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A new intelligent and data-driven product quality control system of industrial valve manufacturing process in CPS

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ABSTRACT

The development of intelligent and data-driven product quality control system are emerging as key engineering technologies for industrial manufacturing process. And many studies have been made to investigate the application of quality control of industrial valve manufacturing process in cyber–physical systems (CPS). The purpose of this article is to provide a quality control and management system by using the modern electronics technology, information technology and network technology. Firstly, we propose an intelligent and data-driven framework model of product quality based on the advanced technology of digital twin (DT) and simulation methods for CPS. Secondly, we emphasize the manufacturing enterprise should hold a data accumulation, and give some useful advises on how to carry out a successful quality analysis system of industrial valve manufacturing process in CPS. Then, as a case, the intelligent method of BP neural network is constructed according to lots of quality characteristics (QCs) of the mechanical and electrical product of industrial valve, and the BP network is trained by using many quality failures of manufacturing process. Finally, the results show that the new quality control system has good accuracy and practicability by the practical example.

1. Introduction

With the increasingly fierce global competition, more and more manufacturing enterprises face an increasing demand for customization and shorter time-to-market. As market competition intensifies, people are more willing to pay more money for high-quality products. So product quality predictive control becomes an important technology in product manufacturing process. The primary challenge at present is how to guarantee the stability of manufacturing process and improve the product quality level by using intelligent control technology. In addition, an intelligent and data-driven control system is an important approach for process monitoring and quality control. Thus, precisely forecast product quality in industrial valve manufacturing process has very important significance to improve the customer satisfaction.

On the other hand, CPS just like a bridge, connects production industry and technological services, which is used in electric industry, transport systems, trade and other fields [1]. CPS is also a major simplification of real physical system in large part, and it captures enough of physics to provide useful insight for administrators and policy-makers to ensure product quality. On some degree, intelligent decision enhances the accuracy and security in CPS, and lessens time lapse in data transmission process [2]. Furthermore, a data-driven intelligent decision method is an important part of CPS. Because the data contain lots of useful information, CPS captures enough intelligent decision support for product quality management person [3]. However, a lot of data are stored but unusable in manufacturing process so that product quality control information processes are hard to be implemented in the practical systems [4]. There will be of great value to design and develop a product quality control system of industrial valve manufacturing process in CPS based on data-driven and intelligent algorithms [5]. Thus, this study presents intelligent methodology, mathematical analysis and analog simulation approach for product quality control system in CPS.

Moreover, dynamic data-driven simulation and analysis has become a hot spot of intelligent system simulation for CPS in current [6,7]. With a solution of data-driven exception reporting or real-time trend monitors, we can do hard work of scrutinizing several of operational analysis reports to find significant data of development trends [8]. In addition, data-driven intelligent control through testing and debugging is indeed effective at improving product quality [9,10]. An intelligent system has automated capabilities for activities such as data-driven testing and scoring process. While lots decision information is data-driven and dynamically generated, most is still largely static in manufacturing process of CPS [11]. So, an intelligent and data-driven product quality control system should include data processing, modeling and optimization. In this paper, we have built many data-driven tests on the industrial valve manufacturing process in CPS for

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increased validity and accuracy of dynamic classification of quality faults [12]. This intelligent approach is an unsupervised, statistical, data-driven approach by using BP neural network algorithm and other network technology. On the other hand, a data-driven product quality control system with fault recognition, report facility, decision models, document library, and more [13]. It can also be useful for tying data-driven events for manufacturing processes in CPS.

In addition, the intelligent and data-driven control system is important in manufacturing process because it affects the product quality directly. A strict quality control system is to ensure the good product quality based on intelligent and data-driven model of workshop manufacturing process [14]. First, this paper suggests that a new control model of quality evaluation of industrial valve manufacturing process in CPS should be introduced product quality control of machining and assembling procedures of CPS. We should set up a strict product quality control system in real physical system. Next, the product quality system is compliant and effective by using those tracing back from the final product through quality control data and batch records [15,16]. Manufacturing enterprises should execute an effective quality system for the monitoring of process performance to ensure the CPS run successfully. Then, product maintenance quality and operating system will directly affect the quality control precision of manufacturing process in CPS [17]. Once the product quality control system were used, we can monitor real situation of product quality control process and make appropriate control measures to improve the production efficiency and product quality [18]. Finally, an intelligent control system is used to ensure international standards of product quality guaranteed to a great extent [19]. The quality control system can achieve lots of QCs of the collection, storage, analysis and control functions, and pass the influencing factors of man, machine, material, method, measurement and environment in CPS simulation product quality forecasts and control.

Based on the research in the literature, a quality control system is to ensure product standards in the whole process of product life cycle in CPS. Combining the intelligent algorithm of BP neural network, the automatic predictive control methods can improve product quality, and upgrade the accuracy and stability of quality control and management system. Based on an effective intelligent decision methods, a new product quality control system of manufacturing process in CPS was constructed and the future development trend was successfully simulated. This study is an extension and improvement of the previous work on intelligent and data-driven product quality control system of industrial valve manufacturing process in CPS.

The rest of this paper is organized as follows. The intelligent and data-driven framework model of quality control system in CPS proposed in Section 2. Section 3 discusses the intelligent method of neural network for quality predictive control. Section 4 presents the implementation details and predictive control process for the experiments of manufacturing process of ball valve in CPS. The experimental results and related analysis have shown that the intelligent and data-driven product quality control system can shorten the time of decision making and improve the productivity of data acquiring of industrial valve manufacturing process in CPS. Finally, some useful conclusions are summarized in Section 5. The main contributions in this paper are proposing the new intelligent and data-driven product quality control system of industrial valve manufacturing process in CPS from the application example.

2. Proposed intelligent and data-driven framework model in CPS

2.1. Framework of product quality control system in CPS

CPS is a kind of intelligent wireless network system which is integrations of computation, networking and physical worlds. Because of its great application prospects, CPS can realize dynamic control, information services and real-time sensing of large-scale engineering systems. The developing trend of CPS is the integrate of digitization, integration, networking and intelligence. Currently, most studies of CPS mainly focused on manufacturing mode of intelligent manufacturing, such as intelligent equipment and intelligent factory. This article focuses on product quality control system of industrial valve manufacturing process in CPS.

In this paper, we firstly introduce a new intelligent and data-driven product quality control system to practitioners with years of product liability practice in many manufacturing enterprises. The product quality control model is a detecting system of workshop manufacturing process management-oriented which detects the abnormal information in the actual production process to control product quality, so as to improve economic benefit and reduce economic loss. At the same time, this paper describes the new framework model, which is a key element of the design and verification methodology for data-driven product quality control system of industrial valve manufacturing process in CPS. The framework model analysis was extended and detailed, and the application was also improved in the new system.

The proposed model represents CPS as a set of floors with properties and connections of equipment floor, data floor, network floor, acknowledge floor and application floor, and each floor of is the projection of the framework model. The three types of frameworks covered in this CPS are modularity, data-driven, and model driven. Based on the above analysis, the product quality can be absolutely guaranteed by using dynamic running information of total quality control system in intelligent plants. The product quality control system has the functions of data-base management, data statistic and query on real time network and the quality control of manufacturing process. The framework of intelligent and data-driven product quality control system of manufacturing process in CPS is shown in Fig. 1.

The framework will automatically locate and execute data processing and decision making for product quality control system, without requiring too much human intervention. The data layer of framework contains the enterprise intelligence data acquisition, data analysis and stores. In the framework, data needs to be normalized across different data layers of the application. In addition, with the widely application of intelligence manufacturing, more and more scholars pay attention to the research for the structural system of data layer in CPS by using intelligent decision making method and data-driven technical.

2.2. Data-driven decision model of product quality intelligent control in CPS

With the development of modern manufacturing technology, the Industry 4.0 technologies are now gaining broader adoption and it has been one of the most prospective industrial applications. New control methods need to ensure a continuously high product quality because of variation and individuation of customers' demands [20]. In case of a product failure in manufacturing process, quality engineers aim to identify the root cause and take measures to stop it. Other than that, it also includes detailed information about the manufacturing process because some changes of managing exceptional situations can cause catastrophic failure of the quality control process. Faults that occur due to errors at the design stage and manufacturing process are the most dangerous because implementation of the product quality control system can be a challenging task. The prevalence of such faults which is related to the fact are designed without the participation of quality experts by using incomplete or inaccurate data.

To accommodate this unprecedented situation, data-driven decision model has been obtained with intelligent algorithm. In addition to product quality monitoring and predictive control, the potential of data-driven analysis along the lifecycle is very necessary in many traditional manufacturing companies. On the other hand, in the light of the development of product quality control system, ensuring high quality products becomes a major challenge for quality managers of enterprises. Hence despite great effort to identify potential problems in product manufacturing process in CPS, product failure cannot be completely avoided due to technical limitations.

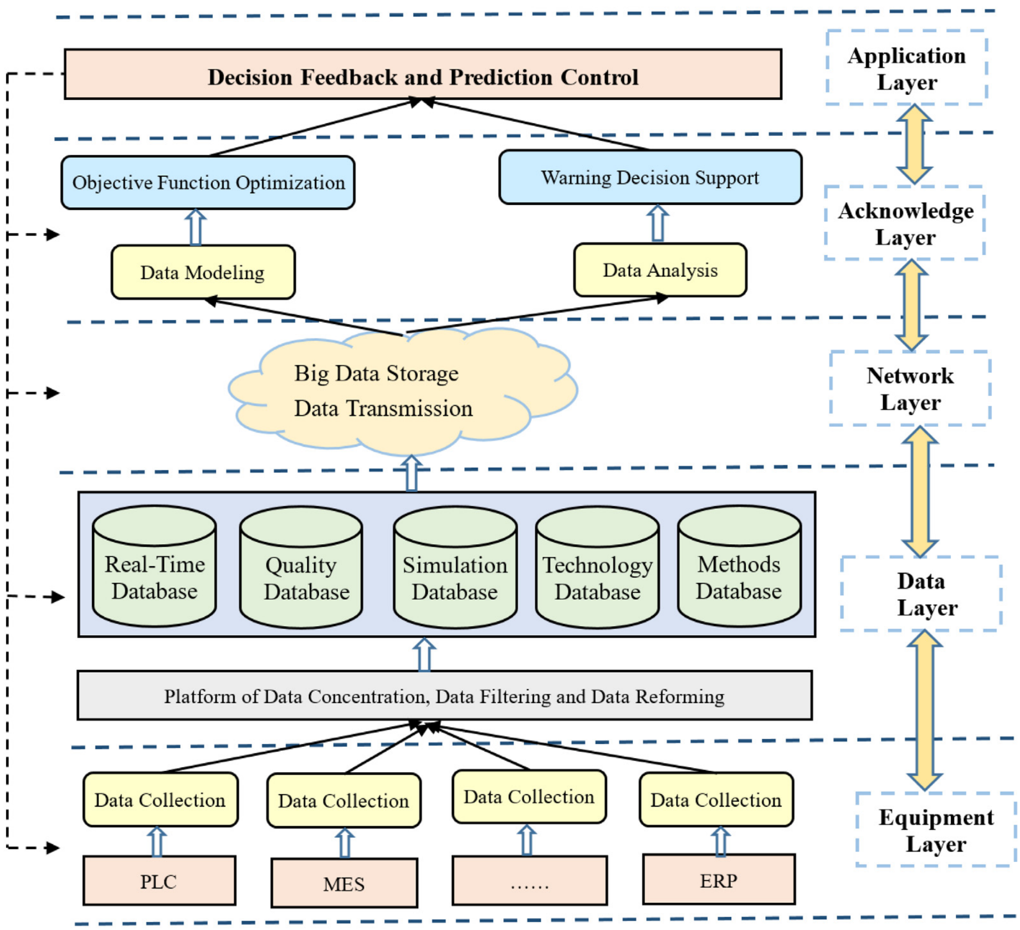


Fig. 1. Framework of intelligent and data-driven product quality control system of manufacturing process in CPS.

However, the vast number of product attributes needs analysis with much time and relies on the experience of quality engineers. Thus, an application of data-driven decision model based on a DT as support tools for knowledge fruition has been designed and developed for CPS [21,22]. For this reason, this paper proposes the elements of DT for the purpose of quality monitoring and control in CPS [23]. The primary purpose of DT is to consolidate product QCs by using different types of data of product structure, processing, assembly, manufacturing and network service process [24]. Moreover, non-standard processes and events of database failure occurs have to be archived in the DT [25]. In addition, the representation of DT is necessary to enable data analytics despite the complex manufacturing processes [26]. The elements of DT for product quality monitoring and control and suggests a data-driven decision model that enables data analytics is presented in this paper. For this purpose, a digital fruit twin is developed based on mechanistic modeling [27]. A data-driven decision model of product quality control in CPS based on DT and intelligent technology is shown in Fig. 2. Then, several intelligent techniques are presented, in which artificial intelligent techniques such as neural network intellectualized control, collaborative computing and decision expert system, network and the database are included.

DT has real-time synchronization and high-fidelity characteristics, which can been used to solve the fusion problem of physical world and information world. Digital technology leverages the intelligence of a digital production model to create twins between the physical and digital worlds by using DT methods for quality control and management through product life cycle. Based on a large number of twin data mapped by physical and digital space, the real-time state value and actual value of QCs are mapped to twin digital model, and a multi-dimensional evaluation model was established to reflect the real-time state of product quality in manufacturing process. Then, digital twin models and twin data that perfectly map to real products are proposed to evaluate the manufacturing process quality state in real time.

Furthermore, through the accumulation of big data and application of DT technology in the whole life cycle of products, lots of manufacturing process errors can be adjusted and verified on the twin virtual body in time, and the quality prediction control level of products can be effectively evaluated and improved. The combination of DT technology and intelligent algorithm can present the real situation of physical entities in the digital world in real time, and predict and rehearse the upcoming events. Besides, combined with big data technology and statistical analysis methods, DT technology can be used to find the optimal quality optimization scheme by using simulated different manufacturing strategies. DT technology can also quickly find quality defects and problems may occur in the manufacturing process, so as to effectively control the process quality and improve the overall products quality level.

3. Intelligent method of neural network for quality predictive control

Neural network is an intelligent diagnosis technique developed in recent years. According to the mechanism of biological nerve, this technique is composed of many simple connected neurons based on the corresponding tissue rules. Neural networks are computer systems which mimic the workings of brain in different situations [28]. At first according to the analysis of techniques principles several major parameters affecting product quality are found out and used as training variables. Moreover, neural networks have many performance advantages, such as nonlinear mapping, self-organization, and fast parallel

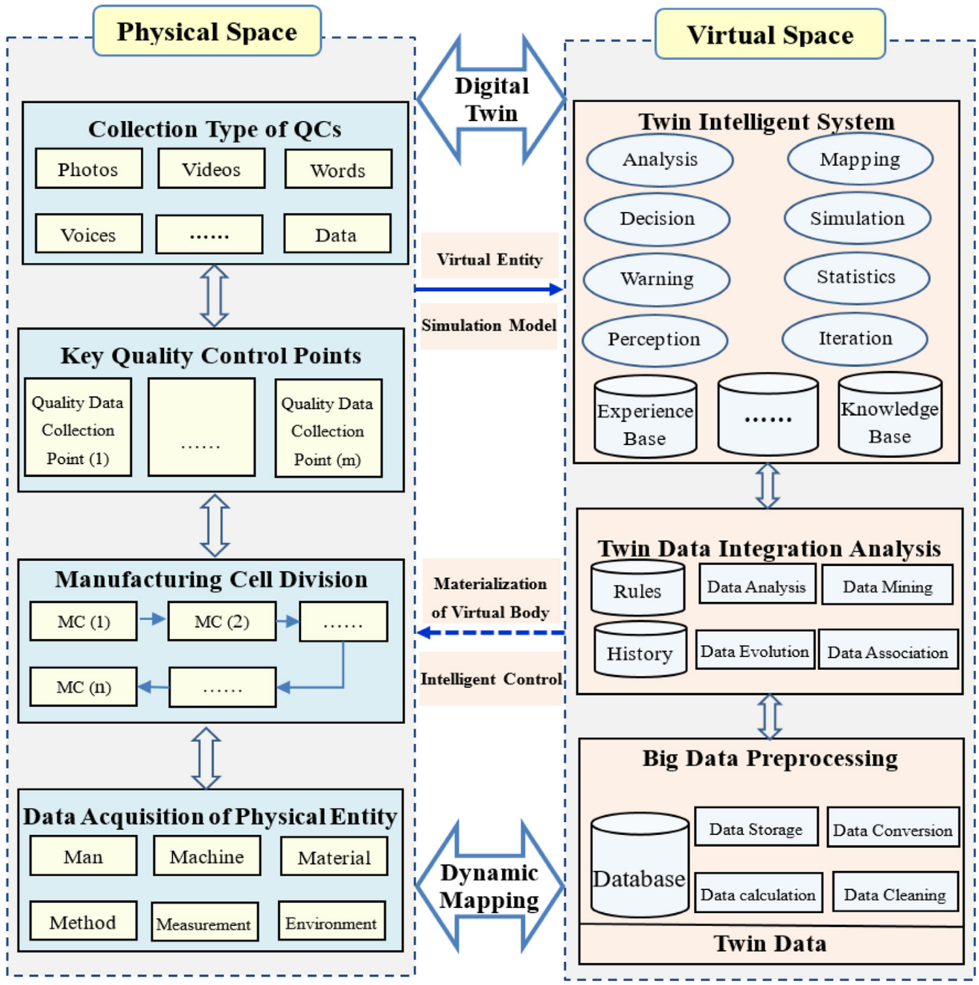


Fig. 2. Data-driven decision model of product quality control in CPS based on DT and intelligent technology.

distribution processing and self-learning. Supervised learning is the most common method for training neural networks by using the linear multi-step method. Neural networks have been applied successfully in many fields, such as pattern recognition, speech analysis, fault diagnosis, nonlinear control, predictive control and modeling of thinking and consciousness.

In this paper, neural network is studied and a fault diagnosis method based on neural network is presented. BP algorithm is used for training neural networks to establish quality predictive control model of industrial valve manufacturing process in CPS. A neural network is studied and a quality predictive control method based on neural network is presented in this paper. The most popular data mining tools already use intelligent technology of neural network and data fusion. In the case study, the modeling neural network of fault diagnosis for valve body is introduced after the neural network was trained. In order to realize the intelligent fault diagnosis of valve body, the causality between symptoms and faults was determined by the collected data from a ball valve manufacturing enterprise.

3.1. Theory of BP neural network

BP neural network is a kind of multi-layer feed forward network trained by error back propagation with some algorithms. Artificial neural network does not need to determine the mathematical equation of the mapping relationship between input and output in advance [29]. Gradient descent method is the basic idea of neural network, which was used to search technology to minimize the error mean square error between actual output value and expected output value of the network [30]. If there is any error between the output layer and the expected output layer, the error of BP neural network will be adjusted from output layer through hidden layer with the back-propagation, and the precision requirement will be reached continuously [31].

Moreover, as an intelligent information processing system, the core of artificial neural network is to realize its function with advanced algorithm. BP neural network algorithm has the learning process of forward signal propagation and backward error propagation [32]. BP neural network has a kind of multi-layer forward neural network [33]. Through its own training and learning some rules, the closest to the expected output value can be received after the input value are accuracy, clarity, and completeness. In general, the BP neural network model are built by using the model of export divisor and input divisor and the model structure with neural network principle. A neural network system has the advantages of self adaptability and fault tolerance, which can been widely applied in a variety of industrial applications.

3.2. The calculation process of BP algorithm

The relationship between the input and the output of BP algorithm for forward multi-layered neural network has a signal propagation process. On the other hand, BP algorithm changes weights and deviations in the direction where the error function decreases fastest in the opposite direction of gradient, which is consistent with the learning algorithm of linear network [34]. The iterative calculation formula of BP algorithm can be expressed as:

$$x_{k+1} = x_k + a_k g_k \tag{1}$$

where, x_k is the current weight and deviation, x_{k+1} is the next weight and deviation generated by the iteration, g_k is the gradient of the current error function, and a_k is the learning rate.

In this paper, the selected neural network has three layers, and the BP network with a total of three layers of neurons was used as an example to deduce the learning algorithm. Let us suppose, for example, the number of inputs is *X*, one of which is represented by *x*. Then, the hidden layer is represented by *H*, which contains *H* neurons, one of which is represented by *h*. The output layer is represented by *K* and contains *K* neurons, one of which is represented by *k*.

Furthermore, the weight between input layer and hidden layer is denoted by w_{xh}, which represents the weight between the *x*th neuron in the input layer and the *H*th neuron in the *H* layer. The weight between hidden layer and output layer is denoted as w_{hx}. Next, the input of a neuron is denoted as *a*, the output is denoted as *b*, the number of layers is indicated by a superscript, and the subscript indicates the serial number of the neuron. Then, the transfer function of all neurons is sigmoid function, the trained sample is denoted as $M[M_1, M_2, M_3, \dots, M_P]$, where each training sample is an multiple dimensions vector, the expected response is $d_k = [d_{k1}, d_{k2}, d_{k3}, \dots, d_{ks}]T$, the actual output is $N_k = [N_{k1}, N_{k2}, N_{k3}, \dots, N_{ks}]$, and *n* is iteration. The number of times, the weight and the actual output are all functions of *n*.

When the input of network trains is the sample $M_k[M_{k1}, M_{k2}, M_{k3}, \dots, M_{kI}]$, the intermediate value for each layer can be given in the following expression. The input variable to the *h*th neuron of hidden layer is given as:

$$a_h^k = \sum_{i=1}^{I} w_{ih} M_{ki} \tag{2}$$

Next, the output variable to *h*th neuron of hidden layer is calculated as:

$$b_h^H = f\{\sum_{i=1}^{I} w_{ih} M_{ki}\} \tag{3}$$

Then, the input variable of *k*th neuron of output layer is calculated as:

$$a_p^P = \sum_{h=1}^{h} w_{hp} b_h^H \tag{4}$$

Similarly, the output variable of the *k*th neuron of output layer is calculated as:

$$N_{kp} = b_k^K = f\{\sum_{h=1}^{H} w_{hp} b_h^H\} \tag{5}$$

Thus, the output error of the *k*th neuron of the output layer is calculated as:

$$e_{kp}(n) = d_{kp}(n) - N_{kp}(n) \tag{6}$$

In this definition, the error energy is $e_{kp}{}^2(n)/2$, the sum of error energy for all neurons in output layer is presented as:

$$E(n) = \frac{1}{2} \sum_{p=1}^{p} e_{kp}{}^2(n) \tag{7}$$

Moreover, to improve the usability of simulation results, a threshold modification method of BP algorithm was proposed to reduce truncation error and propagation error in calculation process. In the BP algorithm, the adjustment of weight and error energy of the output relative to expected response are proportional to the weight, but the symbols are just opposite. From the description above, the process of calculating the partial differential can be given as follows:

$$\frac{\partial E(n)}{\partial w_{hp}(n)} = \frac{\partial E(n)}{\partial w_{kp}(n)} \cdot \frac{\partial E_{kp}(n)}{\partial N_{kp}(n)} \cdot \frac{\partial N_{kp}(n)}{\partial a_p^P(n)} \cdot \frac{\partial a_p^P(n)}{\partial w_{hp}(n)} \tag{8}$$

In the next step, based on the relationship between the error energy formula and various variables, it can be known as:

$$\frac{\partial E(n)}{\partial e_{kp}(n)} = e_{kp}(n) \tag{9}$$

$$\frac{\partial e_{kp}(n)}{\partial N_{kp}(n)} = -1 \tag{10}$$

$$\frac{\partial n_{kp}(n)}{\partial a_P^p(n)} = f'(a_P^p(n)) \tag{11}$$

$$\frac{\partial a_P^p(n)}{\partial w_{hp}(n)} = b_h^H \tag{12}$$

So the local gradient can be described as follows:

$$\delta_p^P(n) = \frac{\partial E(n)}{\partial a_p^P(n)} = e_{kp}(n) \cdot f'(a_p^P(n)) \tag{13}$$

Then, according to the learning rule of gradient descent, the correction amount of $w_{hp}(n)$ is given as follows:

$$\Delta w_{hp}(n) = -\eta \frac{\partial E(n)}{\partial w_{hp}(n)} = \delta_p^P(n) \cdot b_h^H(n) \tag{14}$$

where, η is the learning step size, $\delta_p^P(n)$ can be obtained according to Formula (14), and $b_h^H(n)$ can be obtained by the forward propagation process, which was used to calculate the relevant iteration value of $w_{hp}(n)$. Thus, the next iteration value of the hidden layer *H* and the output layer *K* can be obtained as follows:

$$w_{hp}(n+1) = w_{hp}(n) + \Delta w_{hp}(n) \tag{15}$$

Similarly, according to the above derivation steps, the weight between input layer *X* and the hidden layer of next iteration is derived as follows:

$$w_{xh}(n+1) = w_{xh}(n) + \Delta w_{xh}(n) \tag{16}$$

And finally, some suggestive opinions and measures regarding some existing problems are proposed based on the results of calculation and simulation with BP neural network.

4. A case study

In recent years, the quality control technology is developing more and more rapidly, and the traditional quality control has developed to the present intelligent predictive control. As a new example of the integrated system application, in this paper it was applied for a ball valve for QCs monitoring of industrial valve manufacturing process in CPS in Wenzhou city, China's Zhejiang Province. With advanced testing equipment and perfect decision methods, it has formed an ideal system of quality control from the intelligent product design and manufacturing. As an important part of pipeline transportation, the reliable operation of valve body plays a vital role in the whole pipeline transportation.

On the other hand, the quality control system of valve body include product quality control methods, quality inspection and supervision, quality assurance criteria in this paper. The control precision of the intelligent system of the product quality has been raised by analyzing the data of the system gathering and processing based on neural network algorithm in CPS. Moreover, in the practical process control system, applying intelligent decision making technology can fulfill rapid and accurate on-line fault recognition well. Practice shows that this product quality control system has improved the product quality of manufacturing process by the traditional kind of equipment. After a period of time after the operation, the system is stable and reliable in running, so as to ensure the normal production of coking, improving the product quality and reducing the environmental conditions. The data-driven product quality control system of manufacturing process of ball valve in CPS is shown in Fig. 3.

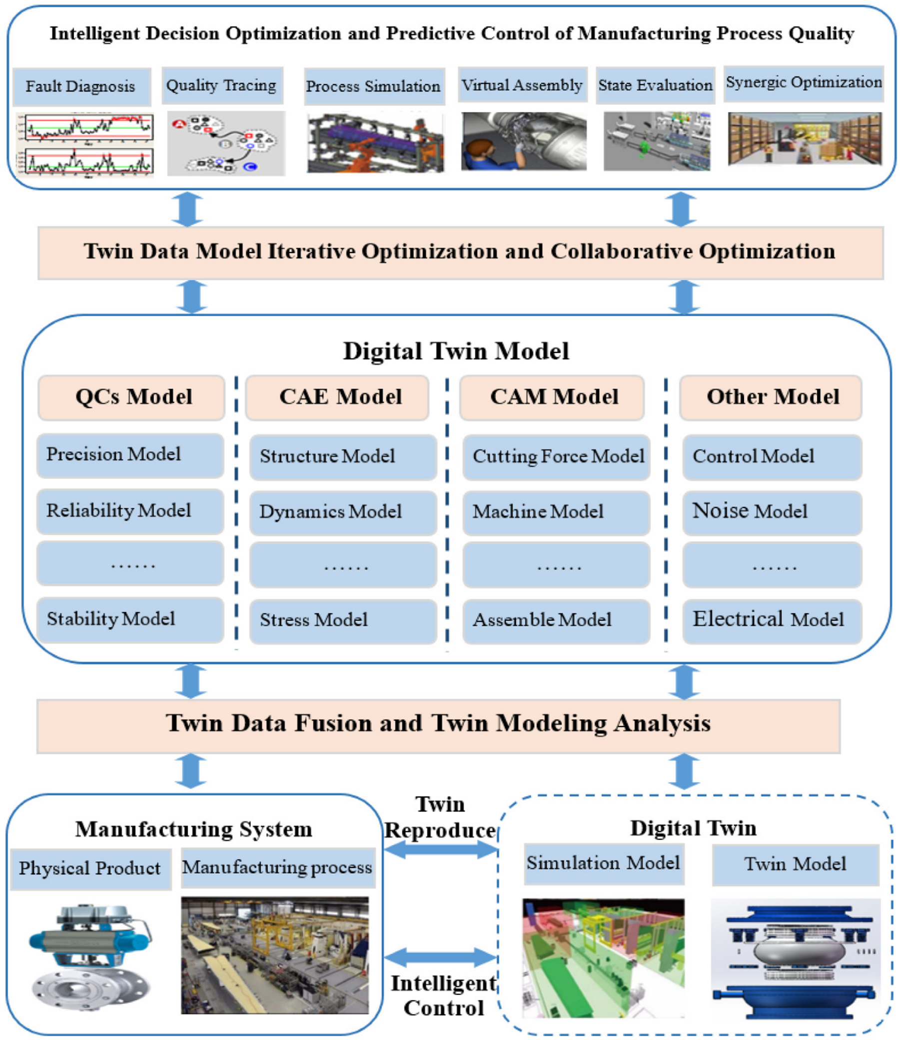


Fig. 3. Data-driven product quality control system of manufacturing process in CPS.

4.1. Modeling principle for quality control system based on BP neural network

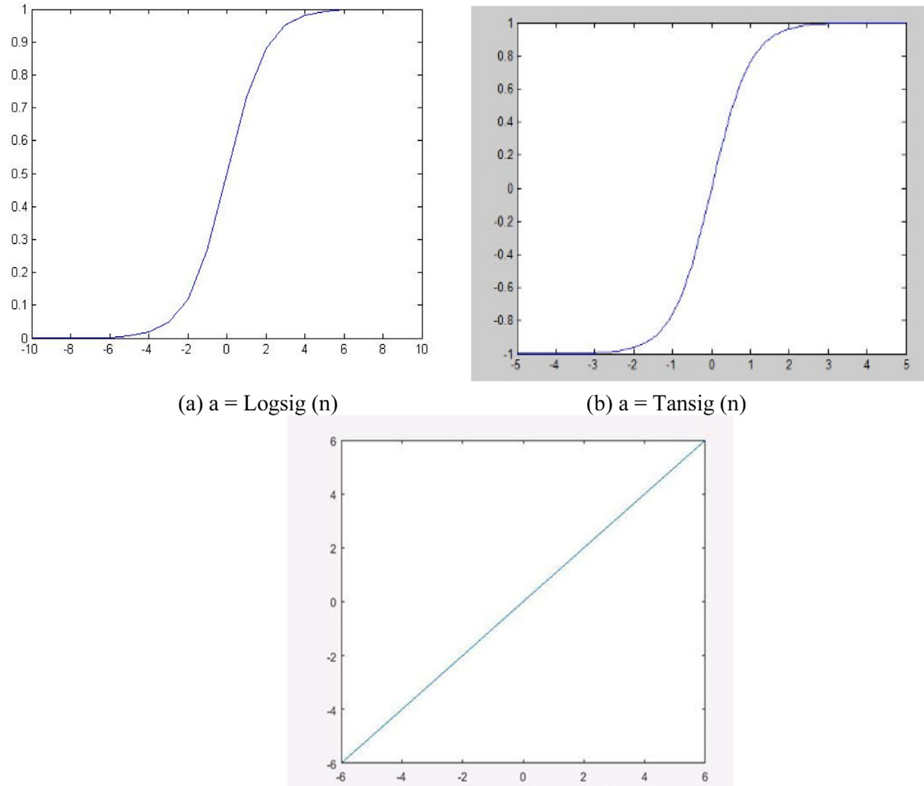
The first step is to make the input and output nodes of BP neural network. The setting of input nodes directly affects the training speed and accuracy of BP network structure. Too many nodes would lead to too complex network structure, too few nodes would reduce the input of relevant information. Therefore, the setting of nodes must be determined according to the task of quality predictive control system. According to the previous content of this paper, it can be determined that the failure of valve body of ball valve is related to the stem torque N, the valve body flow rate is L/s, the leakage amount is L when the pressure was applied, and the valve body leakage amount is I. Therefore, we suppose the number of nodes with input quantity is 4, and the total number of valve body fault types is 5, so the output quantity has been confirmed as 5 nodes.

The second step is to configure hidden layers and nodes. As the number of hidden layers is closely related to the number of nodes, the more hidden layers resulted in the better approximation of the real function to improve the accuracy of diagnosis and control. Therefore, it is possible to reduce the number of nodes by reducing the rate of convergence with a lot of time. Once the number of hidden layers has been determined, the number of nodes would be increased to mapping to the real function, and the accuracy of function fitting also would be improved.

However, if the number of nodes is too many, the convergence speed would drop sharply. The number of layers and nodes should be considered comprehensively and reduced the number of nodes according to the requirements of functions. Moreover, the number of hidden layers and nodes are related to the feature extraction parameters of the input layer and quality fault types of output layer. When input patterns are quite different, an intermediate layer needs to be added. If there are enough intermediate layers, the input patterns can always be converted to appropriate output patterns by setting up a three-layer network for good results. Therefore, this paper chooses to adopt a three-layer neural network of an input layer, a hidden layer and an output layer. Once the training parameters were determined, which can be determined according to the following empirical formula as $i = \sqrt{mn}$, i is the number of nodes in hidden layer, m is the number of nodes in input layer, and n is the number of nodes in output layer. In order to better realize the fault diagnosis for quality control system of the valve body, this paper selects 13 nodes and 16 nodes by comparison.

The third step is actually developing selecting the neuron activation function of BP network. Because BP network belongs to multi-layer network, the transfer functions commonly used of neurons include log-sigmoid type function, tan-sigmoid function and linear function of Purelin, which are shown in Fig. 4.

The shape of the curve of the sigmoid transfer function is S-type, these principles also apply to log-sigmoid and tan-sigmoid functions. The S-type function sigmoid function and the neural network S-type function have the following good advantages:



(a) a = Logsig (n) (b) a = Tansig (n)

(c) a = Purelin (n)

Fig. 4. Transfer functions of BP network.

(1) When the input value of BP network is small, there is also a certain output value corresponding to it. If the signal input to the neuron is weak, the neuron also has output, so as not to lose small information reflection.

(2) When the input value of BP network is large, the output approaches are constant and do not appear zero.

(3) Any BP network has good differential characteristics.

Due to the above advantages, *S*-type function was widely used as the activation function of neurons. In this paper, both the input layer and the activation function of hidden layer adopt the double tangent *S*-type function.

The output layer of the BP network uses a sigmoid-type transfer function, and the output of BP network is limited to the range of [-1, +1]. However, if the linear function Purelin is used as the transfer function of output layer, then the output variables and functions can take any value. Therefore, the sigmoid function is used to transfer intermediate results in hidden layer, and the output results are expanded by the linear transfer function Purelin for the final output layer in this paper. For this reason, the parameters of neural network are more scientific than random selection by experience. In addition, the Levenberg–Marquardt (LM) algorithm is used to train artificial neural network to improve the convergence speed of the network, which reduces the training error and improves the network performance.

4.2. BP network model of quality control system in CPS

By illustrating an example, this study shows the application for valve products of quality control system in CPS, which can provide enterprise managements with reliable information to select, evaluate and predictive control. Valve manufacturers often have a variety of failures in the manufacturing process. In order to improve the fault diagnosis and quality control of the valve products, the type of valve failures in assembly process is classified, which are shown in the following types of faults: appearance damage, valve body leakage, torque failure, valve body through, connection leakage failure and the amount of leakage exceeded the standard. The manufacturer of ball valves must complete all components of factory process, assembly, test, and packaging. The product configuration of the ball valve is shown in Fig. 5.

Table 1
Component parts of valve body in assembling process.

Serial number	Component	Serial number	Component
1	Upper valve body	8	Spring
2	Spring	9	Lower valve seat
3	Sealing ring	10	Under valve body
4	Seal groove	11	Bolt
5	Doutlr end stud	12	Upper valve seat
6	Valve rod	13	Nut
7	Flange	14	Valve element

According to constraint relation of graph, component parts of valve body in assembling process is designed in Table 1.

Next, the fault diagnosis and quality control network model of valve body was build. The fault causes of the above several fault phenomena of product quality are analyzed, and five types of fault causes are obtained. In this paper, y_1, y_2, y_3, y_4 and y_5 respectively represent the five fault causes such as no fault, torque fault, spring fault, valve seat processing fault and valve body trachoma. Take failure mode $X = (x_1, x_2, x_3, x_4)$ as input, and X components of each failure mode respectively represent stem torque, valve flow, pressure leakage and valve leakage. The data collected by each component of fault mode was used as the input of BP neural network, and these fault causes were used as the output of the neural network to diagnose the fault mode. Research dates mainly come from the real-time, quality, simulation, technology and methods database during manufacturing and operating from the valve manufacturers. The data collected from the device for valve body fault is shown in Table 2.

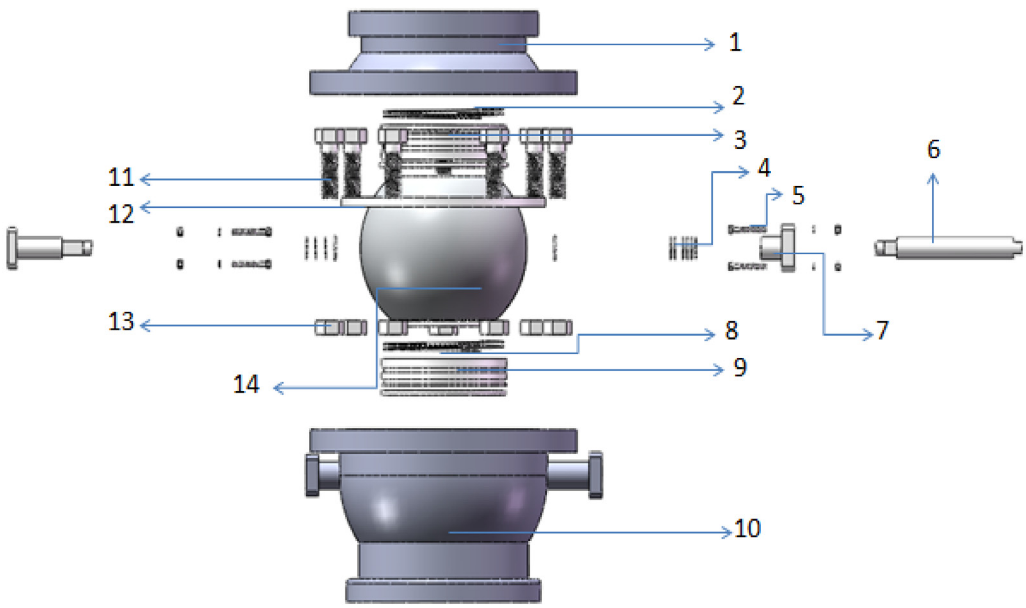


Fig. 5. Schematic diagram of parts and components for ball valve.

Table 2
Data collected for valve body failure.

Fault type	Stem torque *N*	Body flow *L/s*	Leakage during pressure *L*	Leakage of valve body *I*
Trouble-free 1	95	246	5.1	0.02
Trouble-free 2	100	245	5.4	0.01
Trouble-free 3	96	244	5.0	0.03
Trouble-free 4	90	245	5.1	0.05
Trouble-free 5	94	243	5.2	0.02
Torque failure 1	104	231	5.0	0.02
Torque failure 2	100	249	5.0	0.08
Torque failure 3	101	210	5.4	0.04
Torque failure 4	95	250	5.7	0.03
Torque failure 5	100	240	5.2	0.02
Spring fault 1	95	255	5.1	0.02
Spring fault 2	100	245	5.0	0.03
Spring fault 3	105	265	7.1	0.05
Spring fault 4	112	288	6.8	0.10
Spring fault 5	111	270	6.0	0.04
Valve seat processing failure 1	102	245	7.0	0.10
Valve seat processing failure 2	96	249	6.9	0.12
Valve seat processing failure 3	100	252	6.9	0.11
Valve seat processing failure 4	110	260	7.0	0.13
Valve seat processing failure 5	91	242	6.6	0.03
Trachoma failure 1	96	245	5.3	0.10
Trachoma failure 2	91	241	5.0	0.08
Trachoma failure 3	97	252	6.0	0.08
Trachoma failure 4	92	250	5.0	0.04
Trachoma failure 5	94	245	5.7	0.11

Due to some factors induced by processing technology and assembling process, the manufacturing error of product quality is inevitable. Some corresponding quality control methods were proposed to improve the product quality according to the various fault types. From Table 2, we select 20 groups from the 25 sets of data in as the input sample data. Next, we take 20 sets of measurement data value samples of label 1, label 2, label 3 and label 4 as training samples, and the measurement data of label 5 as the samples, which were tested for the neural network data packets in MATLAB for diagnosis.

Then, the neural network was established for different fault types of valve body, and input sample vector was defined. The main program of MATLAB is presented, for example,

p_{11}= [95 246 5.1 0.02]', p_{12}= [100 245 5.4 0.01]'.

So similarly, we can get the simplest answer in the following.

$p = [p_{11}, p_{12}, p_{13}, p_{14}, p_{21}, p_{22}, p_{23}, p_{24}, p_{31}, p_{32}, p_{33}, p_{34}, p_{41}, p_{42}, p_{43}, p_{44}, p_{51}, p_{52}, p_{53}, p_{54}]$;

Table 3
Fault type and output vector.

Number	Fault type	Output vector
1	Normal state	(1 0 0 0 0)
2	Torque failure	(0 1 0 0 0)
3	Spring fault	(0 0 1 0 0)
4	Valve seat processing failure	(0 0 0 1 0)
5	Trachoma/Pore	(0 0 0 0 1)

Then, by using the method of BP network to calculate and analyze the data, the fault type is encoded as shown in Table 3.

In the next step, the expected output data is a 5-dimensional vector, and a fault type of bit represents the corresponding fault. Then, the desired output vector can be defined as:

$t_{11} = [10000]'$; $t_{12} = [1\ 0\ 0\ 0\ 0]'$; $t_{13} = [10000]'$; $t_{14} = [10000]'$;

Table 4
Parameter setting of BP neural network.

Number of network layers	Neurons number in each layer	Transfer function	Training algorithm
Three layers	[4,16,5]	{'Logsin', 'Purelin'}	'Trainlm'

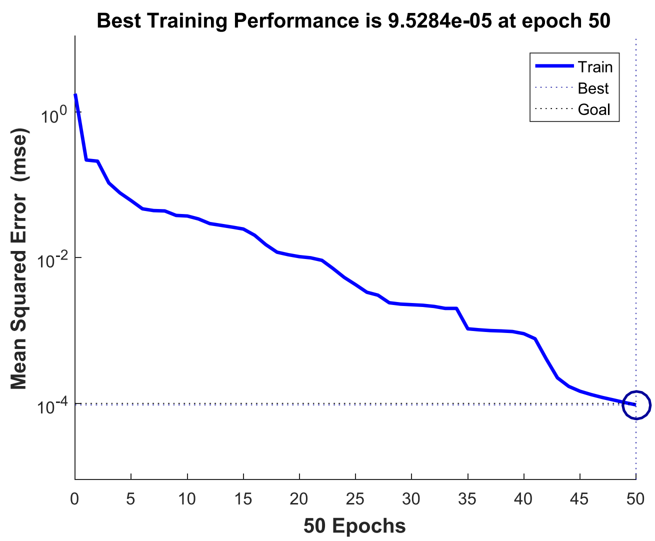


Fig. 6. Error change curve with the number of nodes of 13 hidden layers.

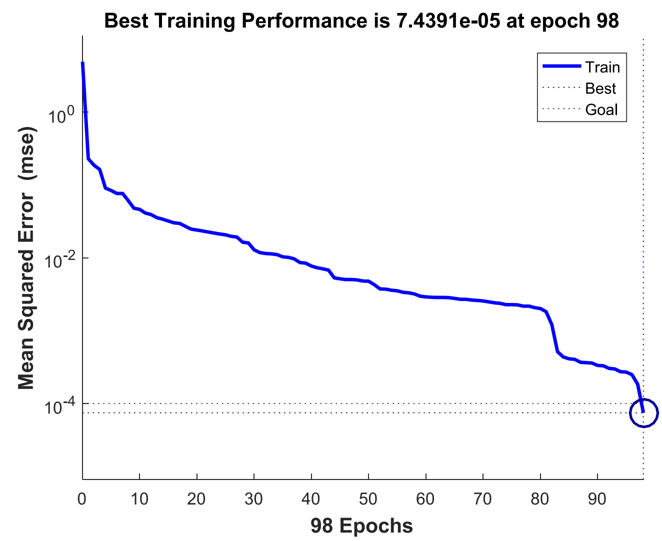


Fig. 7. Error change curve with the number of nodes of 16 hidden layers.

Table 5
Validation samples.

Samples number	*N*	*L/S*	*L*	*I*
Sample 1	100	249	5.6	0.02
Sample 2	100	240	5.3	0.01
Sample 3	102	263	5.7	0.03
Sample 4	102	254	7.1	0.03
Sample 5	101	254	5.8	0.12

$t_{21} = [01000]'$; $t_{22} = [01000]'$; $t_{23} = [01000]'$; $t_{24} = [01000]'$;
$t_{31} = [00100]'$; $t_{32} = [00100]'$; $t_{33} = [00100]'$; $t_{34} = [00100]'$;
$t_{41} = [00010]'$; $t_{42} = [00010]'$; $t_{43} = [00010]'$; $t_{44} = [00010]'$;
$t_{51} = [00001]'$; $t_{52} = [00001]'$; $t_{53} = [00001]'$; $t_{54} = [00001]'$;
$t = [t_{11}, t_{12}, t_{13}, t_{14}, t_{21}, t_{22}, t_{23}, t_{24}, t_{31}, t_{32}, t_{33}, t_{34}, t_{41}, t_{42}, t_{43}, t_{44}, t_{51}, t_{52}, t_{53}, t_{54}]$;

According to the principle of selecting parameters based on the modeling principle of BP network, the parameters are defined in Table 4.

After BP neural network was defined trained, the input and output sample vectors were applied, and the error target was set as 1e-4 to train the network. After the above command of MATLAB was executed, a graph can be get in the figure below. It can be seen that the number of hidden layer nodes is 13 and the iterative network has reached the expected error target by 50 times, and the network with 16 hidden layer nodes has reached the expected error target through 98 iterative networks. The error curves during the training process with the number of hidden layer nodes 13 and 16 are shown separately in Figs. 6 and 7.

Based on the established neural network model, the valve body fault samples with different training sample data are selected for fault diagnosis of product quality control. The data of five valve failure modes are used as the diagnostic sample data by the experiment. The original input sample data are normalized, and the input sample data are shown in Table 5:

Thus, the number of hidden layer nodes is 13, and the output results are shown in Table 6.

Similarly, the number of hidden layer nodes is 16, and the output is shown in Table 7.

Table 6
Diagnostic results of 13 hidden layer nodes.

Actual fault type	Diagnostic data					Diagnostic type
Type 1	0.9934	0.0055	0.0037	0.0080	0.0016	Type 1
Type 2	1.0043	−0.0055	−0.0036	−0.0018	0.0002	Type 1
Type 3	0.0019	0.00002	0.9990	−0.0022	0.0002	Type 3
Type 4	0.9998	−0.0034	0.0011	−0.0020	0.0003	Type 1
Type 5	0.9997	−0.0035	0.0024	−0.0051	−0.0005	Type 1

Table 7
Diagnostic results of 16 hidden layer nodes.

Actual fault type	Diagnostic data					Diagnostic type
Type 1	0.9984	0.0010	−0.0016	0.0017	0.0003	Type 1
Type 2	−0.0066	1.0019	−0.0023	0.0010	0.0041	Type 2
Type 3	0.0012	0.0033	0.9954	0.0017	−0.0009	Type 3
Type 4	0.0020	−0.0005	−0.0004	0.9973	0.0020	Type 4
Type 5	−0.0019	0.0001	−0.0004	−0.0015	1.0019	Type 5

Based on Tables 6 and 7, it is shown that the calculation results coincide with the experimental ones. The modeling results of one neuron and 16 neurons are exact with a lot of training. Thus, it is obvious that the network diagnosis of 16 neurons is more accurate. It can also be seen that the network diagnosis result after training is correct. On the other hand, it is pointed out that the number of selected neurons will also affect the diagnostic performance and quality control of the hidden layer of BP network. Based on the application results, we argue that the product quality control system is a feasible means of industrial valve manufacturing process in CPS. In the case of reasonable neuron setting, BP neural network can carry out fault diagnosis of product quality by using the follow-up collected data. So the optimum programs of BP neural network can be meaningful in future application of product quality situation prediction.

5. Conclusions

CPS has been aroused increasing concern by the industry because of its remarkable economic benefits and extensive application prospects.

At the same time, the product quality control problem is an important task in CPS, which is why various intelligent techniques have been developed into the practice. In this paper, we have developed a data-driven model and intelligent decision methodology for product quality control system in CPS. And the product quality control system was built through the joint effort of different intelligent data processing technology and system development methods in the scope of a manufacturing company. Based on past experience, artificial intelligence technique of neural network, data compression, data mining and database technique is a new way for the research of data processing methods. In this study, we have developed a quality control system in CPS by using intelligent methods of BP neural network. And the results show that the intelligent data-driven system is an important method and efficient tool for product quality prediction control in CPS.

For further work, it is planned to check different intelligent decision making methods for the manufacturing process to improve product quality in CPS. We also regard other mechanical and electrical products as essential to ensure the current and future success. Moreover, we should continue to try to extend the product quality control system at different industrial fields to fit diversiform demand for intelligent manufacturing enterprises.

CRediT authorship contribution statement

Jihong Pang: Conceptualization, Methodology, Writing - original draft. **Nan Zhang:** Data processing, Software. **Quan Xiao:** Writing - review & editing, Validation, Supervision. **Faqun Qi:** Visualization, Investigation. **Xiaobo Xue:** Software, Experimental data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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