Research on the method of machine tool running state management based on digital twin

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Abstract. In order to solve the problems of low monitoring accuracy and inability to handle abnormalities in industrial production, a digital twin based machine tool operation status management method is proposed. On the basis of building the twin model architecture of machine tool operation state management and establishing the method flow, the data flow between virtual machine tools and physical machine tools is realized by building virtual machine tools and establishing communication with physical machine tools. By combining attribute reduction based on rough sets and one-class support vector machine(OC-SVM) algorithms, accurate recognition and warning of machine tool abnormal states were achieved. The abnormal states were relieved by optimizing cutting parameters using BP neural network and virtual real data fusion method. Finally, the effectiveness and practicality of this method were verified through an example of machining a certain type of marine diesel engine frame.

Keywords: digital twin; Rough set; OC-SVM; Running status management

1 Introduction

Machine tools are known as industrial mother-machines. With the development of economy, CNC machine tools are used more and more widely in industrial production, which greatly improves the production efficiency of factories. However, in the actual production process, there is a lack of real-time understanding of the operating status of CNC machine tools. Once the machine tool malfunctions, it will cause huge economic losses to the enterprise. Therefore, it is necessary to manage the operating status of the machine tool.

The traditional machine tool management mode is regular maintenance, in which the staff need to regularly overhaul the machine tool and replace the failed parts. However, this mode is time-consuming and inefficient. With the development of sensors and communication computing, the traditional manufacturing mode has begun to transform to intelligent manufacturing. As an emerging science and technology, digital twin technology has attracted the attention and exploration of many scholars and experts. Zhuang

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Cunbo et al. [1] put forward the concept of product digital twin and expounded its connotation, architecture and development trend. Tao Fei et al. [2-3] applied the digital twin to the workshop and proposed the operation mechanism, key technologies and five-dimensional model of the digital twin workshop, which provided a theoretical basis for subsequent research. There are also researchers applying digital twins to industrial production. Feng Jun [4] developed a digital twin workshop platform combined with digital twins, and realized real-time monitoring of machine tool running status by using FB-NSA, a negative selection algorithm for fixed interfaces. Du Yanbin et al. [5] proposed a predictive machine tool remanufacturing model combined with digital twin technology to solve the problem of lag in traditional machine tool fault solving mode. Through monitoring and diagnosis of normal machine tools, sudden failures and downtime can be effectively reduced. Zhu Zhenyao [6] built a band sawing machine twin based on unity3D, collected real-time operation data, and used BP neural network to achieve fault prediction. It can be seen from the above literature that digital twin technology can realize the real-time interaction of information between virtual space and physical space, timely predict the failure of machine tools, and reduce the loss caused by downtime. Therefore, the digital twin technology can be applied to the running state management of the machine tool to achieve accurate and rapid control.

At present, there are many researches on machine tool running state management, but most of them focus on abnormal state recognition, and there are few researches on how to optimize feedback. To solve the above problems, this paper proposes a method of machine tool running state management based on digital twins, constructs a virtual machine tool model, and realizes data flow between virtual machine tool and physical machine tool by constructing virtual machine tool and establishing communication with physical machine tool, and realizes machine tool running state monitoring, abnormal early warning and optimization feedback by using the collected state data. Finally, it is verified by an example of machine tool processing.

2 Construction of digital twin running state management model

2.1 Machine tool running state management model based on digital twin

Digital twin technology is coupled by multidisciplinary technologies. Based on the five-dimensional model proposed by Tao Fei et al., this paper establishes a device state management model based on digital twins by means of computer technology and big data, as shown in Fig. 1. The physical machine tool is the actual equipment to perform the machining task, which provides data support for the virtual machine tool and various functions of the function module. Virtual machine tool is a digital reconstruction in virtual space based on physical machine tool through 3D modeling software. The function module is the geometry of the processing and monitoring function of the machine tool state parameters, including the function of running state monitoring, abnormal state monitoring and analysis, and optimization and control. Twin data is the bridge connecting physical machine tool, virtual machine tool, machine tool state management system and twin database. Through various sensors arranged on the machine tool, real-time acquisition of the spindle amplitude, spindle temperature and other state parameter data during the operation of the machine tool are stored in the twin database to form the twin data, which is used to drive the virtual machine tool and the machine tool running state management system to achieve corresponding functions. With the help of virtual machine tool and machine tool running state management system, the real-time data obtained are monitored and simulated, and the optimized machining parameters are transferred to the physical machine tool to achieve state optimization. Through the interactive fusion of physical machine tool and virtual machine tool, the digital twin model of machine tool running state management is constructed.

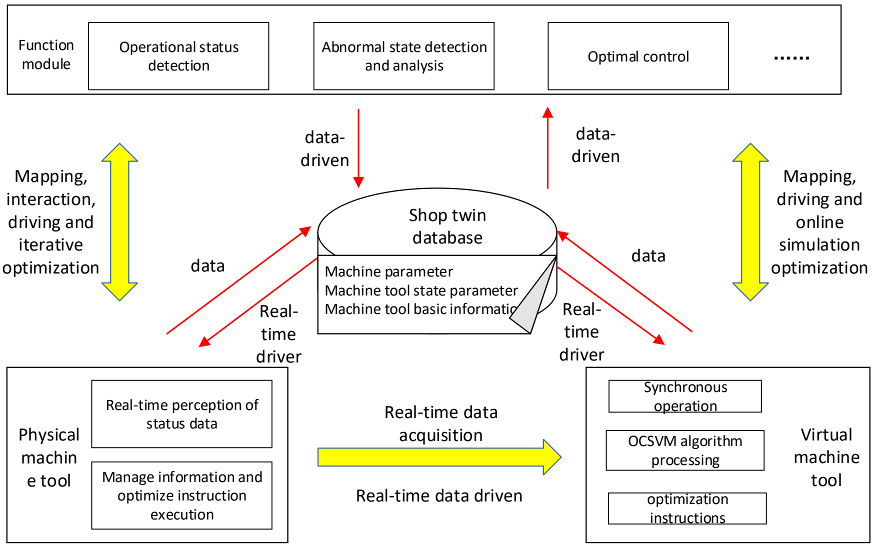


Fig. 1. State management model

2.2 Machine tool state management process design

This paper proposes a method of machine tool running state management based on digital twin. The process is shown in Fig. 2. Combined with digital twin technology, a virtual machine tool is constructed, and various sensors and OPC UA technology arranged on the machine tool are adopted to realize data acquisition and connection with the virtual machine tool under the running state of the physical machine tool. On this basis, the digital twin model of machine tool running state management is constructed. First, the normal state data in the twin database is cleaned and dimensionality reduced based on rough set theory, and then OC-SVM machine algorithm is used to train the processed data to obtain the abnormal state detector. After the relevant processing task is issued, the machine tool processes according to the processing task, and collects and stores the running status data of the machine tool in real time through various sensors arranged on the machine tool. In the virtual machine tool and equipment status management service system, the state parameters of the machine tool are monitored. If the state parameters remain normal, the physical machine tool continues to process. If the parameters are in the abnormal range, the machine tool running state management system will give an early warning, and at the same time, BP neural network and virtual and real data fusion method are called to optimize the cutting parameters, and then the optimization results are transmitted to the virtual machine tool for the simulation and verification of the running state parameters, and then transmitted to the physical machine tool to complete the modification of the processing parameters after meeting the conditions. The above online decision optimization process is repeatedly implemented in the production process until the entire process is completed.

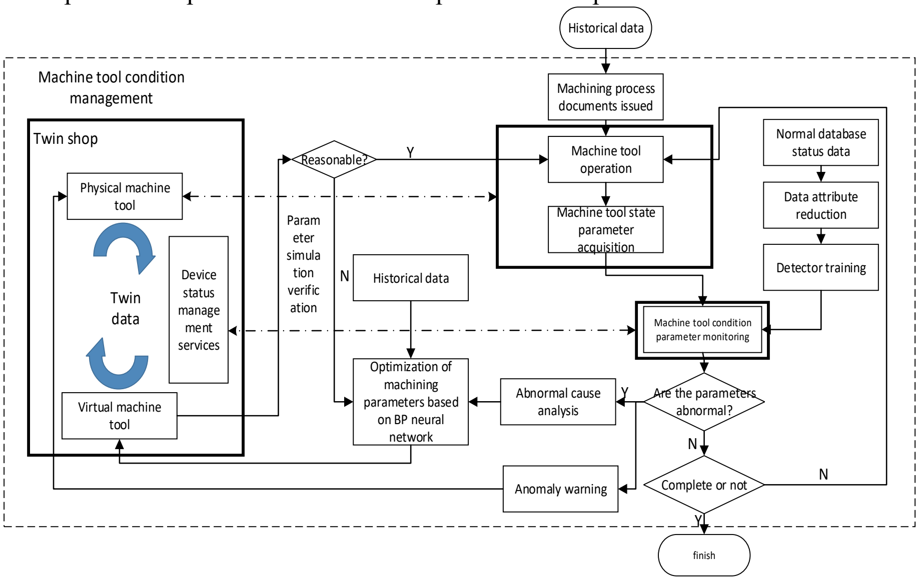


Fig. 2. Machine tool state management process

3 Key technologies

3.1 Data processing technology of improved differential matrix heuristic attribute reduction algorithm

There are many kinds of data generated during machine running, some of which have no influence on the judgment of machine running state. Therefore, in order to reduce the data dimension and shorten the calculation time, the collected data should be reduced. By eliminating unimportant and meaningless attributes, reduction based on rough set theory can obtain reduction results, which can effectively prevent the loss of important information, make the results more accurate, and ensure the classification and decision-making ability of data [7].

This paper uses the attribute reduction method based on difference matrix, and the process is shown in Fig. 3. Firstly, the machine tool historical running state data is extracted from the database and normalized discretized to form a decision table. Then the difference matrix Ms is calculated. The element mij in the difference matrix is shown in formula (1), and the corresponding matrix element of the two samples with the same decision attributes is 0; The matrix elements corresponding to two samples with different decision attributes are sets of different conditional attributes. If a matrix element contains only one conditional attribute, that attribute is a kernel attribute. The importance of non-nuclear attributes is calculated according to formula (2). After removing the elements containing the most important attributes, the difference matrix is updated and the importance of nuclear attributes and non-nuclear attributes is re-calculated, and then the difference matrix is judged whether it is empty. If it is empty, the reduction result is the set of the above kernel attributes; If not empty, the above process is repeated until the difference matrix is empty [8]~[9].

$$m_{ij} = \begin{cases} a \ \ |a \in C, a(x_i) \neq a(x_j), D(xi) \neq D(x_j) \\ 0, \ D(x_i) = D(x_j) \end{cases} \tag{1}$$

$$Sig(\mathrm{a}, \mathrm{R}, \mathrm{D}) = \frac{\mathrm{H}(\mathrm{D}|\mathrm{R} \cup \{\mathrm{a}\})}{\mathrm{H}(\mathrm{a})} \tag{2}$$

Where $\mathrm{H}(\mathrm{D}|\mathrm{R} \cup \{\mathrm{a}\})$ refers to the conditional entropy after adding a non-kernel attribute to the kernel attribute set, $\mathrm{H}(\mathrm{a}) = -\sum_{i=1}^{l} P(a_i) \, logp(a_i)$, $\mathrm{p}(a_i)$ is the ratio of the number of objects whose attribute value a_i to the total number of objects.

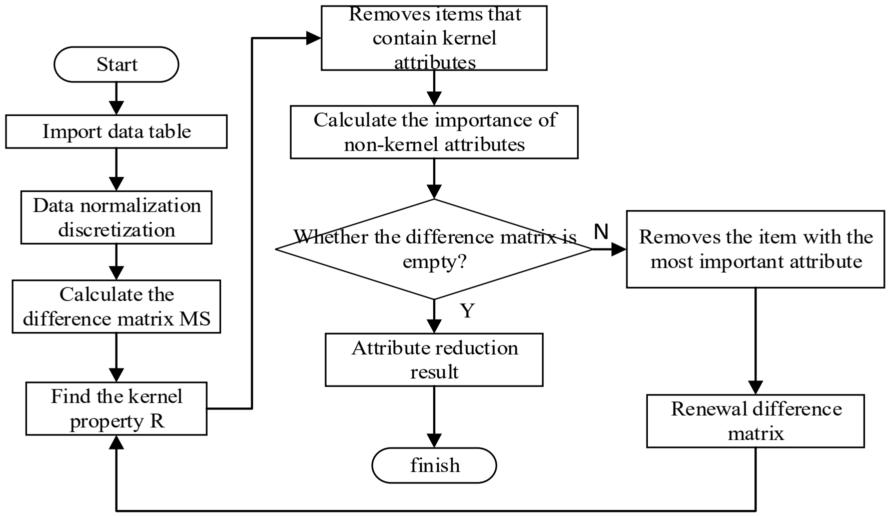


Fig. 3. Attribute reduction process based on rough sets

Table 1. Part of machine tool state characteristic samples

a	b	c	d	e	f	g	h	i	D
400	0.005	60	58.2	15.6	1900.1	195.4	120.4	345.2	0
1600	0.018	30	45.2	16.2	2104.6	340.2	401.2	666.2	0
800	0.015	30	55.4	17.4	1990.2	174.6	140.8	323.2	0
1500	0.022	120	60.4	17.2	1867	463.2	399.2	843.3	1
1800	0.018	30	40.2	16.3	1802.2	401.7	332.5	662.4	0
800	0.025	15	64.2	15.6	2049.1	252.6	154.3	322.5	1
2200	0.007	15	50.5	16.5	1846.4	383.5	472.2	731.4	0
1500	0.012	60	46.7	17.3	2098.9	431.4	372.1	842.1	0
2000	0.006	15	51.9	17.8	1951.6	413.6	332.4	671.5	0
800	0.007	120	45.4	16.8	2234.3	181.5	131.5	322.4	1
				……..					

Table 2. shows the sample after partial reduction

b	d	f	D
0.005	58.2	1900.1	0
0.018	45.2	2104.6	0
0.015	55.4	1990.2	0
0.022	60.4	1867	1
0.018	40.2	1802.2	0
0.025	64.2	2049.1	1
0.007	50.5	1846.4	0
0.012	46.7	2098.9	0
0.006	51.9	1951.6	0
0.007	45.4	2234.3	1
	……		

Through the data transmission scheme developed based on OPC UA communication protocol, the real-time running status data of the machine tool is collected by various sensors installed on the machine tool and transferred to the management platform for real-time monitoring. The collected data are shown in Table 1. a-i is the spindle speed, spindle amplitude, spindle motor load, spindle temperature, spindle current, spindle torque, tool feeding direction force Fx, radial force Fy, tangential force Fz, and D is the decision attribute. The result after attribute reduction is shown in Table 2. The main parameters that affect the running state of the machine are spindle amplitude, spindle temperature and spindle torque.

3.2 Condition monitoring technology based on OCSVM

Because the abnormal state data generated by the machine tool in the production process is less, the data imbalance will make the training results seriously deviate from the accurate range, and eventually lead to false positives, missing positives and other errors in the monitoring system. one class of support vector machine (OC-SVM) can identify abnormal samples from a specific category, so it is generally used for anomaly detection. In this paper, OC-SVM algorithm is used to train abnormal state detector with normal data.

OC-SVM maps the data sample $x_k \in R^n (k = 1, \cdots, n)$ to a high-dimensional feature space by kernel function to make it have better aggregation. By calculating the hyperplane $\omega \cdot \phi(x) - \rho = 0$ between the sample point and the origin in the high-dimensional feature space, the optimal boundary including the entire sample is acquired. The basic algorithm of OC-SVM is shown in formula (3) [10]-[11].

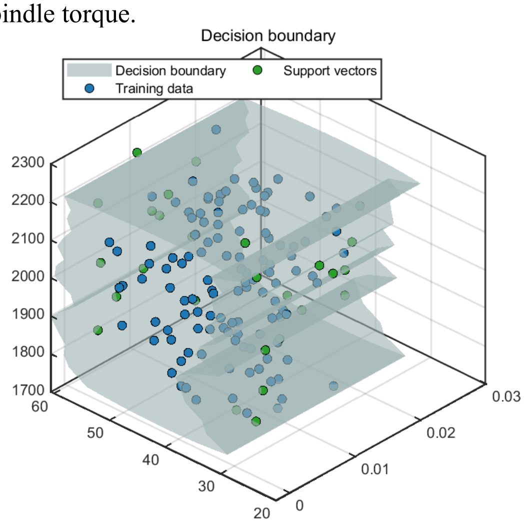
$$\min\left(\frac{1}{2}||\omega||^2 + \frac{1}{\nu n}\sum_{i=1}^{n}\xi_i - \rho\right) \tag{3}$$

$$\text{s.t.}\left(\omega \cdot \phi(x_i)\right) \geq \rho - \xi_i \ and\ \xi_i \leq 0 \forall i$$

Where $\omega \in \chi$ and $\nu \in (0,1]$ are parameters of the hyperplane. $\nu \in (0,1]$ is a predefined percentage parameter representing an upper bound on the boundary support vector rate (classification error rate). To solve this problem, Lagrange function α is introduced. The final decision function is shown in formula (4).

$$\mathrm{f}(x) = \mathrm{sgn}(\sum a_i \mathrm{K}(x_i, x) - \rho) \tag{4}$$

Equation (4) is used to classify the machine tool running state data in Table 2. If the result is "+ 1", it indicates that the data is normal; if the result is "-1", it indicates that the data is abnormal. Finally, the data is drawn into a three-dimensional scatter plot, in which the normal data is marked in blue and the abnormal data is marked in red. For easy viewing and analysis, it is projected onto three planes. The test results using part of the running state data of a certain machine tool are shown in Fig. 4, with an accuracy of 94.2%, indicating that this method can accurately identify the abnormal state of the machine tool. At the same time, the cause of the anomaly can be determined according to the position distribution of the state parameter vector. In the figure below, the anomaly is excessive spindle torque.



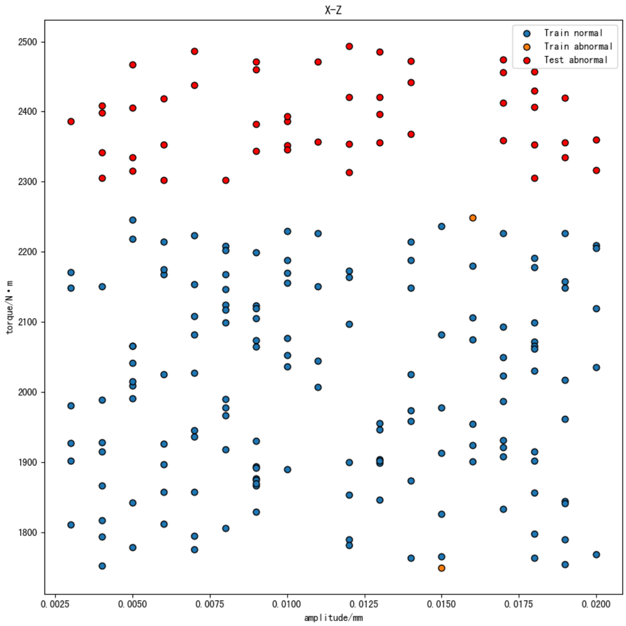


Fig. 4. Machine tool running state monitoring

3.3 Optimization feedback technology based on BP neural network

When the machine tool is in abnormal running state, the abnormal state can be changed by changing the cutting parameters of the machine tool. Because there is no clear correspondence between the cutting parameters and the parameters to be monitored, the relationship between the two needs to be fitted by other methods. As a common method of machine learning, BP neural network has strong learning and approximation ability, and can fit the relationship between input and output according to a small number of samples, so as to achieve accurate prediction[12].

BP neural network has two main processes, including forward propagation and back propagation. Forward propagation uses the input to predict the output, and back propagation updates the weights of neurons in the network according to the error between the output and the actual value. The input layer includes four neurons: feed speed, cutting depth, cutting speed and cutting width; the output layer includes three neurons: spindle torque, temperature and amplitude; and the number of hidden layer neurons is 7 according to empirical method. The sigmoid function is used as the activation function[13].

The ten-fold cross-validation method is a commonly used algorithm model evaluation method, which divides the data set into 10 parts, takes 9 parts each time as the training set and 1 part as the test set, and takes the mean after 10 tests. This method can avoid the chance arising from data coincidence. The verification results of the ten-fold cross-verification method adopted in this paper are shown in Table 3. a-c, in turn, is the relative error of amplitude, temperature and torque. It shows that the network model has good validity.

When the operating state parameter of the machine tool is in the abnormal range, the operating state management system of the machine tool selects the normal processing parameter with the closest Euclidean distance from the processing parameter corresponding to the abnormal state from the database and calculates its average value. As the input, the state parameter is predicted and the state monitoring is carried out. Then the corresponding processing parameters are passed to the physical machine tool to achieve the optimization feedback of abnormal state; If the status parameter is still abnormal, repeat the process until normal.

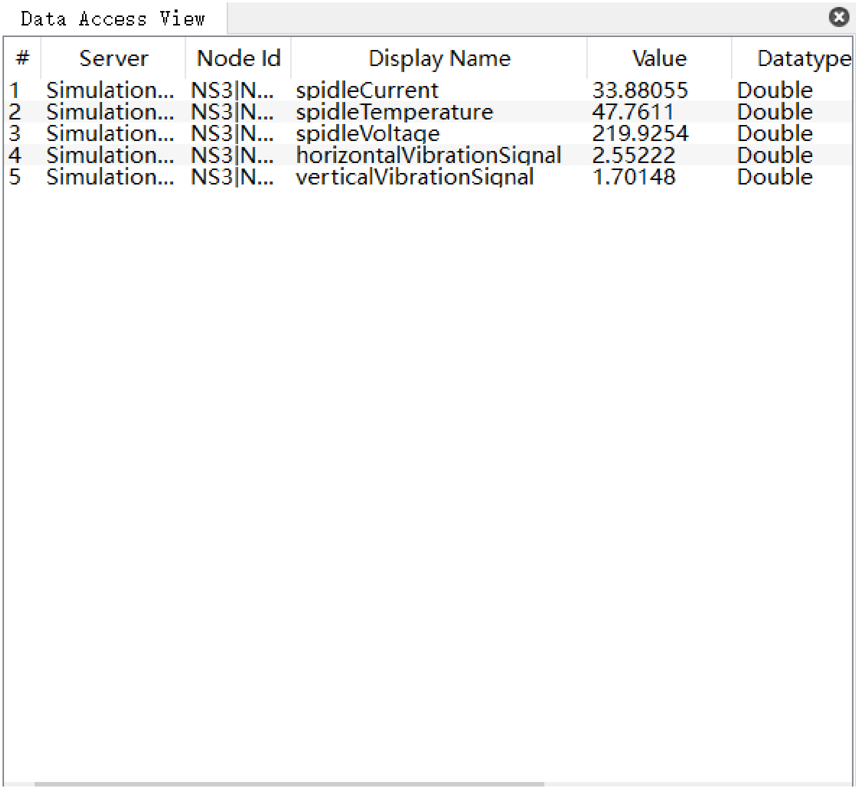
Table 3. Prediction error of BP neural network

number	a	b	c
1	5.22%	4.29%	5.03%
2	6.37%	5.21%	5.67%
3	5.49%	6.23%	5.21%
4	2.67%	3.12%	3.13%
5	3.97%	3.45%	3.27%
6	3.52%	3.61%	3.54%
7	5.33%	5.09%	6.01%
8	5.74%	5.22%	5.79%
9	4.49%	4.43%	4.37%
10	3.88%	4.02%	4.12%
Average	4.67%	4.47%	4.61%

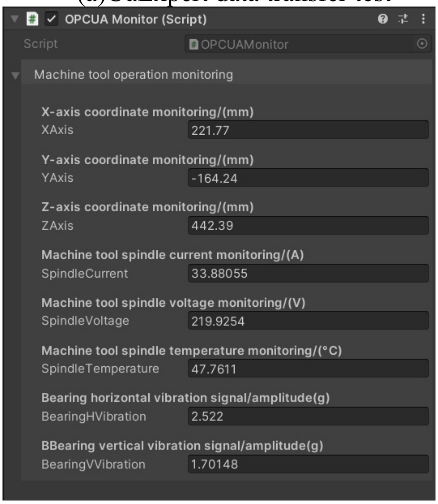
3.4 Data transmission technology based on OPC UA

Due to the diverse types and formats of information in the processing workshop, it is difficult to transmit information in a timely manner, resulting in ineffective implementation of system functions. OPC UA technology is a unified data transmission specification that can be used for data exchange between devices from different manufacturers. This paper developed the OPC UA client based on Python and integrated it into the back-end server, opening up the data path between the back-end and the physical workshop. Real-time data is stored in the database through this method, so that the subsequent data backtracking can be used to drive the workshop to find out the existing problems at that time.

In order to verify the effectiveness of Unity3D's integration of OPC UA client, the OPC UA server simulation software is used to simulate the machine side server for connection test. As shown in Fig. 5 (a), the professional OPC UA client UaExpert connects to the OPC UA server on the machine side for data reading. Fig.5 (b) shows that the OPC UA client developed based on Unity3D connects to the machine tool server and reads data.



(a)UaExpert data transfer test



(b) Unity3D OPC UA client data transfer test

Fig. 5. Data Transmission Verification Based on OPC UA

4 Case verification

In order to verify the feasibility of the proposed method, this paper takes a type of CNC gantry milling machine as the research object, and establishes a running state management system to monitor the process of machining a type of Marine diesel engine frame. Use solidworks to build the machine tool model and import it into unity3D to build the virtual scene shown in Fig. 6. At the same time, Microsoft Visual Studio 2017, SQLServer 2017, Pycharm and Matlab 2020a were used to develop relevant intelligent algorithms and integrate them into unity3D, and finally complete the construction of the machine tool running state management platform. As shown in Fig. 7. In the virtual scene, on the one hand, the data-driven virtual model is used to realize the mapping from real to virtual, which is convenient for workers to understand the process of processing tasks. On the other hand, the OPC UA technology is used to transmit real-time data to the equipment status management platform for display, to achieve accurate monitoring of machine tool running status.

As shown in Fig. 7a, the interface displays basic information such as name and alarm information. When real-time status parameters exceed the normal range, the system will issue an early warning. Click the "Details" button to jump to the machine tool monitoring interface, as shown in Fig. 7b, which displays the machine tool cutting parameters and running state parameters and other monitoring information. The system determines and displays the anomaly type according to the position of the anomaly state parameter vector. In the figure, the anomaly state type is " Excessive amplitude". Click the " Optimization" button, the management platform calls the optimization algorithm to optimize the machining parameters and carry out simulation verification, and then through the connection between the virtual machine tool and the physical machine tool, change the machining parameters of the machine tool to achieve the lifting of abnormal state, and at the same time, the optimized machining parameters are displayed visually and click the "Save parameters" button to save them into the database. It is used as a reference template for the next abnormal status, as shown in Fig. 7c and Fig. 7d. The above examples show that the method can monitor, analyze and correct the running state of the machining process of the machine tool, and ensure the qualified and stable machining process and machining quality.

Fig. 6. Workshop scene model

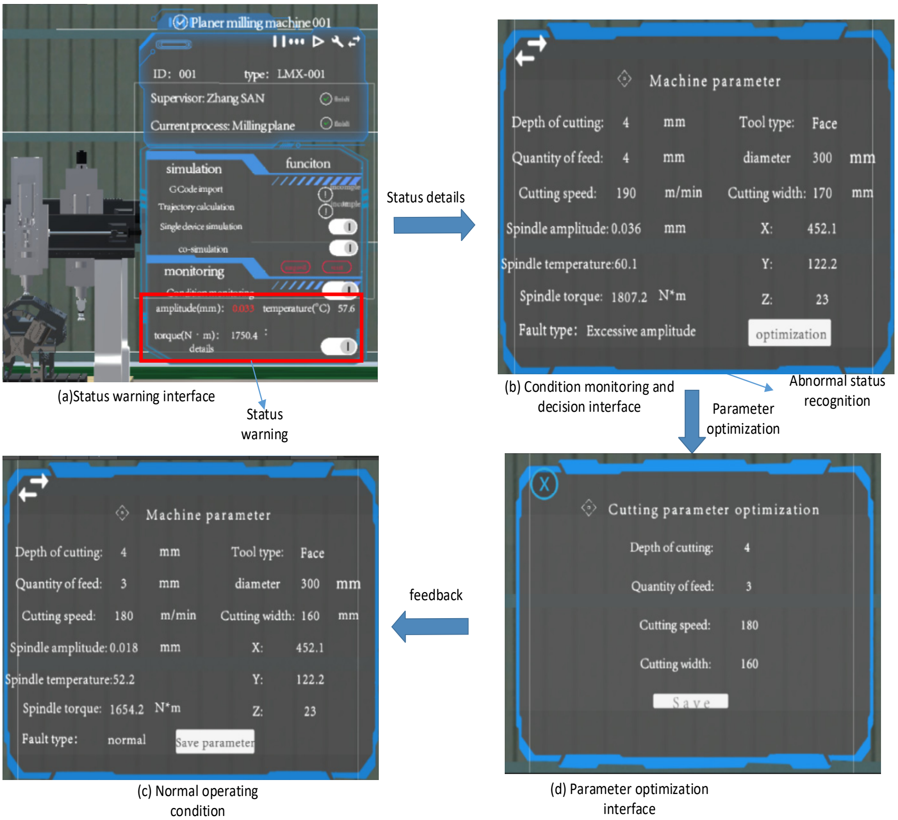


Fig. 7. Management and control interface

5 Conclusion

This article introduces digital twin technology into the problem of machine tool operation status management. By constructing a digital twin model for machine tool operation status management, real-time data transmission between physical and virtual machine tools is achieved, and accuracy and real-time performance are improved. On this basis, the management process of machine tool operation status was elaborated in detail, and an abnormal state recognition method combining rough set based attribute reduction and OC-SVM algorithms was proposed, as well as an abnormal state removal method based on BP neural network and virtual real data fusion algorithm to optimize cutting parameters. Finally, the effectiveness and practicality of this method were verified through an example of machining a certain type of marine diesel engine frame, indicating that this method can accurately identify and handle abnormal states in a timely manner. In the future, we will improve the recognition accuracy and processing speed of abnormal states through optimization of operational state monitoring algorithms and BP neural networks, ultimately improving practicality.

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