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Evaluation model and algorithm of intelligent manufacturing system based on pattern recognition and big data

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Abstract

With the development of the big data era, the manufacturing industry is focusing on integrating the technologies related to the evolving intelligent industry. Intelligent manufacturing is the latest form of advanced manufacturing development. In order to pay attention to the design and evaluation status of manufacturing system, we understand the connotation of manufacturing system from the perspective of actual manufacturing production and sales. In this paper, the evaluation model and algorithm of Intelligent Manufacturing System Based on pattern recognition and big data are proposed. In the process of studying the information transmission of intelligent manufacturing system, the evaluation hierarchy algorithm of intelligent control system is improved with reference to several modeling methods. Finally, an intelligent manufacturing system suitable for processing big data is designed. In the experiment in workshop A, with the help of computer simulation of artificial intelligent activities, the intelligent manufacturing system analyzes the processing and production data, obtains the dynamic requirements of products in the machining workshop, and provides judgment basis for the construction of dynamic units in enterprises. The experimental results show that after the change of the production organization model using the seasonal change forecasting method, the introduction of the smart manufacturing system, the sales production of this shop has been increasing, and in the 20th month has increased seven times more than the initial, while the overall situation of the predicted sales and actual sales and costs, the superiority of using the smart manufacturing evaluation model is derived.

Keywords Pattern recognition · Big data · Intelligent manufacturing system · Evaluation model

1 Introduction

1.1 Background

With the advent of many key development processes such as "cloud manufacturing", "big data" and "Internet of things", the manufacturing industry is facing great challenges and has become the theme of this era. Manufacturing industry is the pillar industry of many countries in the world. Intelligent industry is the key driving force for the development of manufacturing industry in many countries in the future. It is listed as one of the most important industry competitors by developed countries such as Europe and America, and so is China. The current development sites are based on the Internet platform. Through the transmission of information and monitoring tools and the use of intelligent devices, the intelligent production network can complete the production work efficiently. With the change of product demand and the

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gradual shortening of product cycle, multi-variety and multi-level intelligent production system is being recognized by more and more enterprises. Intelligent manufacturing system designs a high-performance mode of manufacturing industry, which not only combines many emerging technologies, but also pays more attention to energy consumption and resource utilization, reflecting the organic integration of technology and environmental protection.

1.2 Significance

The construction process of intelligent production system is closely related to the production capacity of the whole intelligent industry, which directly affects the production cost and the overall quality of products. In the Internet era, consumers commonly use online ordering methods, resulting in low and variable market demand. Therefore, fast production systems are needed in order to streamline production, and it also helps to transform Chinese high-tech manufacturing companies from a digital industry model to a smart company. In order to adapt to the development of the times, it is imperative to research and improve an intelligent manufacturing system to assist intelligent workshop production.

1.3 Related Work

In recent years, scholars have not stopped studying the model of intelligent manufacturing system. Pacaux-Lemoine emphasizes people's insufficient attention to the appropriate integration of intelligent manufacturing system into cognitive development plan, and provides technology-based solutions to keep people in the automation of control process and setting different participation levels. Taking artificial intelligence (ASO) as an example, these principles are explained in detail and applied to intelligent production system. This paper mainly studies the implementation of testing to evaluate the system and its effectiveness in improving the performance of electronic system, as well as its acceptance of human factors. Finally, the results show the benefits of this method, but its effectiveness is very weak (Pacaux-Lemoine et al. 2017). The purpose of the test is to use. Qian designed an omni-directional mobile robot based on four mechanical wheels in order to move materials easily and smoothly in a small industrial environment. The control system is composed of two-level controllers, which are respectively responsible for motion control and data transmission of multiple sensors. The mobile robot is integrated into the intelligent production system of moving objects to become the "Porter" of the intelligent manufacturing system and assist the system in processing and production. The experimental results show that the omni-directional robot can work safely and efficiently indoors and in industry. However, at present, large-scale implementation is also difficult (Qian et al. 2017). Intelligent manufacturing system includes software that constitutes the basis of computer, storage and network resources. Bai analyzes the characteristics and significance of intelligent processing system, which leads to the problems faced by cognitive processing system, which is also a part of the advantages of SDN. At the same time, it is the combination of SDN design model of information production system. He has conducted in-depth research on cognitive development in terms of technical interpretation and machine model. However, the results are not very clear (Bai 2017). At present, the Internet of things project is also a research field of colleges and universities. Lin proposed a heat treatment system based on the Internet of things. Web technology, bar code technology and RFID technology are comprehensively used. Web technology is a lightweight and independent communication technology that can receive requests transmitted from the Internet or intranet. It has good cross-platform performance. Bar code is a graphical representation of information and fast information input, while RFID is a non-contact automatic

Table 1 Comparison of some studies in the literature with this paper

Scholars	Major Contributions	Comparison of arguments	Improvements to this paper
Pacaux-Lemoine	Performed tests to evaluate the system and its effectiveness in improving the performance of electronic systems, as well as its acceptance of human factors, were studied	No consideration of the sheer volume of data in real-world applications	The problems that should be dealt with in practical applications are considered and practiced in the workshop, and efficiency is improved
Qian	Designed mobile robots and integrated them into intelligent production systems for moving objects	Cannot help humans with data analysis, situational prediction	This paper improves the intelligent evaluation system and allows for multi-stage product requirements assessment
Wang	Analyzed the high-resolution assembly failure in the IoT environment built an early warning system	Fewer available fields	This paper has more practical areas of intelligent analysis

identification technology. The RFID tag can be read and written. The RFID reader can exchange information with the tag and modify the stored information within the allowable range of the tag design. Thus, an intelligent identification system is created to integrate, network and understand the laboratory management and thermal management. The field application results show that the system can improve production and product quality, and is effective in improving productivity, programming, monitoring and reading. But the actual operation is very complex (Lin et al. 2017). The connection between the Internet of things and intelligent production system is inseparable. Based on the research on cognitive development, Wang analyzes the fertility, development site and Internet of things in cognitive production, then solves the problems existing in Internet application technology in manufacturing industry, and introduces the importance of research speed. It also analyzes the characteristics of high-resolution assembly fault and early warning system in the Internet of things environment, and realizes the construction of the system by defining the characteristics of the system. Finally, the implementation of the scheme is simulated from a real case, which confirms the feasibility and effectiveness of the study, but there are few available fields (Wang et al. 2020). In recent years, the problem of big data analysis has continued to heat up. Zhu focuses on big data analysis in intelligent production system. These systems can automatically adapt to the changing environment and changing process requirements without operator supervision and assistance. It is an important physical development plan in cyberspace, which enhances understanding through learning, thinking, adaptation and decision-making. Effective use of big data can improve the understanding and automation of production processes, provide high-quality products and production time, improve productivity and reduce costs. However, the current technology is not developed enough (Zhu et al. 2019).

1.4 A Summary of some of the literature and some improvements to this paper

1.5 Innovation

By analyzing the information transmission process of intelligent manufacturing system and the modeling method of intelligent production system, this paper refines the evaluation hierarchy algorithm of intelligent control system. The conclusion of the reliability system of intelligent manufacturing system is defined in detail, which provides a research framework and research suggestions for the development of the system reliability system. Through the structural topology of the production system, the structural elements of the production system are described in detail and compared with the traditional production chain. According to the definition of reliability (the ability to complete specific tasks), the functions of system equipment are further discussed.

2 Design method of intelligent manufacturing system evaluation model based on pattern recognition and big data

2.1 Two categories of pattern recognition methods

(1) Unsupervised learning

Unsupervised learning is an artificial intelligence algorithm. Its purpose is to distinguish the known original data in order to retrieve the relevant general data information. Different from supervised learning algorithm, unsupervised learning algorithm cannot determine whether the training result is accurate at runtime, that is, it does not try to improve (such as the correct learning type) (Wang et al. , 2017). Its approach is to provide only input models for this model, and automatically detect its production rules from these models. After training and testing, it can be applied to new cases. The common unsupervised learning method is necessary for group analysis. It collects similarity and identifies them as the same category according to the similarity, and does not need to be interested in specific information (Jokic et al. 2022).

(2) 2) Supervised learning

Supervised learning training executes the best training model on the identified training data based on the evaluation model, and then uses the obtained model to judge the unknown data, training data and known results in the stream. When the model result is a continuous value, it is called regression, and when the model result is a class symbol, it is called division. The goal of supervising students is to predict any possible input data according to the training results after viewing the identified training samples (Guo et al. 2022). To reach this range, students need to find general features from available data in some way and apply them to general anonymous data. The main training methods are: decision trees, plain Bayes, neural networks, support vector machines, linear least square fitting, KNN, maximum entropy, etc. (Vasudevan 2018, 2019).

Supervised learning is to learn the labeled training samples to classify and predict the data outside the training sample set as much as possible. Unsupervised learning is to train and learn unlabeled samples, and compare and find the structural knowledge in these samples.

2.2 Information transmission process of intelligent manufacturing

The information flow of intelligent manufacturing system is transmitted and fed back among the three-level systems to ensure the real-time performance of information. The information transmission process is shown in Fig. 1. The release of upper data is determined at the control layer. MES monitors the operation status of equipment at the lowest control level, collects application status data, analyzes, calculates, processes and transmits the results to system control to help the company make compliance decisions and corrections. In the enterprise information construction of process manufacturing industry, the process control technology (PCS) represented by advanced control and operation optimization is used for production control in the bottom workshop. PCS emphasizes the control of equipment—reducing the influence of human factors and improving product quality and operation efficiency through control optimization—while ERP emphasizes the planning of the enterprise (Wang et al. 2019).

The template function of intelligent production system is similar to that of assembly line production system. In the intelligent production system, the single target model can be divided according to the production aspects, such as scale, cost, utilization rate and use source of materials (Sierra-Perez et al. 2016). In addition, the intelligent manufacturing system also includes the mine with minimum robot travel and minimum power consumption. The multi-concept model is the integration of a single target model, which greatly improves the complexity and difficulty of the model. A model can combine multiple sites into a platform. The specific structure and production system of the model are shown in Fig. 2 (Aldosary et al. 2021).

Several modeling methods can be used to model a single target and multiple concepts of intelligent production system (Cao 2016), as follows:

(a) Standard methods to reduce production scale.

In order to shorten the production cycle, it is necessary to reasonably arrange the total production time, robot walking time and standing time at the same time. The traditional large-scale manufacturing industry has a single product category and relatively stable process, and there are obvious weaknesses in the production of large quantities and small products. The functions of each module unit in the intelligent manufacturing system are different, and the product design is very flexible, which can be used in a wide range according to the requirements (Lachapelle and Ferguson 2017).

(b) Standard methods to reduce production costs.

Production cost is directly related to the financial income of enterprises, affects commodity cost, and is the main competitive factor of enterprises. Intelligent manufacturing companies reduce production simulation costs and labor and time costs and increase the entry of robots and mobile devices.

(c) Standard method for increasing equipment utilization.

Equipment utilization refers to the ratio between the actual running time and execution rate of the application in the overall planning period. It is a technical and economic index to measure the production performance and efficiency of an enterprise. In the intelligent manufacturing industry, all materials are relatively expensive, and materials account for more than 50% of the company's total investment. Therefore, the consumption of materials is directly related to the manufacturing capacity. Therefore, saving manufacturing materials is equal to reducing production costs (Uchikawa et al. 2016).

(d) Standard method for maximum material utilization.

The optimal allocation of resources in the network production area is related to many indicators such as energy efficiency cost, production capacity, product delivery date and efficiency. In the intelligent production unit, the higher the material utilization rate, the lower the product cost.

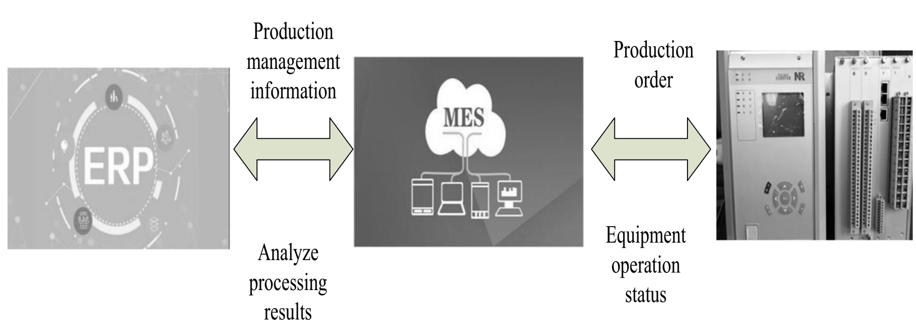


Fig. 1 Intelligent manufacturing information transmission process

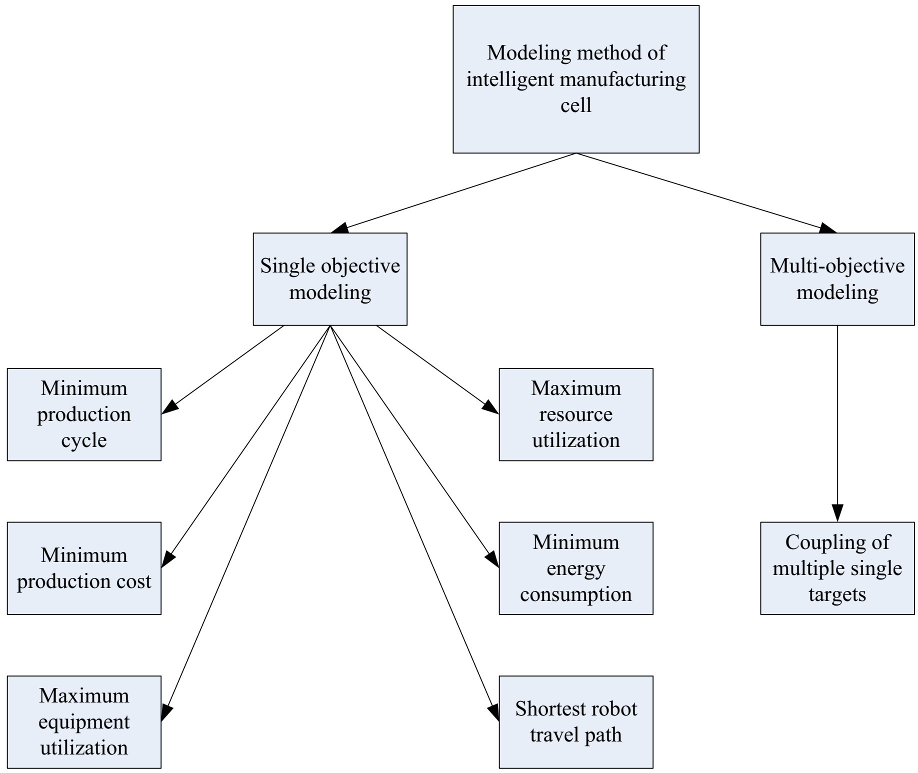


Fig. 2 Modeling classification of intelligent manufacturing units

(e) The goal is to minimize the energy consumption to complete the processing task.

The minimum energy consumption is to complete the specified processing and manufacturing tasks with the minimum energy consumption within the specified time. According to the statistics of China science network, if the energy consumption of manufacturing enterprises per unit of GDP is reduced by 20%, the emission of sulfur dioxide will be reduced by 26%, and the total emission of chemical demand will be reduced by 15%. Improving the cost performance of resource products and eliminating high energy-consuming and backward industries have become the main objectives of environmental protection.

(f) Multi-objective modeling method.

The change of market and the explosion of product types make single objective modeling unable to fully meet the necessity of production. Therefore, it is often necessary to consider two or more optimization objectives (Meng et al. 2016).

2.3 Evaluation index system of intelligence level

Intelligent system is a system with anthropomorphic understanding. Anthropomorphic intellectual characteristics are the cognitive characteristics of imitating, expanding and expanding individuals. The cognitive characteristics of personification are reflected in: thinking level, behavior level and perception level. The thinking level refers to the brain's systematic thinking of a thing, and the behavior level refers to self-adjustment, self-organization, self-softening, self-correction, self-reproduction, etc. Perceptual level refers to the acceptance and understanding of information through organs. In addition, the level of understanding and performance of the program are affected by the overall design process. Therefore, the system is also used as part of the evaluation. As an intelligent system serving people, it ultimately depends on the role of serving individuals. Therefore, the impact of understanding level on role should also be changed as an evaluation index (Kaur et al. 2019).

To sum up, the evaluation of intelligent system includes primary index system, information manager, sensor, intelligent controller and intelligent control role. The primary indicators are divided into secondary monitoring indicators, and the secondary indicators are divided into tertiary indicators. The tertiary indicators can be calculated directly or in proportion.

The evaluation of information management system starts from the lowest level of three indicators. It should be noted that testing multiple reports requires the participation of relevant experts. Implement the functions, procedures and methods of different understanding management systems. The findings here can only be general programming, especially real understanding. The scheme also needs to be further improved according to the actual situation, and a test method meeting the requirements can be developed, which can be combined with the specific understanding management system (Donno et al. 2016).

For experienced auditors who use a variety of audit methods, it is very important to compare their strengths and weaknesses and be able to measure them, without paying attention to the intermediate stability process and how to know the implementation process. This is a method of calculating system index at random rate. The net interest rate can be defined by formula (1) (Adewuyi et al. 2016):

$$A_i = \frac{1}{i}\sum_{i=1}^{I} a_i \tag{1}$$

where I represents the number of typical test points. a_i represents the control compliance rate of the ith typical test point, and i is the serial number of the test point.

$$O = \left|F^P - F_O^P\right| / \Delta^P \tag{2}$$

$$\mathrm{B} = \sum_{p=1}^{p} O \tag{3}$$

$$a_i = 1 - \frac{1}{P}\sum_{p=1}^{p} \frac{\left|F^P - F_O^P\right|}{\Delta^P} \tag{4}$$

P represents the number of output variables, F^P represents the output value of the p-th output variable, and A_o^P represents the output expected value of the p-th output variable corresponding to the test point; Δ^P represents the output value range of the p-th output variable. When the output is divided, it is the total number of divided gears minus 1, where $0 \le A_i \le 1$ has normalized characteristics (Sansone et al. 2016).

Min–max normalization performs linear transformation on the original data. It is assumed that MAXF and MINF represent the maximum and minimum values of attribute F, respectively, min–max normalization by calculation.

$$\Delta F = \mathrm{Max}F - \mathrm{Min}F \tag{5}$$

$$v = \frac{F - \mathrm{Min}F}{\Delta F} \tag{6}$$

There are two common function forms:

(1) Membership functions of benefit index (the bigger the better):

$$f(x) = \begin{cases} 1, x \ge b \\ \dfrac{x-a}{b-a}, a < x < b \\ 0, x \le a \end{cases} \tag{7}$$

(2) Membership functions of cost indicators (the smaller the better):

$$f(x) = \begin{cases} 1, x \ge a \\ \dfrac{b-x}{b-a}, a < x < b \\ 0, x \ge b \end{cases} \tag{8}$$

$$v = \frac{F - \overline{F}}{\sigma_F} \tag{9}$$

Decimal scaling normalization is achieved by moving the decimal point position of attribute F. The number of decimal places moved depends on the maximum absolute value of F, and the calculation formula is

$$v = \frac{F}{10^i} \tag{10}$$

where i is the smallest integer in makes Max ($|v|$) < 1. For example, if the value of F is 125, then $|F|$= 125, then i = 1 and v = 0.125.

2.4 Evaluation algorithm of intelligent manufacturing system

(1) Absolute IQ Algorithm

The absolute IQ algorithm is expressed as:

$$\mathrm{IQ}_F = \sum_{i=1}^{N} A_i \cdot W_i, \tag{11}$$

where A_i represents the score of evaluation index items, W_i represents the weight of evaluation index items, and the number of evaluation index items is represented by N.

(2) Relative IQ Algorithm

We call the IQ calculated by formula (12), (13) or (14) relative IQ or proportional IQ (Cheng et al. 2016).

$$X = \sum_{i=1}^{N} \frac{A_i - T_i}{T_i} \tag{12}$$

$$IQ_B = 100 \times \left(1 + \frac{1}{N} \times X \times W_i\right), \tag{13}$$

$$\mathrm{IQ}' = 100 \times \mathrm{IQ}_F / \mathrm{IQ}_o, \tag{14}$$

of which:

$$\mathrm{IQ}_o = \sum_{i=1}^{N} T_i \times W_i \tag{15}$$

$$\mathrm{IQ}''_B = 100 \times \mathrm{IQ}_F / \overline{\mathrm{IQ}}_F, \tag{16}$$

of which:

$$\overline{\mathrm{IQ}}_F = \frac{1}{M}\sum_{i=1}^{M} \mathrm{IQ}_{Fi}, \tag{17}$$

where M is the number of similar intelligent products participating in the evaluation. By Formula (13) and (14), the calculation results are basically the same, through the IQ′ value, can know whether the product meets the demand criteria, you can also know the level of intelligence of the intelligent product in the relative position of similar products. The advantage of Eq. (16) is that it does not require the standard value of T_i, and the intelligence level of each product in similar products can be known according to the value IQ_F the intelligence level exceeds the average value at $\mathrm{IQ}''_B > 100$, is exactly equal to the average value at $\mathrm{IQ}''_B = 100$, and is less than the average value at $\mathrm{IQ}''_B < 100$. Formula (16) is applicable when T_i is not known. The disadvantage is that it is not known whether the product or even similar products meet the demand standard, and sufficient samples are required, otherwise IQ_F in (16) is meaningless. Note that the average value and standard value are not the same concept. The average value reflects the average level of similar products, and the standard value reflects the instrumental requirements of human beings for intelligent products (Zhang et al. 2016).

The values calculated by Eqs. (13), (14) and (16) are only meaningful in similar products and have no comparative significance with other types of products, because the standard values T_i and IQ_F of different types of products are different.

(1) Dispersion IQ Algorithm.

This algorithm is similar to the deviation IQ algorithm of human IQ test, which can be expressed as follows:

$$G = \frac{\mathrm{IQ}_F - \overline{\mathrm{IQ}}_F}{S} \tag{18}$$

$$\mathrm{IQ}_D = 100 + \frac{\mathrm{IQ}_F - \overline{\mathrm{IQ}}_F}{S} \tag{19}$$

where S is the standard deviation of the group score of the category of the tested product.

$$S = \sqrt{\frac{1}{M} \times \sum_{i=1}^{M} \left(\mathrm{IQ}_F - \overline{\mathrm{IQ}}_F\right)^2} \tag{20}$$

This is a standardized evaluation method. G is the standard score, which represents the number of standard deviations from the group average (Maffezzoni et al. 2017).

The farther an individual's score is from the average, the greater the absolute value of the standard score, and the farther away the corresponding IQ_D value is from 100, if the standard score is positive, the measured IQ will be higher; otherwise, if the standard score is negative, the measured IQ will be lower.

(19) The advantages and disadvantages of equation are basically the same as Eq. (16). However, compared with formula (16), formula (19) highlights the position of individuals in the group, especially when the $\overline{IQ}_F$ value is large.

2.5 Design of intelligent manufacturing system evaluation system

In the evaluation process of intelligent manufacturing system, there is a large amount of data processing. If it is all manual, the workload is heavy and easy to make mistakes. Therefore, the intelligent level evaluation software is developed. This system is based on the previous research results. The evaluation of intelligent level of intelligent manufacturing system is in the research stage, and some aspects need to be further discussed and improved. This system is designed and developed based on the current research results (Paeschke et al. , 2016).

(1) Function module

The system is divided into the following functional modules, as shown in Fig. 3.

1) System management module. In order to ensure the security of the system, different passwords should be set for different users and different use rights should be specified during operation. The module also provides perfect data backup function, which can recover quickly and accurately once the data is damaged.
2) Evaluation index module. Based on the Mau method and the description of the characteristics of intelligent control system in the control field at home and abroad, a reasonable intelligent-level evaluation index system is formulated and improved. According to the main idea of the evaluation model, firstly, according to the actual situation, some evaluation contents that can effectively reflect the intelligence level of the intelligent control system are proposed, which constitute the highest level of the evaluation model. Then, each evaluation contents is decomposed layer by layer until an evaluation index that can be accurately defined and accurately tested is generated.
3) Evaluation and scoring module. According to the evaluation index system, the indexes of the system are tested and the test results are reduced. When testing each index in the

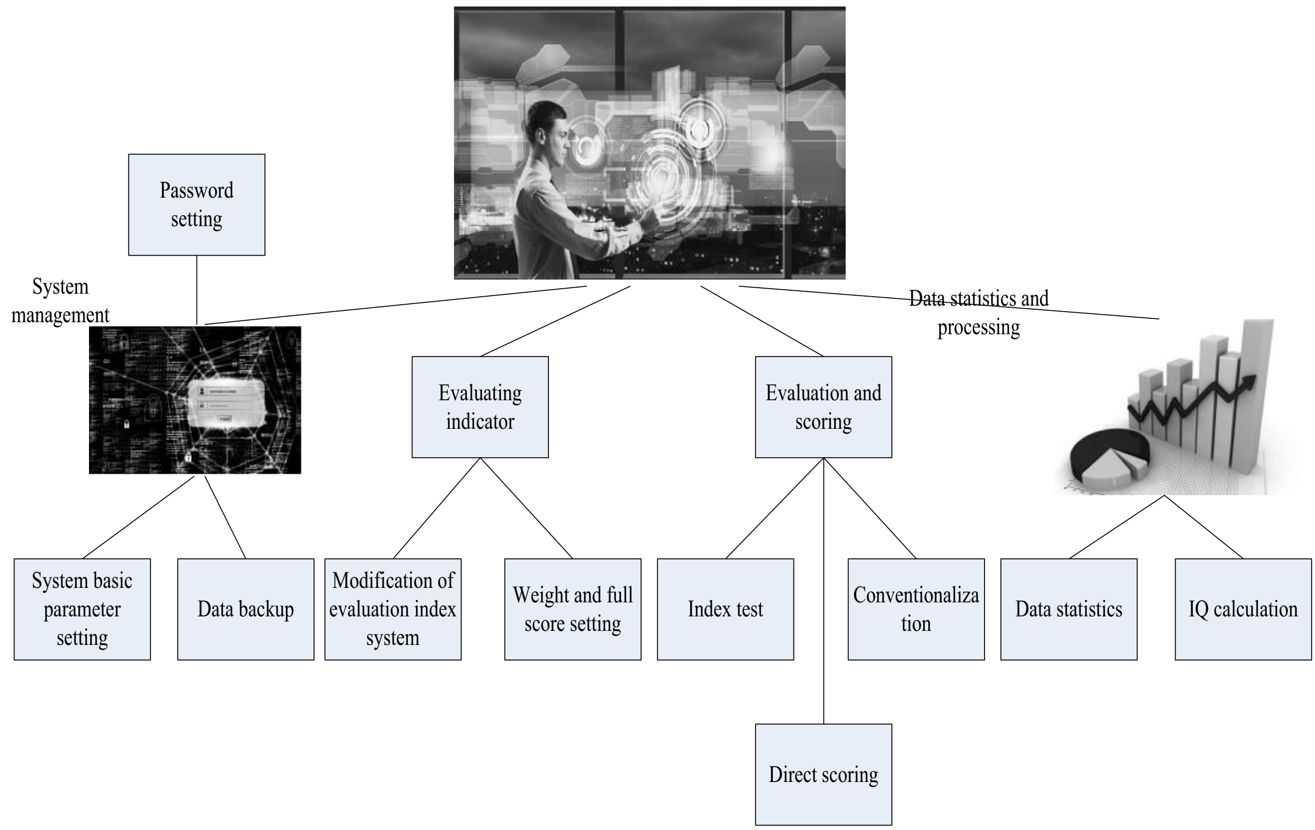


Fig. 3 Schematic diagram of system functions

evaluation model, we get some results in different units, different dimensions and different types. For example, the test result data may include current value, voltage value, time value, count value, percentage, granularity value, logic value, etc. Therefore, they must be converted into unified measurable and evaluable results.

4) Data statistics and processing module. The first step is the statistical analysis of the test data in a certain sample space. The main is to find out the standard value of each index of a certain category of intelligent control system. The second step is to calculate the absolute IQ and relative IQ of the intelligent control system according to a certain algorithm.

The evaluation index system is relatively stable but not invariable. As the basis for the evaluation of system intelligence level, the evaluation index cannot be changed at will, but it must be adjusted accordingly with the continuous development of scientific and technological level. The functions provided by this module include creating, modifying or deleting the evaluation index system, setting the weight of each evaluation index, and setting the full score of each evaluation index as a reference for direct scoring. The functions of this module can only be used by system level users.

(2) Database design

The evaluation of intelligent control systems starts at the bottom level (Level 3 metrics). The three-level indicators are the indicator items that are easy to test or can be tested directly. By testing these indicators, the most primitive evaluation data are obtained, which, reflecting the intelligence level of the intelligent control system in all aspects, are synthesized according to the comprehensive evaluation algorithm, and the intelligence level of the system is obtained.

After analysis, it is concluded that the entity relationship is shown in Fig. 4.

According to ER diagram, six tables are designed as follows:

First level indicator attribute table = first level indicator number + first level indicator name + weighted value of first level indicator;

Secondary indicator attribute table = secondary indicator No. + secondary indicator name secondary indicator weighted value + primary indicator No;

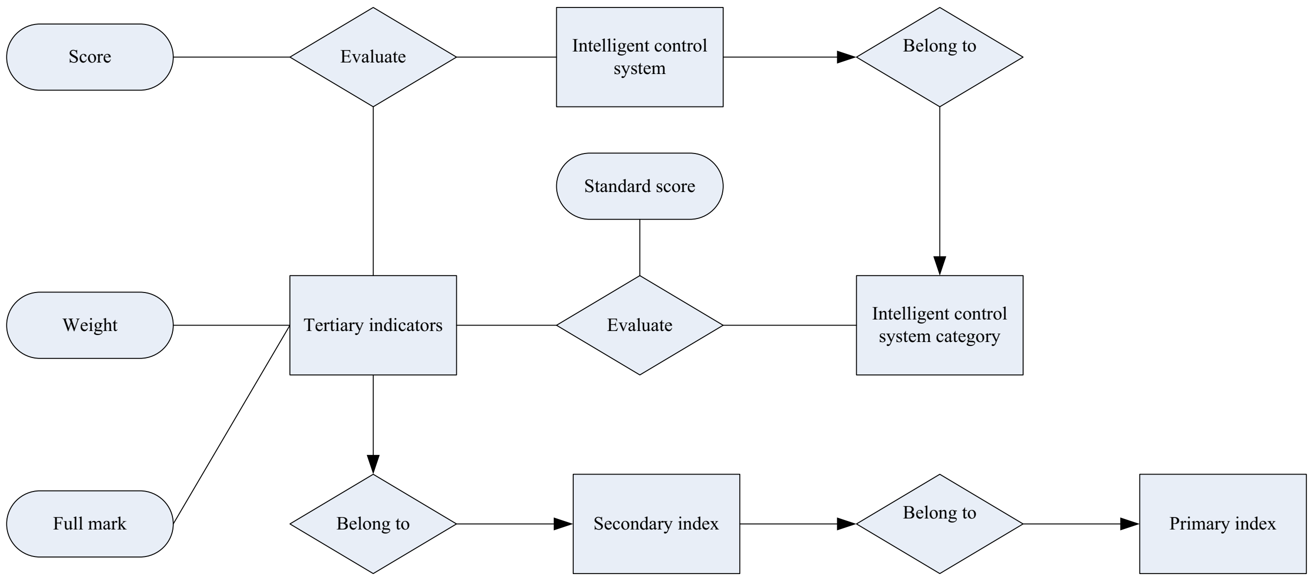
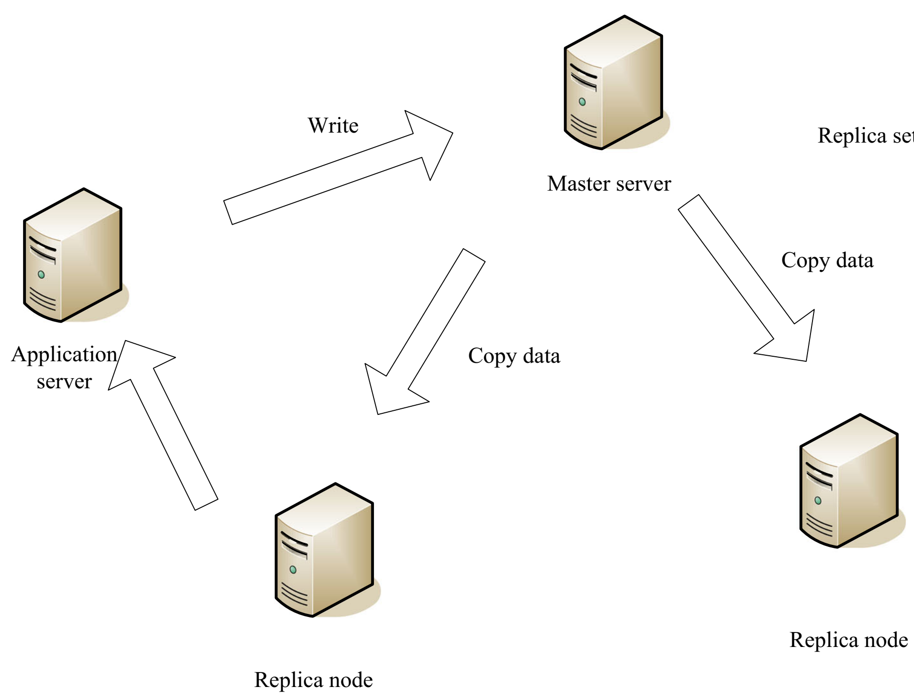


Fig. 4 Entity relationship (ER) diagram

Fig. 5 Operation diagram of replication system cluster



Level 3 indicator attribute table = level 3 indicator number + level 3 indicator name + level 3 indicator relative weighted value + level 2 indicator number + level 1 indicator number + full Score of level 3 indicator.

Grade III index score table = grade III index number + intelligent control system name + grade III index score.

Intelligent control system category table = intelligent control system name + intelligent control system category name.

Standard score table of level III index = category name of intelligent control system + level III index number + standard score of level III index.

The MongoDB database is a distributed file-based database that serves to provide a scalable, high-performance data storage solution for WEB applications. The design of distributed file systems is based on a client/server model. A typical network may include multiple servers for multi-user access. In

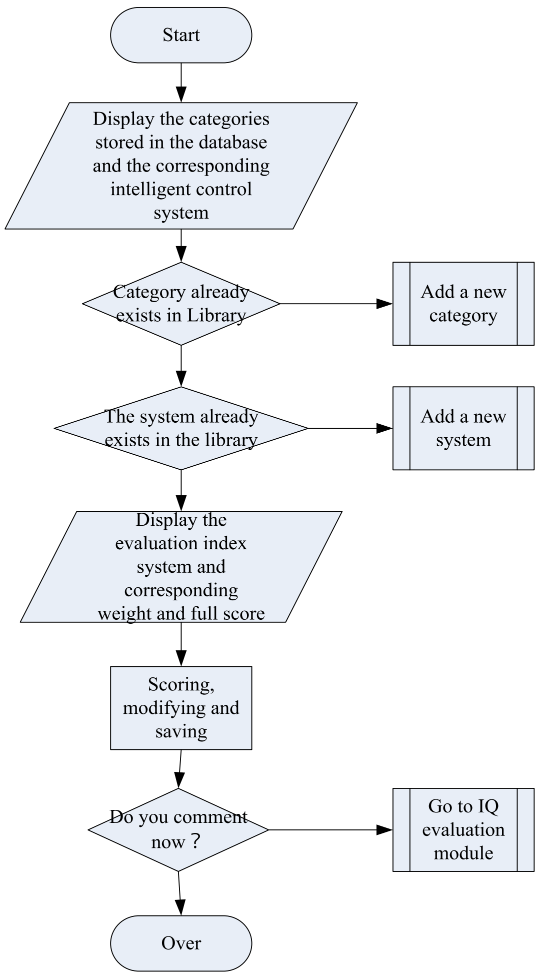


Fig. 6 Program flowchart of scoring module

addition, peer-to-peer capabilities allow some systems to play the dual role of client and server. MongoDB is between database and unrelated database. It can store more complex data types and has more data processing languages. MongoDB is suitable for large-scale processing of real-time data and high-resolution scenarios embedded with dozens or hundreds of servers.

There are two main concepts for MongoDB to create a cluster: creating a new slave and replication. The operation of replicating the system cluster is shown in Fig. 5. The server is mainly divided into master node, replica node and arbitration node. The replica node is responsible for reading data to identify the data set. When the master is encountered randomly, the arbitration node uses the bull algorithm to select the master session from the replica part. At the same time, MongoDB cluster distributes a large amount of data to a shared machine equipped with sharing technology to increase server capacity to withstand pressure.

(3) Detailed design

Taking the scoring module as an example, the detailed design of the system is given. The program flowchart of scoring module is shown in Fig. 6.

3 Experiment of intelligent manufacturing system evaluation model based on pattern recognition and big data

Whether it is decision-making or production control, the reliability of production system is an important index to measure efficiency. Due to the growth of the company, the market demand for some types of construction equipment is relatively stable, so the workshop is also facing the transformation of production organization mode. The grouping process and production process previously focused on machines cannot meet the current market demand. For this test, several manufacturers were closely monitored and finally selected factory a laboratory for testing. Working in the center of cutting, winch and distributor required by this construction machinery can

Table 2 Demand for parts in three stages

Part type		1	2	3	4	5	6
Demand for parts at different stages	1	60	89	30	126	65	111
	2	45	90	36	135	63	111
	3	49	86	35	122	62	126

Table 3 Demand for parts in three stages

Part type		7	8	9	10	11	12
Demand for parts at different stages	1	100	78	64	88	120	199
	2	96	76	65	86	121	210
	3	95	86	65	85	132	201

improve production efficiency and reduce the trouble of on-site control. This paper selects the reliability index in the redesign process. Therefore, how to realize the high reliability and low reproducibility of the system in the redesign process has become the focus of this work, and it is also the concern of enterprise executives.

In this work, the design cycle is divided into three time stages, i.e., $t = 1$, 2 and 3. For the static machine construction model, $t = 1$, 2 and 3 in each stage are solved, respectively. Finally, the total system cost of these three levels is obtained to increase the reliability of system delivery, and the resulting price is compared with the comprehensive department. The matching decision can be generated by comparing the total cost during the whole design period of model construction with the reliability value of system delivery date.

The examples in this paper include seven equipment and 12 types of parts. The requirements of each type of parts in different production stages are shown in Tables 2 and 3.

Table 4 Equipment purchase cost and resettlement cost table

Cost	Purchase cost	Installation cost
1	40,000	200
2	52,000	330
3	36,000	620
4	45,600	350
5	35,000	420
6	49,000	520
7	50,000	600

Table 5 Total output and the number of defective products in the workshop of the factory A in the previous 12 months

Months	Total output	Quantity of defective products
1	50	10
2	60	9
3	62	8
4	52	5
5	58	6
6	95	4
7	32	0
8	65	6
9	66	6
10	95	10
11	56	3
12	78	5

The cost of purchasing different equipment and installing different equipment into the unit are shown in Table 3.

The total output and quantity of defective products of the workshop in factory A in the previous 12 months are shown in Table 5.

4 Evaluation model and algorithm analysis of intelligent manufacturing system based on pattern recognition and big data

There is only one assembly line at the end of the workshop, with four stations, and each station has one worker for assembly operation. Therefore, this assembly line is a multi-product assembly line. The experimental data in this paper are from the assembly line in workshop A. Because the workshop currently implements the pull production mode, and the assembly line is in the end link, which is the beginning of pull production, it is particularly important to evaluate the ability of the assembly line to complete different orders according to different orders. This paper selects the machining workshop A as the case application background, because the parts produced in the workshop are the core parts used in the finished products of construction machinery, and most of them belong to self-made parts. Therefore, workshop A belongs to the key production workshop of the enterprise. In addition to the machining workshop, the enterprise also has structural parts workshop, boom workshop, general assembly workshop, etc. The calculation method adopts the seasonal change prediction method. In this paper, the month is used for prediction. The sales data for 20 consecutive months have been randomly taken, as shown in Fig. 7.

It can be seen from the figure that after the change of production organization model and the introduction of intelligent manufacturing system, the sales output of the workshop has been increasing. In the 20th month, it has increased seven times compared with the original. Because the technology was immature at the beginning, the sales unit price was a little low, reaching 500 yuan. Although there were increases and decreases in the middle, the overall trend is still increasing, and the final unit price is set at 600 yuan. It shows that the introduction of intelligent manufacturing system has a great positive effect on our industrial production.

Due to the multi-stage dynamic unit construction, based on the previous data, the impact of month on sales volume should be removed as much as possible, and the future product demand needs to be predicted accordingly. According to the sales situation in the last 12 months, the sales trend in the next 12 months can be obtained, as shown in Fig. 8.

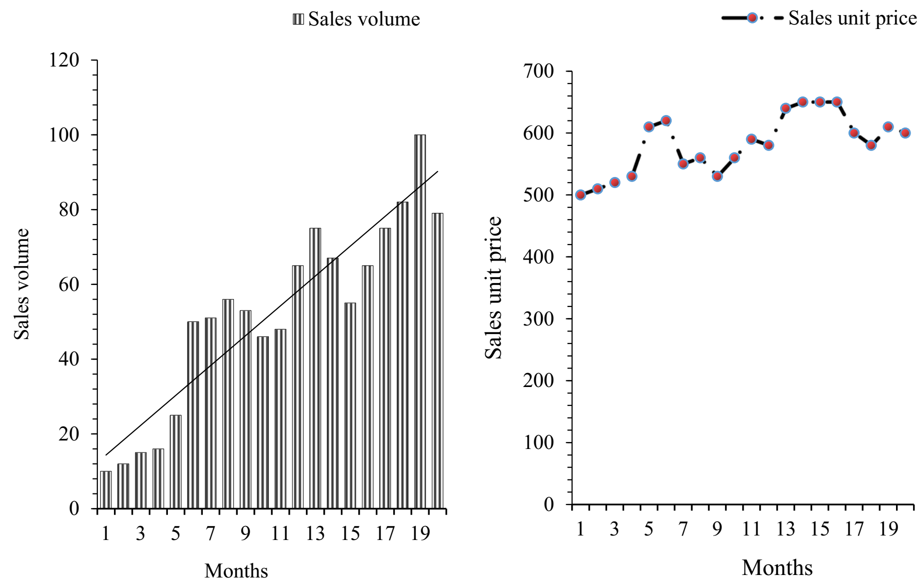


Fig. 7 Sales situation of the workshop in 20 months

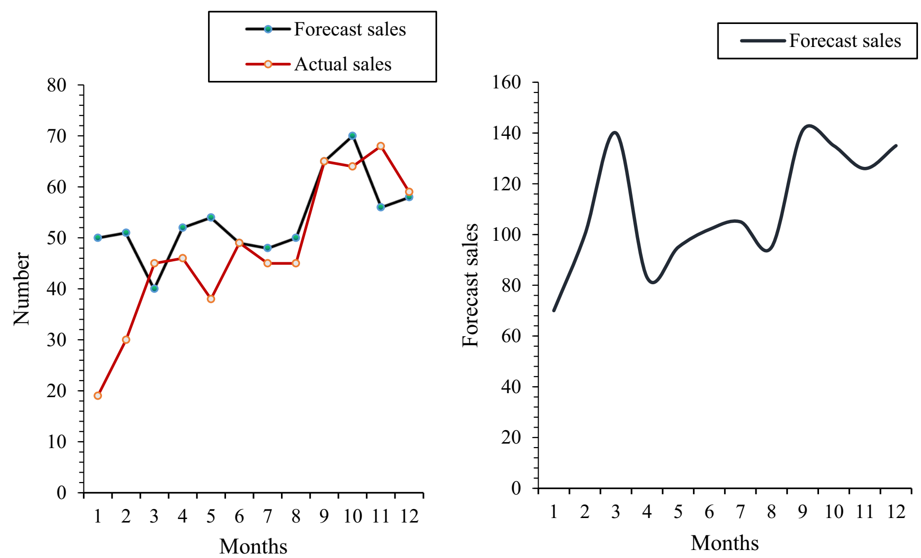


Fig. 8 Sales volume trend fitting graph and last year's twelve-month forecast graph

As shown in Fig. 8, except for the large gap in the first month, which is 31 sets different from the actual value, the trend of predicted sales volume and actual sales volume is basically consistent on the whole. According to this method, we can calculate the production forecast value of the next year and judge its trend. It shows that the predictions of the smart manufacturing evaluation model are valid. The dynamic demand of products in machining workshop is obtained by this method, which provides a judgment basis for the dynamic unit construction of enterprises. Figure 9 shows the output in the last 12 months.

It can be seen from the figure that the total output of products is high every month, up to 110 sets. The number of defective products is relatively stable, no more than 10 per month.

According to the number of defective products produced in the workshop, the loss cost can be estimated. The sales profit is excluding some raw material costs, labor costs and transportation costs. It can be seen from the figure that the overall situation is shown in Fig. 10, except that the cost of raw materials should be as high as 6500 yuan.

5 Conclusion

This paper studies the working capacity of the manufacturing system to evaluate the ability of the manufacturing system to meet orders. The input data of the model is closer

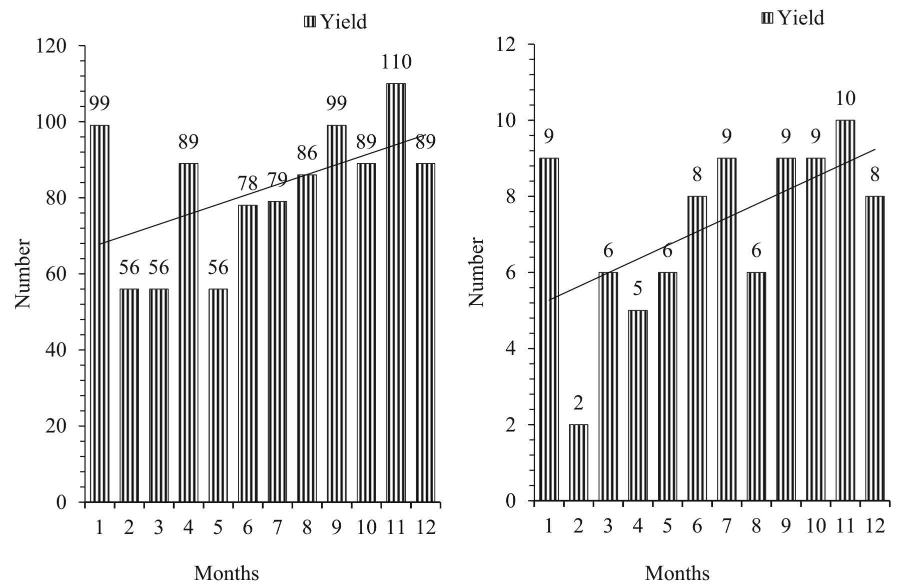


Fig. 9 Total output and the number of defective products in the last 12 months

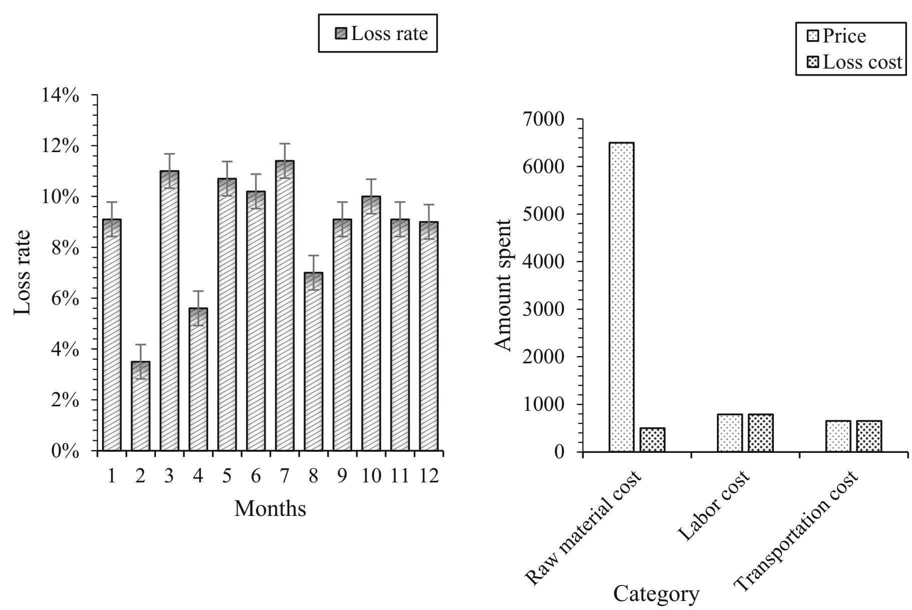


Fig. 10 Loss and cost in the workshop

to the production practice because it considers the random capacity, qualification rate and production beat of the workstation at the same time, that is, the evaluation process comprehensively considers the reliability of the manufacturing system in terms of output and product quality. However, due to time and personal problems, there are still some deficiencies in the research process. For example, the research results prove the superiority of the evaluation system, and the research scope can be further expanded. The comparison can also further study the improvement of work efficiency and utilization of intelligent manufacturing system. Many enterprises may have multiple assembly lines for the same type of products, and the assembly capacity will be different. How to evaluate the reliability of multiple assembly lines to complete orders, how to allocate orders to maximize the delivery reliability, which is worthy of further research. At this time, the algorithm construction of the model will become difficult. At the same time, the sensitivity analysis of reliability related factors should also be carried out, which will make the model more complete.

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Availability of data and material Data sharing does not apply to this article because no data set was generated or analyzed during the current research period.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethics approval This article is ethical, and this research has been agreed.

Consent to participate This article is ethical, and this research has been agreed.

Consent for publication The picture materials quoted in this article have no copyright requirements, and the source has been indicated.

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