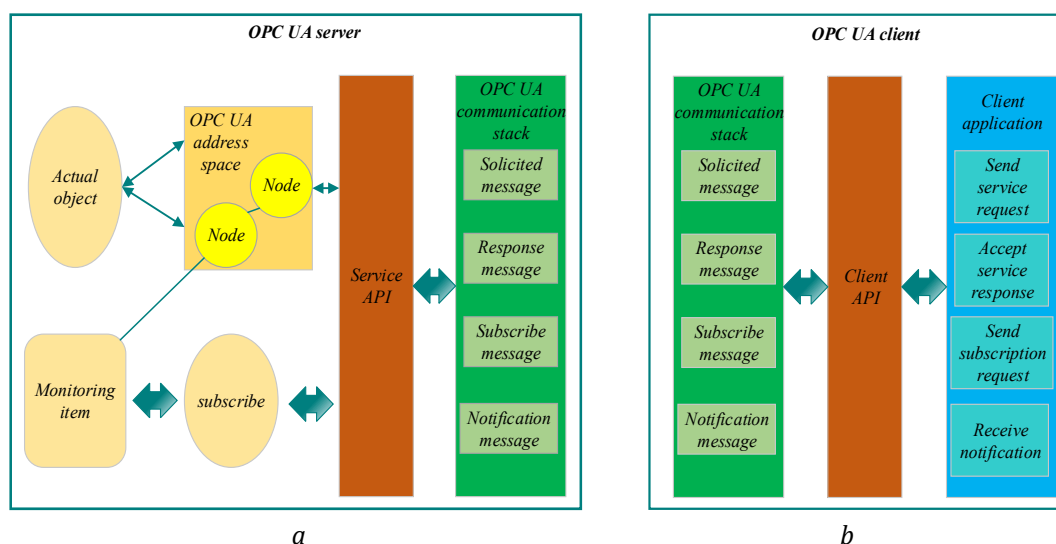


Figure 3: OPC UA application framework (a is OPC UA server architecture; b is OPC UA client architecture)

In Figure 3, the client and server of OPC UA are the supports for the operation of applications and send and receive information based on their respective Application Program Interfaces (APIs). Additionally, the APIs establish the application connection between the communication stack and the client and between the communication stack and the server to realize connection management, message processing, and other functions.

The OPC UA communication stack is used between the client and the server to realize message encoding and transmission. For example. The client's request and subscription information are sent to the server through the communication stack. The server's corresponding information and notification messages are returned to the client based on the communication stack.

According to the traditional solidified design, all software system functions are closely related to the code. Any adjustment in the practical application needs to re-edit the code, so the system's adaptability is poor [15]. The configurable design of the system has the advantages of high flexibility and strong adaptability. When adding new acquisition equipment for data acquisition, the required change is minimized, which will effectively reduce designers' workload [16]. Siemens CNC is used to design a real-time data configurable acquisition system for garment mechanical parts processing production line. The system can meet the requirements of monitoring and perception of the processing state and process parameters of the processing machine under different granularity and improve the applicability and scalability of the monitoring and perception system for different types of data sources of the garment machinery parts processing production line.

2.4 Optimization Algorithm based on Back Propagation Neural Network

The continuous development of advanced technologies such as intelligent manufacturing and Artificial Intelligence (AI) has stimulated enterprises to accelerate the pace of improvement and upgrading gradually.

Product quality is the core of enterprise development. The continuous improvement of product quality helps enterprises cope with increasingly fierce market competition. With the continuous improvement of data mining and AI algorithms, constructing a quality prediction model can analyze the product processing quality problems of the quality-related data generated in the processing process. Deep learning algorithm has obvious advantages in data prediction with their good performance.

Back Propagation Neural Network (BPNN) is a multilayer FNN composed of input, hidden, and output layers. It's training mainly includes information propagation and correction of connection weights and thresholds [17]. The Standard Genetic Algorithm (SGA) simulates the evolutionary law of "survival of the fittest" through selection, crossover, mutation, and other operations, providing a new way to solve complex optimization problems. Multiple Population Genetic Algorithm (MPGA) introduces multiple populations based on SGA, sets different training parameters, and realizes the co-evolution of multiple populations [18]. BPNN can be optimized using MPGA. The main flow of BPNN and its optimization algorithm is shown in Figure 4.

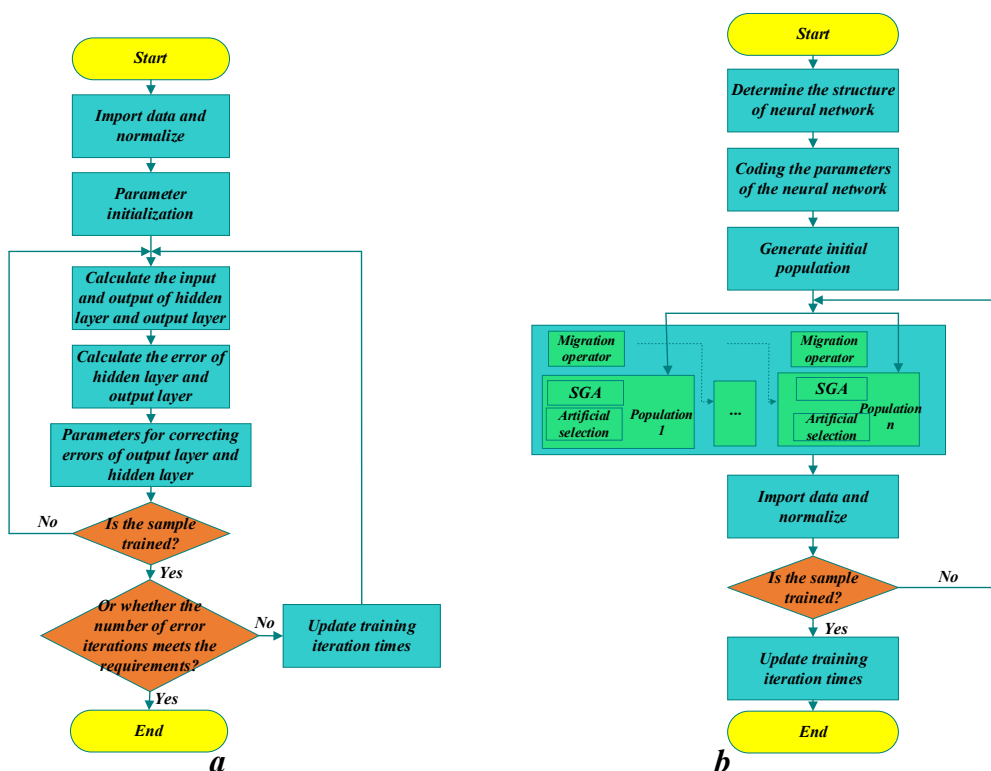


Figure 4: Main processes of BPNN and its optimization algorithm (a: BPNN training process; b: MPGA-BPNN process)

The initial weights and thresholds greatly impact the prediction ability of BPNN. Poor initial values

will cause the network to require a long training time and easily fall into local minima. The initial

weights and thresholds of BPNN are optimized based on the MPGA, which will greatly improve the performance of the BPNN prediction model.

The main flow of the MPGA-BPNN algorithm is shown in Figure 4 (b). The elements of the MPGA-BPNN algorithm mainly include individual coding mode selection, objective function setting, immigration operator setting, manual selection operator setting, etc.

2.5 Quality Prediction Algorithm based on BPNN and MPGA

In order to reasonably select the processing parameters of parts and reduce the unnecessary economic losses caused by experience, the quality prediction algorithm is proposed based on MPGA and BPNN, as shown in Figure 5.

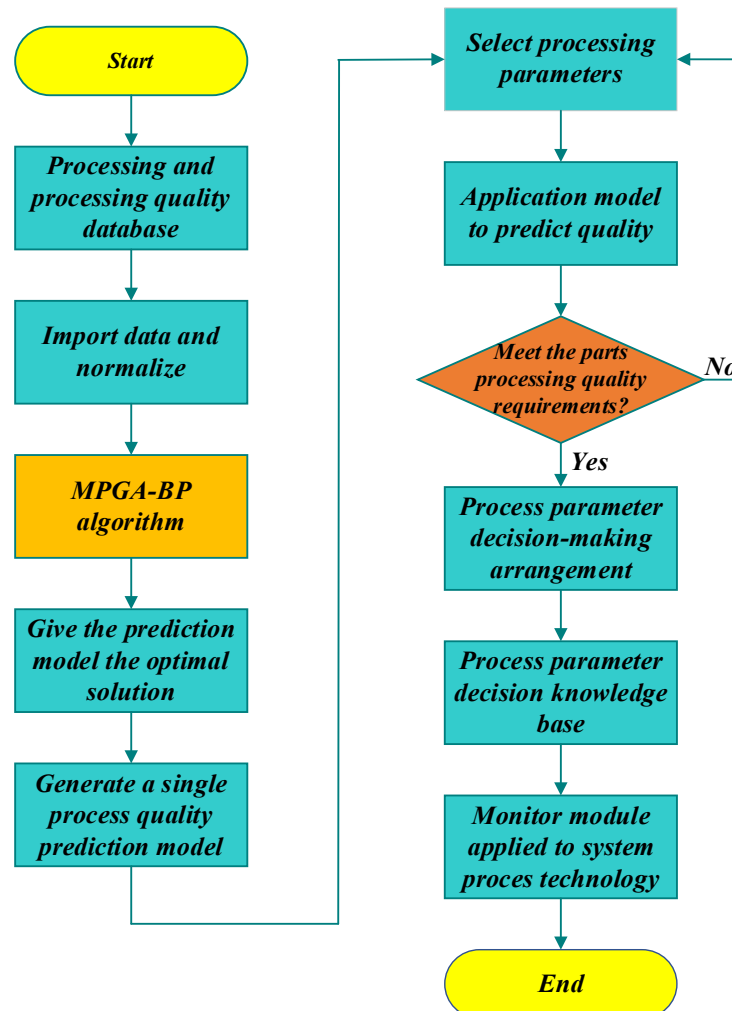


Figure 5: Quality prediction algorithm based on BPNN and MPGA

In Figure 5, using the optimization algorithm based on MPGA and BPNN, the processing technology parameters are used as the model input. The processing quality evaluation indicators are used as the model output to build a processing quality prediction model, which can predict the processing quality of parts corresponding to different processing technology parameters.

The accuracy of the prediction method is measured by root mean square error (RMSE). The calculation method is shown in Eq. (1) [19].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{s}_i - s_i)^2} \quad (1)$$

In Eq. (1), $\hat{s}_i$ is the model prediction output result. s_i is the expected output result. n is the number of samples.

3. Simulation Experiment Design

3.1 Simulation Experiment Environment

The simulation experiment test is used to design the real-time data configurable collection system of the garment mechanical parts processing production line and the quality prediction algorithm based on BPNN and MPGA. The computer operating system used is Windows 10, the processor is Intel (R) Core (TM), the central processing unit (CPU) is i7-7700HQ

2.8GHz, the memory is 16GB, and the hard disk is 1TB. The system performance test database is Microsoft SQL Server 2008 R2. When testing quality prediction methods, the quality and representativeness of the dataset directly impact the model's performance and generalization ability. Therefore, choosing an appropriate dataset is crucial. In this study, the selection of Muhammad's processed dataset from Kaggle (<https://www.kaggle.com/datasets>) for validation is primarily justified in the following aspects: Problem Matching: The dataset focuses on surface roughness as the target variable, with input features including feed rate, cutting depth, and cutting speed. These factors align with the core objectives of quality prediction methods. Feature Selection: Feed rate, cutting depth, and cutting speed are identified as key input features for the model.

This choice reflects the practical considerations of machining processes, aiming to enhance the model's generalization capabilities. Output Labels: Surface roughness is the target label to be predicted. This output label is accurately measured and recorded in the dataset, covering a sufficient range of variations to enable the model to capture surface quality differences under different machining conditions. Scale: The dataset consists of 27 sets of machining data for different parts. Of these, 24 sets are designated for training and 3 for testing. This scale provides ample samples to train the model constructed in this study. The meticulous consideration of these aspects in dataset selection contributes to the robustness and applicability of the quality prediction model in this research. The algorithm training parameter settings are shown in Table 1.

Table 1: BPNN Training Parameter Setting

Project	Parameter
Number of BPNN terminations	1000
BPNN convergence precision	0.001
BPNN learning rate	0.01
Initial population number of MPGA	10
Number of single populations	40
Cross probability of various groups	[0.7,0.9]
Variation probability of various populations	[0.001,0.05]
Generation gap	0.9
Optimal individual least preserving algebra	10

3.2 Simulation Experiment of System Performance Test

Firstly, data is collected, and the client is subjected to concurrent stress testing. The production data of employees is finally inserted into the database based on wireless network transmission. The concurrency of network transmission is not considered here. The production message transmitted in the production process is simulated. The number of database link users is

increasing to test the average data insertion time and the concurrency of system client software when multiple users log in and use under different connection numbers. In the second experiment, the number of database link users is continuously reduced, and the experimental results of the two groups of experiments are compared. The concurrent stress test of the client is conducted on 20 computers. Ten peers complete the first experiment, and these ten students conduct the second experiment on another ten computers. The results of the two groups are shown in Figure 6.

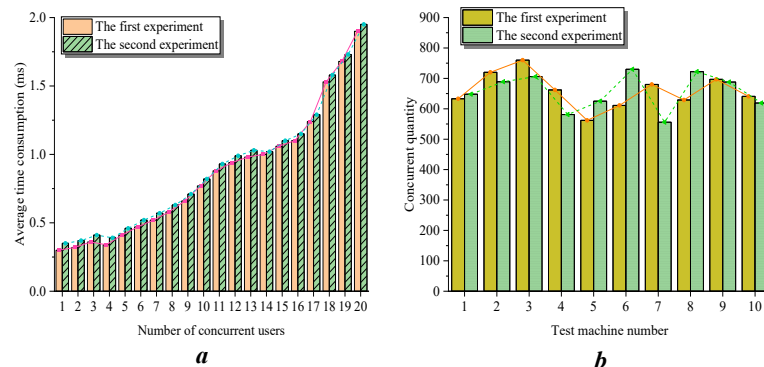


Figure 6: Data Collection and Client Concurrency Stress Test (a refers to data collection concurrent stress test; b refers to client concurrent stress test)

In Figure 6 (a), in the two experiments, the average time spent inserting a piece of data increases with the number of concurrent user connections. When the number of concurrent connections is 20, it takes 1.86ms on average to insert a piece of data that meets the system's requirements. In Figure 6(b), the same personnel conducts the test of simulating the concurrent login pressure on different computers, and the concurrent quantities of the two experimental systems are 659 and 654 users, respectively. The concurrent capacity of the system is about 650 users, which fully meets the scale requirements of the installation and use of the client software in the garment machinery parts production factory.

Next, the page response time of the system is tested. The page response time of the system refers to the time consumed by the user from sending a page request to obtaining the corresponding data. The system page is the medium for interaction between the system and the user and is the most intuitive evaluation standard for the system. According to the unwritten system page response time standard of 2/5/10 seconds, a system with a page response time of 2 seconds is considered to bring a very good user experience. Five seconds is considered to bring a good user experience. Ten seconds is a bad user experience. The page response time test results of the system are shown in Figure 7.

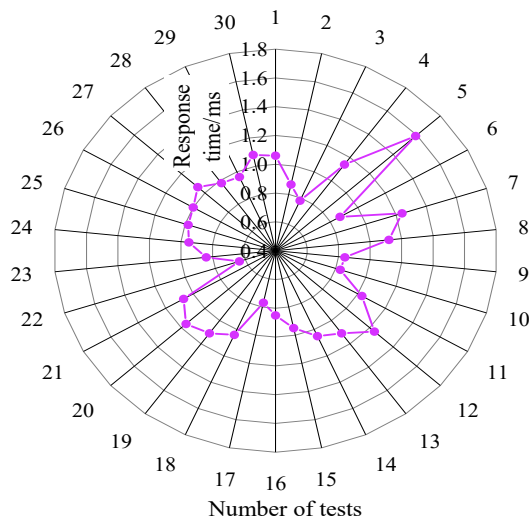


Figure 7: Response time of system page

In Figure 7, in 30 tests, the response time of the system page is different. The maximum response time is 1.59s, the minimum response time is 0.61s, and the average response time is about 1s, meeting the 2s standard. The data indicate that the system can bring users a good user experience.

3.3 Quality Prediction Method Test Simulation Experiment

The proposed quality prediction algorithm based on BPNN and MPGA is tested. The evolution of the optimal solution of the error norm is shown in Figure 8.

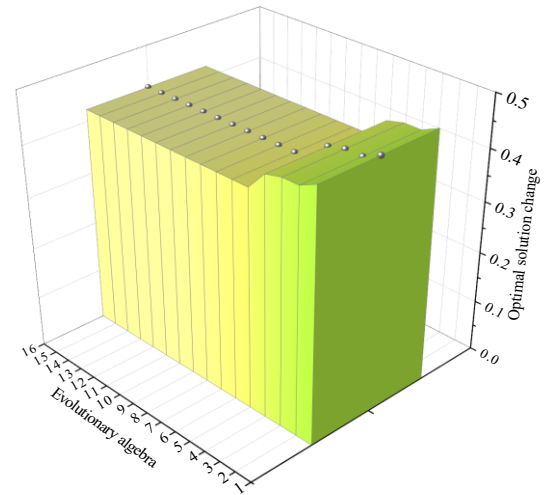


Figure 8: Evolution of large error norm optimal solution

In Figure 8, when the evolution algebra is 1, the error norm optimal solution is 0.481, and then the optimal solution gradually decreases. When the iteration is five times, the optimal solution starts to be stable, then stable at 0.422. Therefore, the optimal solution of quality prediction error norm based on BPNN and MPGA is 0.422. The quality prediction algorithm based on BPNN and MPGA is compared with the traditional BPNN prediction method for surface roughness results. The prediction results of the test set are shown in Figure 9.

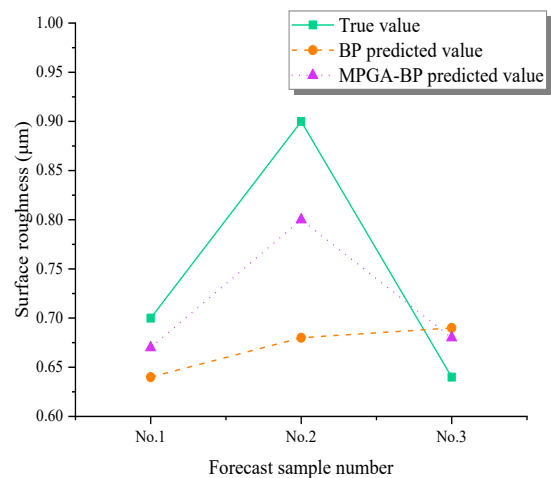


Figure 9: Comparison of predicted results of surface roughness of test set

In Figure 9, compared with the prediction result of traditional BPNN, the prediction result of the MPGA-BPNN algorithm is closer to the true value. The second sample is the largest difference from the true value, which is $0.1\mu\text{m}$. The first sample with the smallest difference is $0.03\mu\text{m}$. However, there is a big difference between the prediction result of traditional BPNN and the real value, with a maximum difference of $0.22\mu\text{m}$. The minimum difference is $0.05\mu\text{m}$.

Finally, the RMSE of BPNN and MPGA-BPNN algorithm is compared. According to Eq. (1), the RMSE of the traditional BPNN is 0.1348, and the MPGA-BPNN algorithm is 0.0645. The RMSE of the surface roughness prediction method based on MPGA and BPNN is relatively small, and the precision of the part surface roughness prediction in this processing process is higher.

4. Conclusions

This paper takes the parts processing production line of clothing machinery as the research object, analyzes the requirements of its running state perception system, and studies the source and collection method of data to be collected. Additionally, based on BPNN, MPGA is introduced, and a quality prediction method based on MPGA and FNN is constructed. The effectiveness of the system and algorithm is tested based on the simulation experiments. The following conclusions are obtained: (1) when the number of concurrent connections is 20, the average time for inserting a piece of data is 1.86ms. The system's concurrency is about 650 users, which fully meets the system's requirements. (2) The maximum page response time of the system is 1.59s, and the minimum is 0.61s. The average response time is about 1s, which conforms to the user experience response time standard. (3)

The prediction results of the MPGA-BPNN algorithm are more accurate than those of BPNN, and the RMSE is smaller. The results are more accurate and closer to the real value. However, there are still some deficiencies. When testing the performance of the MPGA-BPNN algorithm, fewer datasets are used, which may lead to inaccurate results. The sample size will be expanded in the future to make the results more accurate.

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