Design and Research of Digital Twin Machine Tool Simulation and Monitoring System

Mingyi Guo
Xifeng Fang (xffang2006@163.com)
Jiangsu University of Science and Technology
Zhongtai Hu
Qun Li

Research Article

Keywords: CNC, Machine tool, Digital twin, Monitoring system, Tool wear

Posted Date: February 3rd, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1255881/v1

Design and research of digital twin machine tool simulation and monitoring system

Mingyi Guo[a], Xifeng Fang[a,1],Zhongtai Hu[a] , Qun Li[b]
a. Institute of advanced manufacturing technology, Jiangsu University of Science and Technology, Zhenjiang, 212003, China
b. Hudong Heavy Machinery Co..LTD, Shanghai, 200129, China

Abstract:

With the application of digital manufacturing technology and intelligent manufacturing technology in manufacturing industry, the existing simulation and monitoring methods of machine tools can not meet the requirements of enterprises, and gradually tend to use digital twin, OPC and other technologies to remote simulation and monitoring of machine tools. In order to prevent the accidental collision of machine tools, this paper builds the virtual model of machine tools based on the digital twin (DT) technology, detects the tool and machine tool collision model based on the improved GJK collision detection algorithm, and automatically controls the machine tool to stop when the tool and machine tool are about to collide. In order to improve the level of machine tool intelligent management, potential information extraction machine run time, this paper proposes a fast simulation method, machine tool CNC code used to detect the code is correct, and in the process of running through a visual component implementation monitoring the running state of the machine tool manufacturing process by monitoring data visualization and testing of large data, extracting the potential information, Realize the online prediction function of tool wear. Taking a turning process of Marine diesel engine cylinder liner as an example, the experimental test results show that the system can quickly judge the correctness of CNC code, effectively monitor the data of machine tool, predict tool wear degree and reduce the risk of tool collision.

Keywords: CNC Machine tool Digital twin Monitoring system Tool wear

1. Introduction

In recent years, with the rapid development of industrialization in various countries, the production workshop has gradually realized intelligence and informationization, which has improved the production efficiency of manufacturing enterprises to a certain extent **Error! Reference source not found.**. As the basic unit of manufacturing process and an indispensable part of intelligent and informationized manufacturing, CNC machine tools, are known as "industrial machine tools". And as one of the most important equipment in manufacturing process, their intelligence has an important influence on the implementation of intelligent manufacturing **Error! Reference source not found.**. However, it is complex structure, low monitoring degree, prone to failure affect the machining efficiency [1].

In the early stages of design and production preparation, true CNC machining commissioning takes a long time and is risky and costly. At the same time, it also has higher technical level requirements for technicians. Therefore, in the actual production process, technicians' mistakes in the process design of CNC machine tools will cause serious processing accidents[4].Consequently, the deep integration of machine tool condition monitoring with network communication technology, sensing technology and

[1] Corresponding author.
E-mail address: xffang2006@163.com (Xifeng Fang).

information processing technology has important research significance, which can accelerate the machine tool to move towards intelligence, improve its intelligence level and reduce the accident rate[5].

The existing machine tool monitoring has some problems, such as single form, less monitoring content, unclear mapping to the actual situation of machining process, insufficient data utilization, and lacks the ability of efficient simulation and monitoring of machine tools. With the development of sensor and communication technology, it is becoming easier to connect physical manufacturing equipment with Internet applications. For machine tool data acquisition, the current acquisition methods can generally be divided into three categories: circuit, PLC and interface communication. The first two methods get data from built-in or external auxiliary hardware, which is very common in old machines that do not support communication modules. PLC is a typical implementation method. For the latter, the new generation of machine tools mostly adopt this data interface, and there are corresponding OEM development API packages and tools[6].

At the same time, some raw data can be displayed on our panel in real time, such as temperature, spindle speed and cutting force. But some data can't be directly used, we need to effectively filter, extract and analyze these data to turn complex data into useful manufacturing information[7]. This information can be analyzed and applied by processing workers and application algorithms, and then serve the machine tool simulation and monitoring system.

Digital twin refers to the construction of a twin model corresponding to a physical entity. During the running process, the twin model is always highly consistent with the entity, so that the twin has the ability to accurately reflect the running state of the physical entity, thus realizing the effective monitoring of the physical entity[8].

In this paper, numerical control machine tools are combined with digital twinning technology, and a method of constructing simulation and monitoring system based on digital twinning machine tools is proposed to realize the functions of collision simulation of CNC codes, tool collision monitoring and big data monitoring. The rest of the article is as follows: Section 2 expounds the current research status of numerical control machine tools and digital twins. The third section is the system architecture of this paper. The fourth section explains the main methods of system function realization in detail. Section 5 takes a machine tool as an example to verify the article. Finally, the sixth section summarizes the full text and points out the future research direction.

2. Technical background

2.1 CNC machine tool

CNC machine tools are high-end mechatronics equipment with high technical content, which is composed of mechanical systems and control systems, and involves high-precision technologies in many fields such as machinery, control and hydraulic fields. With the continuous development of numerical control technology and the continuous improvement of the automation level of enterprises, more and more brand-new manufacturing modes emerge as the times require and are widely used. CNC machine tools can solve the problems of complex, small-batch, precise and multi-variety parts processing. However, if problems such as tool collision and failure occur during the operation of CNC machine tools, it is likely to delay the production plan and bring losses to enterprises, so the monitoring of CNC machine tools is particularly necessary[9].

In the aspect of machine tool monitoring, Carlos Felipe Erazo Navas et al. integrated the machine tool and machining process with CPMT technology by using computing and network technology, providing technical support for production planning, preventive maintenance and energy consumption analysis[10]. Xavier Desforges et al. proposed an intelligent actuator service design approach for machine tools to achieve monitoring and control tasks [11]. B.Schmucker et al. developed an efficient system structure, which can realize the data collection inside the machine and the high-frequency sampling of external sensors and monitor the machine current based on these data[12]. B.Denkena et al. monitored the machine parts based on data, used the sensor data of normal state of the machine for semi-supervised anomaly detection training, and obtained high-quality spindle torque information by comprehensively considering the characteristics of power spectral density and peak value of fast Fourier transform[13]. Su Chunyan and others explored the construction method of CPS-based intelligent manufacturing system, and adopted C# programming language and SQL Server database management system, which not only realized the collection, processing and preservation of the operation data of networked machine tools, but also realized the management of production information[14].

Tool wear is one of the important monitoring information during machine tool operation. In the aspect of tool wear prediction, X.Li et al. proposed a fuzzy neural network (FNN) for mechanical fault prediction and monitoring, which integrated fuzzy logic reasoning into neural network structure, accelerated the learning process of traditional complex neural network structure, and improved the prediction accuracy and convergence speed. Taking tool life prediction in dry milling as an example, the feasibility of fuzzy neural network in tool condition monitoring was verified[15]. Ultrasonic machining is an unconventional machining method**Error! Reference source not found.**[16], Singh and Khamba studied ultrasonic machining of titanium and its alloys. The effects of different input parameters on tool wear rate, surface roughness and material removal rate in ultrasonic machining were studied. The results show that the hardness of abrasive particles should be greater than that of workpiece in order to obtain higher MRR[16]. Juho Ratava et al. analyzed tool failures and used accelerometers to detect chip and small fractures at tool edges[16]. Vigneashwara Pandiyan et al. used genetic algorithms to optimize the sensor signals obtained by acceleration sensors, acoustic sensors and force sensors to predict tool life in real time based on a support vector machine approach[18]. Based on the analysis of vibration signals, K. Gomathi et al. estimated the tool state in the high-speed micro-machining process of PCB milling machine, and used the micro-tool state monitoring system composed of spindle acceleration to measure the vibration and analyze the collected vibration signals, which improved the service life of the instrument[19][19].

2.2 Digital twin

As one of the ten strategic technology trends for 2020[21], digital twin technology is a way to solve the interconnection and convergence of the physical world and the information world[22], it has been widely used in many fields such as aerospace, medical treatment, urban construction[23]and plays an important role in many aspects such as design, production and fault prediction**Error! Reference source not found.**[25][26]. Digital twining can realize the functions of depicting, simulating and optimizing the physical world[27], which provides an effective way to solve the problems existing in the current operation of CNC machine tools. The virtual model can be used to represent and reflect the running process of physical objects, machine state and various data generated by real-time updating of historical data and sensor data[28]. At present, the concept of digital twin has been applied and verified in some fields, and it is also being gradually applied to manufacturing industry and CNC machine tools. Among them, Angkush Kumar Ghosh proposed two kinds of computer systems, digital twin construction system and digital twin adaptation system, to interact seamlessly with real-time sensor signals and automatically perform monitoring and troubleshooting tasks. Taking milling torque signals as an example, the effectiveness of the two systems was verified[29]. Yueze Zhang proposed a fast equipment model construction method for discrete manufacturing digital dual-plant system, which improved the efficiency and quality of equipment-level DT model construction and minimized the construction time of machine DT model [30]. Weichao L studied a hybrid predictive maintenance algorithm based on DT model and DT data and made an example analysis of tool life prediction[33].

3. System architecture

At present, although enterprises have provided great help to workshop manufacturing through Internet and other technologies, they have not fully analyzed and utilized the operation information and status of processing machine tools. In order to improve the simulation speed of machine tools, monitor the operation of machine tools and reduce the risk of tool collision, a simulation and monitoring system ( ) based on digital twin machine tools is proposed. This system consists of physical machine tools (PM), virtual machine tools (VM), system services (Ss), digital data (DD), Connection (CN) and Front-end Display (FD)[23]. The framework is shown in Figure 1.

$$M_{VM} = (PM, VM, Ss, DD, FD, CN) \quad (1)$$

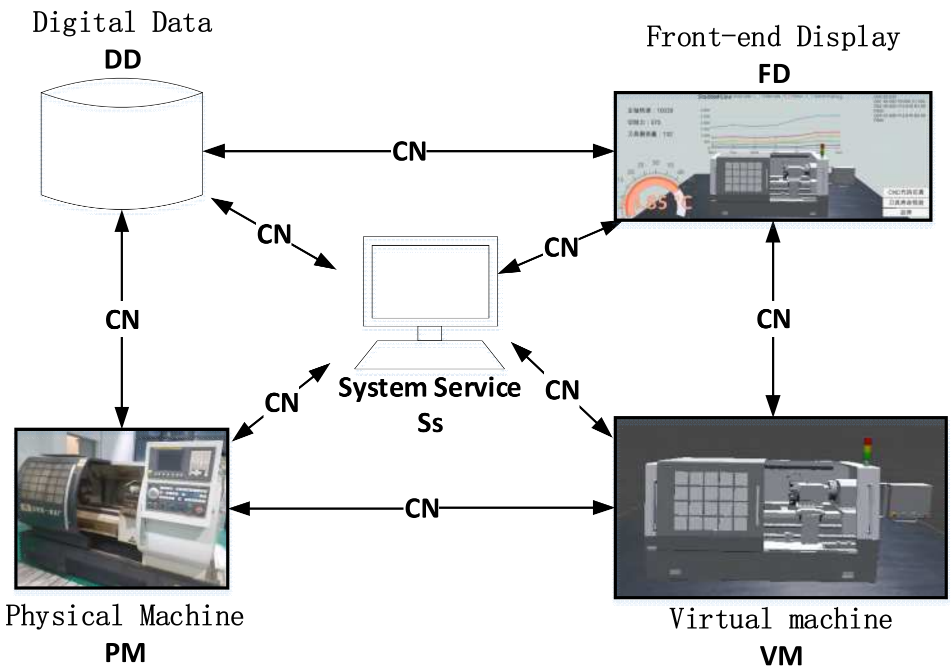


Fig.1 Six-dimensional model of system

（1）Physical machine tool (PM). The physical machine tool is the basis of realizing this digital twin system, which is mainly used to receive and execute the production tasks and control instructions issued by the production unit service system, and is responsible for real-time perception and transmission of production data in the multi-source heterogeneous network physical environment.

（2）Virtual machine tool (VM). Virtual machine tool is a virtual model constructed according to the physical machine tool entity. It is a mapping of the physical entity. It is mainly responsible for the digital mapping of the dynamic behavior and production state of the physical machine tool. CAD software was used to establish the 3D shape and assembly relationship of the machine tool, and 3Ds Max was used to render the model and import the rendered model into Unity3D.

（3）System services (Ss). Service refers to the collection of services required by the implementation process of digital twin system, which is mainly provided by industrial Internet of Things platform, 3D modeling software, virtual reality development software, etc[32]. This service system mainly includes: 1. Simulation of machine tools based on CNC codes; 2. Detect various data of machine tools, display the data to users through digital visualization, and provide guidance for production, processing and enterprise decision-making; 3. Through the collision detection model in the machining process of the machine tool, the remote emergency stop of the machine tool can be automatically controlled in case of possible tool collision.

（4）Twin data (DD). Twin data is the basis of digital twin copper operation. Virtual machine tool drives the model and analyzes the operation status of the machine tool through real-time data transmitted by physical machine tool. DD mainly includes PS data ( ), VS data ( ), Ss data ( ) and knowledge data ( ).

$$TD = (D_P, D_\gamma, D_s, D_k) \quad (2)$$

Where: D_P is mainly used to describe the attribute data of physical elements that constitute PS equipment and the dynamic process data that can reflect the running state of PS. The attribute data of physical elements are mainly provided by the equipment manufacturer or measured on the spot, while the dynamic process data are collected by sensors, equipment interfaces, embedded acquisition cards, Internet of Things technologies, etc. D_γ mainly includes data related to VS, such as data related to PS model (including geometric model, physical model, behavior model and rule model, etc.); D_s mainly includes service system related data (model, algorithm, database operation, model dynamic process data, human-computer interaction data, etc.); D_k includes expert knowledge, industry standards, common algorithms, common databases, common API interfaces, common model building methods, etc.

（5）Connection (Ss). Ss is data connection. It is the key to realize the interconnection of all parts of the system, mainly including the connection between PS and VS, PS and Ss, DD and Ss, DD and FD, FD and Ss. The system uses communication protocol and PLC to complete the connection of each part of the data.

（6）Front-end display (FB). FB is a display of various services and data of machine tools. Real-time display of machine information and attributes through the status panel; The behavior visualization, state visualization and data visualization of machine tool manufacturing process are realized through 3D virtual model. The use of augmented reality technology to achieve the machine tool in color and other details more consistent with the physical machine tool, increase the sense of user experience.

4. System implementation

4.1 Realization of data communication and monitoring function

Data communication is the basis of digital twinning. There are mainly three ways to achieve data acquisition for CNC machine tools, one is to collect data from CNC side, the second is to collect data from PLC and its connected I/O modules, and the third is to collect data directly from the body side of machine tools themselves. The CNC side has a communication interface for transmit information to external devices, such as network connection, RS232, DNC, OPC etc. The ladder diagram program compiled by PLC is used to drive machine tools according to certain logic[6]. Because this system uses communication protocol and PLC to complete data transmission together, the feedback emergency stop function uses PLC to control the machine tool by sending simple signals to PLC from PC. The physical machine tool and virtual machine tool are connected by PLC as shown in Figure 2.

Firstly, the system data and sensor data of CNC machine tools are collected, and the data is uploaded to the database and system platform by means of communication protocol and PLC. The data is divided into display data, driving data and algorithm data in the system platform. The display data is displayed in the form of data reports, two-dimensional charts, etc. through ECharts; The driving data is used to drive the virtual model in real time to monitor its behavior. The algorithm data is used to input the algorithm data. Through the real-time data, the running status and health of the machine tool can be analyzed in real time, so as to prevent the machine tool failure and tool collision.

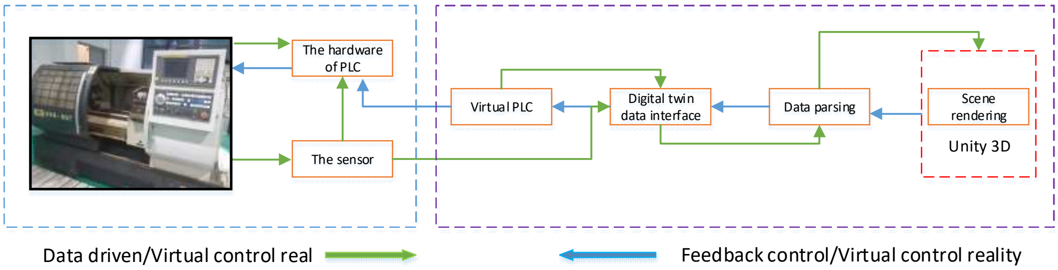


Fig.2 Physical machine tool and virtual machine tool through PLC connection layout

4.2 Fast simulation of CNC code path

Machine tool industry is the basic industry in manufacturing industry, and its level and quality are very important for the development of manufacturing industry. At present, the automation technology of the machine tool industry is relatively mature, but there is still a long way to go for future-oriented intelligent manufacturing. Therefore, the digitization of machine tool industry has become one of the mainstream trends at present[34]. The existing simulation system can't meet the requirements of development gradually. At present, almost all simulation software can simulate cutting paths, which has the advantage of simplicity and ease of use, but the safety of machine tools and the characteristics related to controllers can't be reflected. By constructing the virtual model of machine tool, not only can the tool machining path be verified by simulation, but also the CNC code can be directly analyzed and executed to avoid the collision and interference between mechanical parts, and the simulation time can be significantly shortened by simulating one action every 0.02s. The realization process is as follows:

Step 1: Use SolidWorks software for 3D modeling of the parts of the controlled equipment. After all the parts are matched together, output STEP format to 3D max software to endow the parts with materials and maps. Use Polygon Cruncher to optimize the number of triangular patches in the model, and export them as FBX format files after optimization and import them into Unity 3D[35][36].

Step 2: Reorganize the model in Unity 3D, he reconstructed model can be divided into fixed parts, moving parts and rotating parts according to grades and components. The method of reorganizing model can effectively reduce the workload of virtual model coordination, the number of sensors, the amount of circulating data and the system delay and improve the running speed of the system. Since the machine tool already has the assembly relationship when imported into Unity 3D, it is not possible to directly move and rotate the model to destroy the original assembly relationship. The reorganization model method is as follows:

1) Firstly, make clear which parts are fixed parts, moving parts and rotating parts;

2) Secondly, adding rigid body properties to the machine tool as a whole, creating a second-level catalog under the first-level catalog of the machine tool and naming it as fixed parts, moving parts and rotating parts, moving all the fixed parts in the list to the fixed parts catalog, moving parts to the moving

parts catalog and rotating parts to the rotating parts catalog;

3) After that, the whole machine tool is moved to the target position, and the sub-files in the fixture directory are fixed relative to the world coordinate system by adding scripts;

4) Finally, in the form of step 2, create a third-level directory and a fourth-level directory under the second-level directory, and finally drive the smallest unit of the machine tool with a single data source.

Step 3: Add scripts to read CNC files in MySQL line by line. Extract the keywords in CNC code, correspond the keywords to the reorganized model, and use the data behind the keywords to drive the model simulation[37]. Add rigid body components and rigid body collision detection to the virtual model, and returns the name and location of the part that collided with it after the collision occurs.

4.3 Implementation of collision detection algorithm

4.3.1 Method comparison

Generally speaking, the research content of collision detection algorithm is how to detect the collision between different objects in virtual scene faster and better. Collision detection between virtual scene and physical scene is the key to test the feasibility of path [38]. The existing collision detection algorithms are generally divided into three main methods: spatial partition method, hierarchical bounding box method and GJK method. Among them, the spatial partition method takes a long time to preprocess and tends to produce a large number of polygons, which are not suitable for the virtual space of large-scale scenes. Therefore, this paper mainly compares the hierarchical bounding box method and GJK method[39]. The two-dimensional diagram of the four bounding boxes is shown in Figure 3, and the comparison of methods is shown in Table 1:

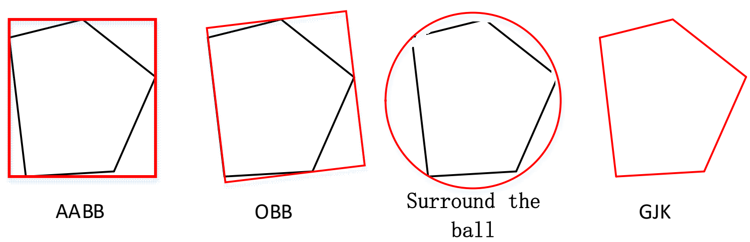


Fig. 3 Two-dimensional diagrams of four bounding boxes

Table 1 Comparison of collision detection methods

Way	Simplicity	Compact type	Update speed
Surround the ball	**simple**	**clearance leakage**	**fast**
AABB	**simple**	**Tighter**	**fast**
OBB	**More complicated**	**Tighter**	**Slow**
GJK	**complex**	**close together**	**Slow**

In the process of collision detection, it is necessary to protect the tool, so it is necessary to send a dangerous signal at a certain distance before the collision. Combining with the comparison of several methods above, this paper adopts GJK collision detection algorithm and improves it.

4.3.2 Collision detection algorithm based on improved GJK

This algorithm was first proposed by Gilbert, Johnson and Keerthi, so it is called GJK algorithm for short. This model is based on calculating the distance between two objects, so as to detect the collision. Assuming that two convex bodies A and B are represented by d(A,B), the distance between A and B can be represented by the following formula (3):

$$d(A,B)=\min\{\|x-y\|: x\in A, y\in B\} \quad (3)$$

GJK algorithm can calculate the nearest two points A and B between two objects, which meet the following requirements:

$$\| a-b \| = d(A,B), a \in A, b \in B \quad (4)$$

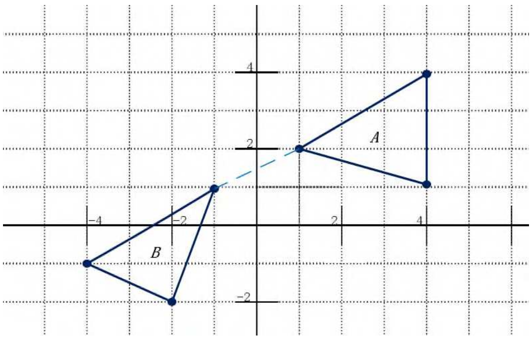
Let v(C) represent the point closest to the origin in convex set c, that is, v(C)∈C and satisfy the following formula:

$$\| v(C) \| = \min\{\| x \|: x \in C\} \quad (5)$$

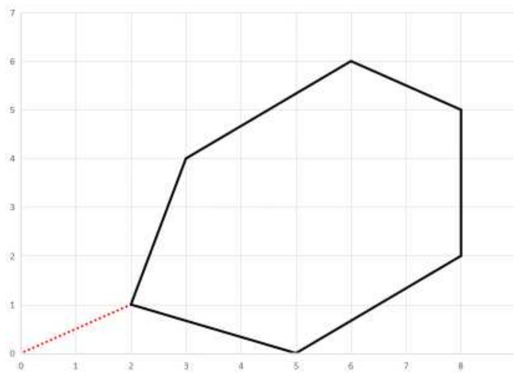
Then the distance between A and B can be expressed as Minkowski difference:

$$d(A,B) = v(C) \quad (6)$$

Among them, $C = A \ominus B$. According to formulas (3), (4), (5) and (6), the minimum distance between objects A and B is equal to the minimum distance from the convex hull formed by Minkowski difference (C ($C = A \ominus B$)) between objects A and B to the origin. Trajectory space obstacle (TSO) is a convex hull formed by Minkowski difference of two point sets, which represents a set of all shapes of objects colliding with obstacles . As shown in Figure 3, the distance between two triangles A and B is equal to the distance from their Minkowski difference C to the origin.



A) the distance between a and b



B) the distance from the convex hull C formed by the point set Minkowski of A and B to the origin

Fig.4 Distance transformation diagram of two objects based on Minkowski difference

This algorithm is based on the calculation of the distance between two objects for collision detection, and the calculation of the distance between convex bodies A and B is equivalent to the calculation of the distance between Minkowski difference C(C=A-B) and the origin[40][41]. Generally speaking, the algorithm based on GJK model is essentially a gradual descent method to gradually find the nearest point to the origin on TSO(A-B). In each iteration, a new simplex is created in TSO, which is closer to the origin than the simplex created in the previous iteration. The so-called simplex is a convex hull formed by an affine independent point set, which generally contains 1 to 4 vertices, so the simplex can be a point, a line segment, a triangle or a tetrahedron. When the estimation error of the calculated distance reaches a given error, the algorithm will be terminated immediately.

When judging whether there is an origin in C, due to the complexity of the machine tool model and the large number of fixed points, there may be a phenomenon that the result is wrong due to insufficient iteration times, and the selection of the initial point also affects the correctness of the algorithm when the iteration times are low. In this study, the collision model between machine tool and props can't collide, that is, the two models need to design a distance threshold (M), which requires the original algorithm to calculate the distance from Minkowski difference between objects to the origin compared with the threshold (M), which is relatively troublesome. To improve the above problems, an improved GJK collision detection algorithm is proposed, which is as follows:

Minkowski difference between computer (a) and tool

$$C = A \ominus B \quad (7)$$

At this time, the distance between A and B is C, make a circle D with threshold M as radius and origin as center, and calculate Minkowski difference between convex body set C and circle (D):

$$F = C \ominus D \quad (8)$$

For convenience of calculation, circle D is replaced by regular octagon E, the distance between C and E is shown in Figure 4, and Minkowski difference between C and E is shown in Figure 5:

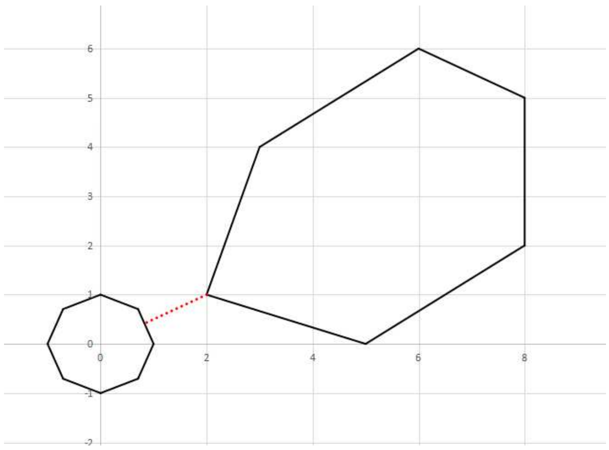


Fig.5 Distance between C and E

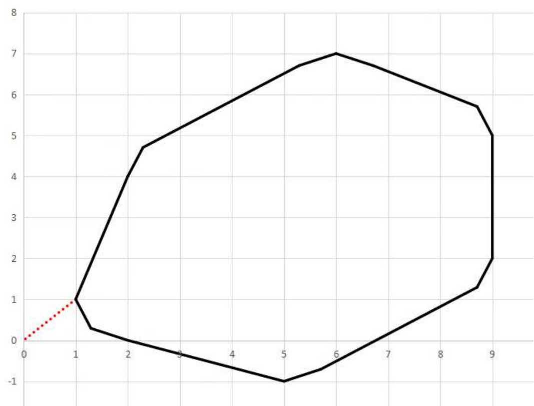


Fig.6 Minkowski difference between C and E

The area sum method is used to judge whether the convex body set f includes the origin:

Polygon composition area: S_1 :

$$S_1 = \frac{1}{2}\left|\sum_{i=1}^{n}\begin{vmatrix} x_i & y_i \\ x_{i+1} & y_{i+1} \end{vmatrix}\right| \quad (9)$$

Area formed by each side of polygon and origin: S_2 :

$$S_2 = \frac{1}{2}\sum_{i=1}^{n}\left\|\begin{matrix} x_i & y_i \\ x_{i+1} & y_{i+1} \end{matrix}\right\| \quad (10)$$

Among them $x_{n+1} = x_1, y_{n+1} = y_1$

It is judged whether the triangle area sum formed by the origin and each side of the polygon is equal to the polygon area. If it is equal, the origin is inside the polygon, and then the model C collides with the model E. If it is not equal, the model C does not collide with the model E.

5. Case study

In this paper, a simulation and monitoring system based on digital twin machine tool is developed by taking a certain turning process of key parts of Marine diesel engine as an example. The framework of the system is designed as a six-layer structure, and the detailed structure diagram is shown in Figure 7. This system realizes the twin modeling of physical machine tool, using the front display to show the data of machine tool cutting, tool wear and machine tool movement in the form of data visualization, and can also complete machine tool code simulation, machine tool remote start and stop and predictive collision detection on the client side.

5.1 Machine tool simulation realization

As the necessary preparation before the machine tool runs, the simulation can ensure the safer operation of the machine tool and avoid risks to a certain extent in advance. In this study, the simulation step 4.2 chapter. In this study, the recombination model scheme in step 2 of Section 4.2 of simulation is shown in Figure 6. Create a C# script to read the CNC file in MySQL. Extract the keywords in CNC code and match the keywords with the restructured model. See Table 2 for the corresponding table.

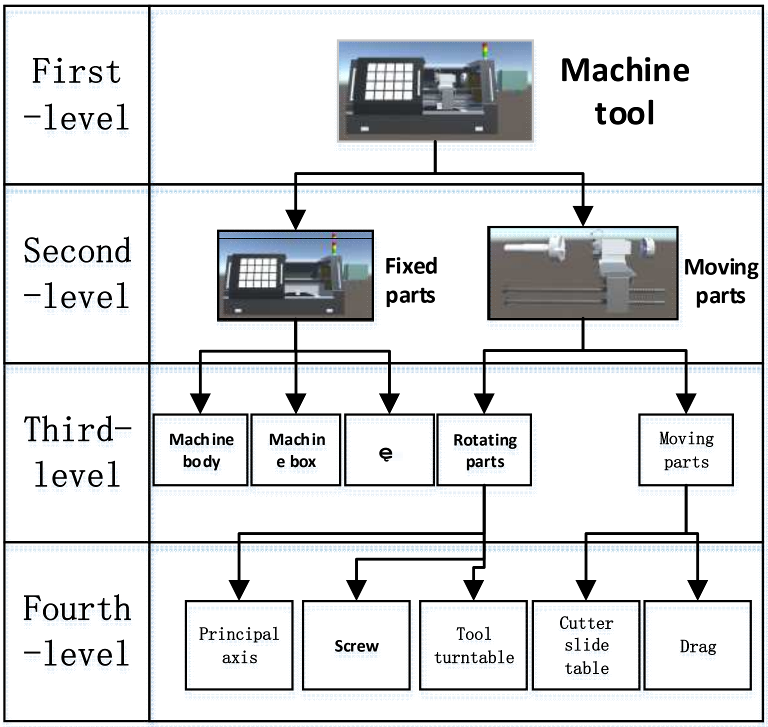


Fig. 7 Reassemble the model layout diagram

Table 2 CNC code keyword and model correspondence table

CNC code keyword	Corresponding module
M	**principal axis**
S	**principal axis**
F	**drag**
X	**drag**
Z	**Cutter slide table**
G	**Moving parts**
R	**Moving parts**
T	**Tool turntable**

CNC code instructions often have more than one line, so how to deal with code input and compilation between each line is also a problem that must be considered. This article has tried three approaches to the code, as shown in Figure 8. One scheme needs to read data several times to process a piece of CNC code. Practice has proved that reading a large number of data across carriers will reduce the reliability of software. The third scheme involves a large number of parameters passing on time during the machine tool operation. This method is bound to generate a large amount of data accumulation, increase the development difficulty of the drive module, and even affect the operation of the machine tool, resulting in sluggish response.

In this paper, the second scheme is adopted, in which all CNC codes are input at one time, read sentence by sentence, compile and run sentence by sentence. The burden of reading and writing data between different programs is reduced, the difficulty of compiling the driver module is also reduced, and the possibility of machine tool running errors is reduced. The model driving simulation is carried out by reading row-by-row driving with keywords and the data behind them. For example, S800 indicates that the spindle speed is 800r/min. Finally, for the machine tool model, add a rigid body component, add a script to hang on the machine tool to detect rigid body collision, and return the name of the colliding parts when the collision occurs by using OnCollisionEnter callback method.

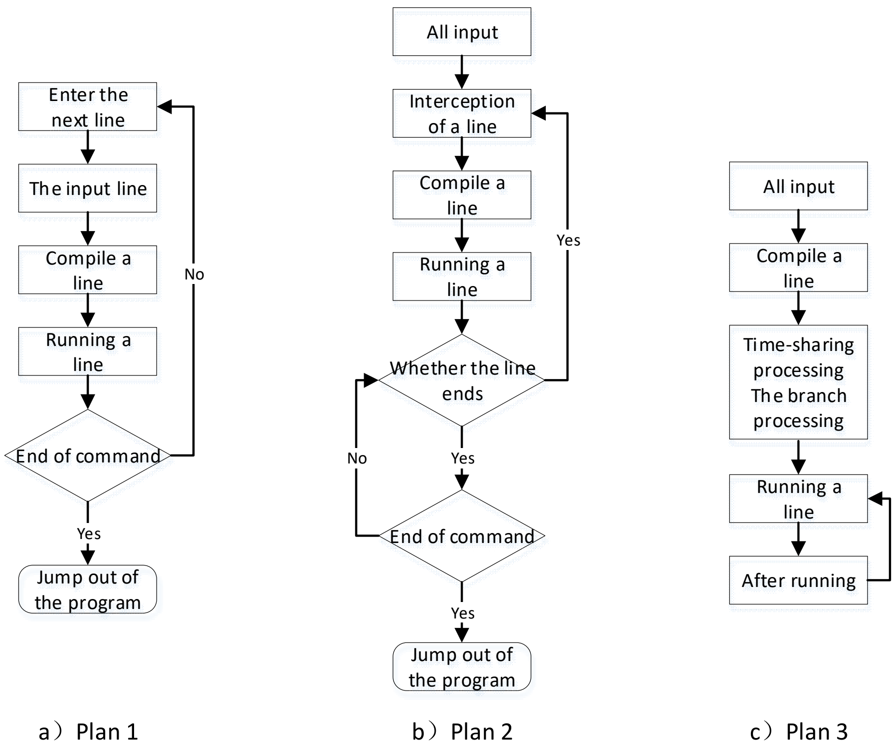


Fig.8 CNC code processing mode

5.2 Realization of machine tool monitoring

5.2.1 Machine tool data monitoring

In this paper, based on JavaScript language, the ECharts chart is developed individually, and the graph and tachometer are designed to meet the data display requirements respectively. The methods of integrating ECharts charts into Unity3D platform are as follows: First, personalized front-end development of ECharts charts through JavaScript can meet the data display requirements. Secondly, deploy the HTML(Hyper Text Markup Language) file of ECharts on the local side. Then, the back-end queries the vibration signals in the database through C# program and converts them into Json format readable by ECharts. Then, the connection between the front end and the back end is realized by asynchronous communication. Finally, the deployed ECharts chart webpage is integrated into the browser plug-in of Unity3D, so as to display the collected vibration data accordingly. The specific process is shown in Figure 9 , and the main interface of the system is shown in Figure 10:

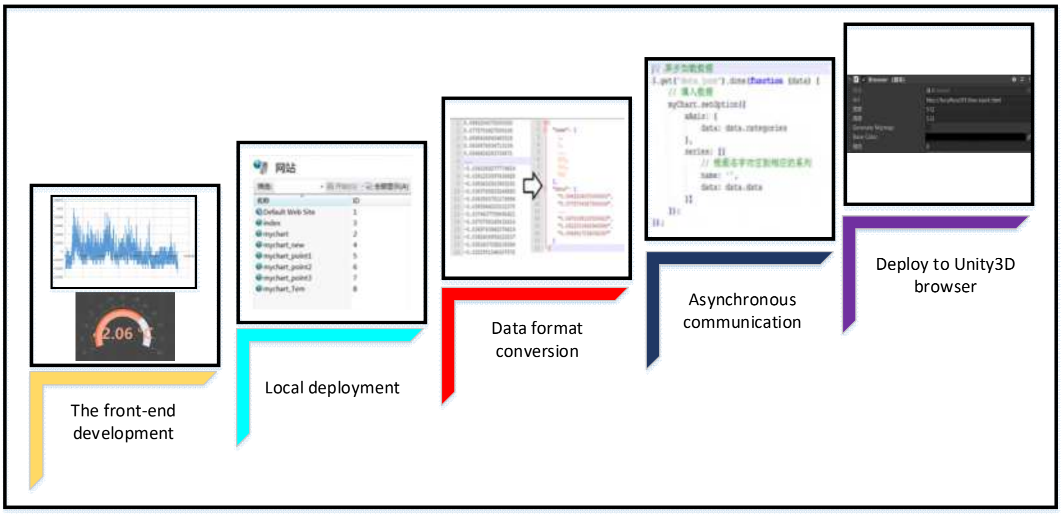


Fig. 9 The integration process of E Charts charts

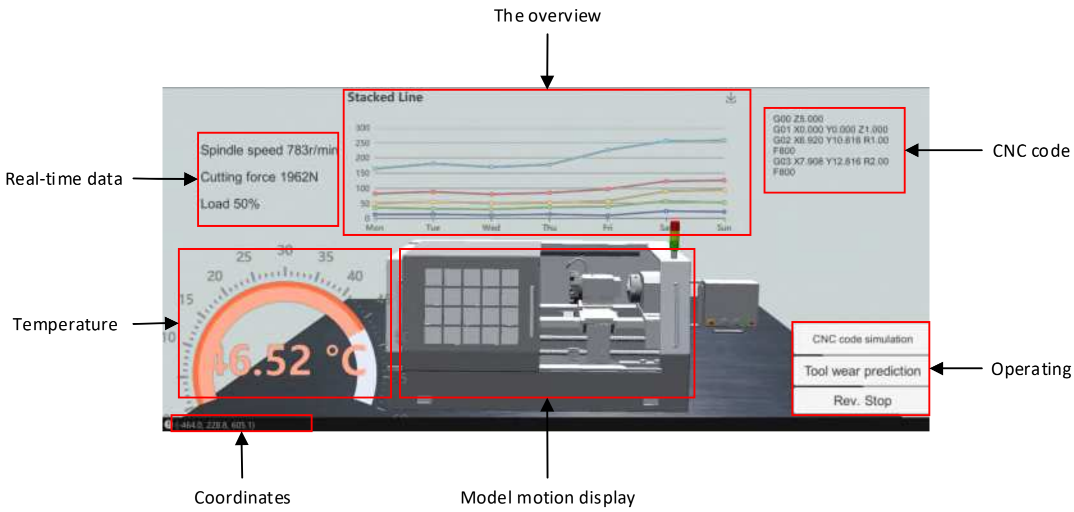


Fig.10 System main interface

The system can be divided into real-time machining data, historical statistical data, CNC code display, tool position data and system operation. The real-time machining data includes cutting speed, cutting force and load. Historical data include A blank quantity, A completed quantity, B blank quantity, B completed quantity and damaged quantity. The system operation includes CNC code simulation, tool wear prediction and machine tool start-stop operation.

5.2.2 Machine tool behavior monitoring

With the communication method proposed in 4.1 of this paper, sensors are used to acquire data for the speed or position of moving parts, spindle, screw, tool turntable, tool slide table, carriage and so on. Based on the cooperation relationship between the reorganized model in 5.1 and the machine tool model built by C# language, the incoming data is mounted on the corresponding module to drive the model to move.

5.3 Realization of tool wear value prediction

The tool life prediction is mainly based on the installation of different types of sensors on the main components of the machining machine tool, the pre-processing of multi-mode signals and feature extraction to find the mapping relationship between features and tool wear[42]. In this paper, the data set of the open Data Competition provided by PHM Society in 2010 was used as validation[43]. All the cutting forces mentioned in this data set were milling forces. Hampel filtering was performed on the sampled data to eliminate the intermediate outlier data. Fig. 11 shows the comparison results before and after removing the intermediate outliers from the signal of the 001st cut of Y axis cutting force in the C1 data set (the circle is the outlier data point.

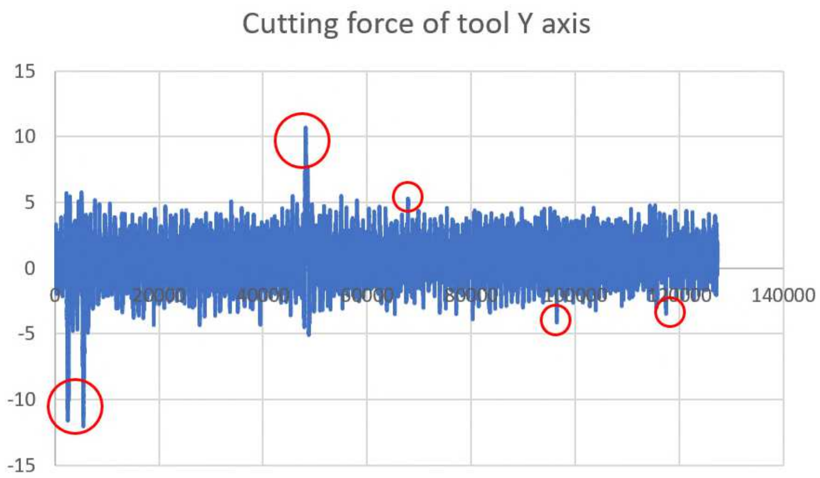


Fig.11 Abnormal data in C1_001

After all abnormal data in C1 are eliminated, feature extraction is carried out. The extraction method in this paper refers to the research of S. Huang, Yaodong T[44][45] and others in this respect. Through the optimal feature selection process, the features with better wear value of flute1 can be obtained, as shown in Table 3. Build multi-layer neural network to fuse features. As shown in Figure 12, one input layer, one output layer and two hidden layers are used to establish the relationship between features and tool wear. There are 9 neurons in the input layer and 1 neuron in the output layer. The number of neurons in the two hidden layers is 6 and 2 respectively. A total of 418 samples are selected from C1, C4 and C6. The number of training samples is 70%, and the number of test samples is 30%.

Table 3 Selection of characteristic

signal	characteristic	The formula
X axis of cutting force	root mean square	$X_{rms}=\sqrt{\frac{\sum_{i=1}^{N}X_i^2}{N}}$
Y axis of cutting force	average value	$\tilde{x}=\frac{\sum_1^n x_i}{n}$
Z axis cutting force	root mean square, absolute average amplitude	$X_{rms}=\sqrt{\frac{\sum_{i=1}^{N}X_i^2}{N}}$, $\lvert\tilde{x}\rvert=\frac{1}{N}\sum_{i=1}^{N}\lvert x\rvert$
Vibration signal x axis	standard deviation	$S=\sqrt{\frac{\sum_{i=1}^{n}(x_i-\tilde{x})^2}{n-1}}$
Y axis of vibration signal	square root amplitude	$X_r=(\frac{1}{N}\sum_{i=1}^{N}\lvert x\rvert)^2$
Vibration signal z axis	standard deviation absolute average amplitude	$S=\sqrt{\frac{\sum_{i=1}^{n}(x_i-\tilde{x})^2}{n-1}}$, $\lvert\tilde{x}\rvert=\frac{1}{N}\sum_{i=1}^{N}\lvert x\rvert$

Acoustic emission signal RMS	**average value**	$\tilde{x} = \frac{\sum_1^n x_i}{n}$

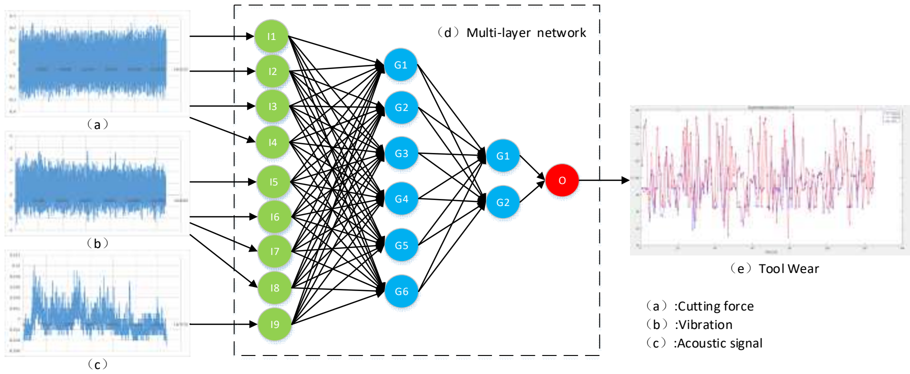


Fig.12 Tool wear prediction

The root mean square error (RMSE) is used to express the fluctuation range of the error between the predicted value and the true value, which is expressed by formula (11), where N represents the number of observations, $observed_t$ represents the observed value, and $predicted_t$ represents the predicted value. According to formula (12), the root mean square error range of this method is between 5.0 and 6.5. The error between the predicted value and expected value of the test set is shown in Figure 13. The accuracy was 100% in the 25-micron error range and 95.2% in the 10-micron error range.

$$RMSE = \sqrt{\frac{1}{N}(observed_t - predicted_t)^2} \quad (12)$$

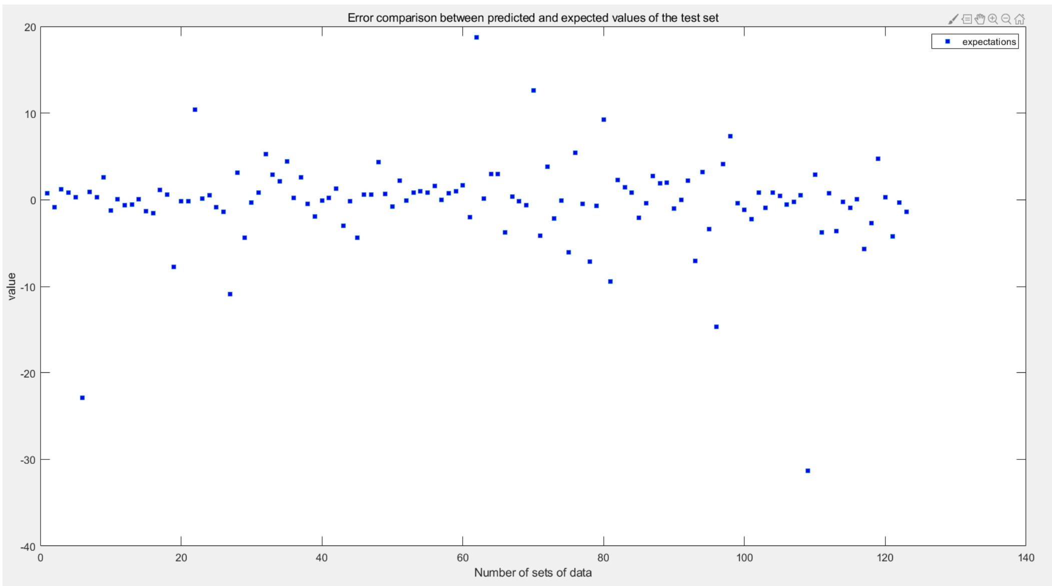


Fig.13 Error between predicted value and expected value

6. Conclusion and future work

In order to prevent tool accidental collision and improve the intelligent management level of machine tools, and to extract the potential information of machine tools during operation to guide production and processing, this paper combines numerical control machine tools with digital twin technology, and proposes a method to build a simulation and monitoring system based on digital twin machine tools. The main functions of the system are as follows:

1). By constructing the twin model of CNC machine tool, the CNC program to be run is simulated in advance before processing, and the correctness of the program is detected;

2). In the actual process of machining, the data transmitted by the machine tool is used to drive the model synchronous movement to monitor the running state of the machine tool;

3). By constructing the machine tool and tool collision detection model, using the improved GJK collision detection algorithm to detect the tool and tool collision model, automatic remote control machine tool emergency stop when the machine tool and tool will collide, in order to achieve the purpose of tool protection;

4). Personalized development of ECharts chart based on JavaScript language, using visualized form of real-time data and historical data in charts, text and other forms, and through monitoring production data, using neural network to predict tool wear degree, guide machine tool production and processing.

However, this system still has some limitations. Firstly, there is no complete twin model of machine tool, and there are blind spots in the stress of machining process, machining quality of workpiece, health of machine tool, etc. Secondly, data mining and prediction algorithms can be further improved. We will further improve the system for the above problems, and dig more data to show all aspects of machine tool processing.

Funding This research is strongly supported by Hudong Heavy Machinery Co., LTD , the Open Fund of Jiangsu Provincial Key Laboratory of Advanced Manufacturing Technology (HGAMTL-1905) and Zhenjiang Key Research and Development Program (GY2019003).

Conflicts of interest/Competing interests Not applicable.

Availability of data and material The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability Not applicable.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent to publish Written informed consent for publication was obtained from all participants.

Author contributions Mingyi Guo: Methodology, Software, Writing-original draft. Xifeng Fang: Supervision, Writing-Review & Editing. Zhongtai Hu: Software, Writing-Review. Qun Li: Operating the machine.

References

[1] Tao F, Cheng JD, Qi QL, et al (2018) Digital twin-driven product design, manufacturing and service with big data. Int J Adv Manuf Technol 94:3563–3576

[2] F. Ridwan, X. Xu (2013) Advanced CNC system with in-process feed-rate optimization. Robotics and Computer Integrated Manufacturing 29 :12–20

[3] Zhang R J (2018) Research and application of real-time monitoring and management system for CNC machine tools based on HTML5. Shanghai: Shanghai University of Applied Sciences

[4] Pan L, Guo X, Luan Y, et al (2021) Design and realization of cutting simulation function of digital twin system of CNC machine tool. Procedia Computer Science 183(9) :261-266

[5] Xiao T, Jiang H, Ding G, et al (2019) Research on modeling and monitoring of digital twin of five-axis grinder. Mechanics

[6] Liu W, Kong C, Niu Q, et al (2020) A method of NC machine tools intelligent monitoring system in smart factories. Robotics and Computer-Integrated Manufacturing 61:101842

[7] Nordrum A (2016) Popular internet of things forecast of 50 billion devices by 2020 is outdated. IEEE spectrum 18(3): 1

[8] Rosen R, Wichert G V, Lo G, et al (2015) About the importance of autonomy and digital twins for the future of manufacturing. IFAC-Papers On Line 48(3): 567-572

[9] Wan Shan, Li Dongbo, James G, et al (2019) A knowledge based machine tool maintenance planning system using case-based reasoning techniques. Robotics and Computer Integrated Manufacturing 58:80-96

[10] Navas C F E, Yepes A, Echavarria R, et al (2021) MTConnect-based decision support system for local machine tool monitoring. Procedia Computer Science 180(1) :69-78

[11] Xavier Desforges, Abdallah Habbadi, Bernard Aerchimede (2011) Design methodology for smart actuator services for machine tool and machining control and monitoring. Robotics and Computer Integrated Manufacturing 27:963–976

[12] Schmucker B, Trautwein F, Semm T, et al (2021) Implementation of an intelligent system architecture for process monitoring of machine tools. Procedia CIRP. 96(2) :342-346

[13] Denkena B, Dittrich M, Noske H, et al (2021) Data-based ensemble approach for semi-supervised anomaly detection in machine tool condition monitoring. CIRP Journal of Manufacturing Science and Technology 35(1) :795-802

[14] Su CY, Meng XY, Cui J H (2021) Operation monitoring and production information management system of networked CNC machines based on C#. Manufacturing Technology & Machine Tool . 1(4) :14-19

[15] Li X, Lim B S, Zhou J H, et al (2009) Fuzzy neural network modelling for tool wear estimation in dry milling operation. Proceedings of the Annual Conference of the PHM Society. Singapore

[16] Mirad MM, Das B (2021) A critical review of the state of the art literature in the monitoring of ultrasonic machining process and tool failure prediction. Engineering Failure Analysis 130(1) :105769

[17] Singh R, Khamba JS (2006) Ultrasonic machining of titanium and its alloys: a review. Journal of Materials Processing Technology173(2) :125-135

[18] Juho Ratava, Mika Lohtander, Juha Varis (2017) Tool condition monitoring in interrupted cutting with acceleration sensors. Robotics and Computer Integrated Manufacturing 47:70-75

[19] Vigneashwara Pandiyan, Wahyu C, Tegoeh W, et al (2018) In-process tool condition monitoring in compliant abrasive belt grinding process using support vector machine and genetic algorithm. Journal of Manufacturing Processes 31:199-213

[20] Guo HF, Zhu YX, Zhang Y, et al (2021) A digital twin-based layout optimization method for discrete manufacturing workshop. The International Journal of Advanced Manufacturing Technology112:1307–1318

[21] Wei YL, Hu TL, Wang YQ, et al (2022) Implementation strategy of physical entity for manufacturing system digital twin. Robotics and Computer Integrated Manufacturing 73 :102259

[22] Yuqian L, Chao L, Kevin I W, et al (2020) Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer Integrated Manufacturing 61:101837

[23] Tao F, Liu W, Zhang M, et al (2019) Five-dimension digital twin model and its ten applications. Computer Integrated Manufacturing Systems 25(1): 1-18

[24] Tao F, He Z, Liu A, et al (2019) Digital twin in industry: state-of-the-art. IEEE Transactions on Industrial Informatics 15(4): 2405-2415

[25] P. Aivaliotis, Z. Arkouli, K. Georgoulias, et al (2021) Degradation curves integration in physics-based models: Towards the predictive maintenance of industrial robots. Robotics and Computer Integrated Manufacturing 71:1021177

[26] Timotej Gašpar, Miha Deniša, et al (2020) Smart hardware integration with advanced robot programming technologies for efficient reconfiguration of robot workcells. Robotics and Computer Integrated Manufacturing 66:101979

[27] Tao F, Zhang M, Cheng J, et al (2017) Digital twin workshop: a new paradigm for future workshop. Computer Integrated Manufacturing Systems 23(1): 1-9

[28] Glaessgen E S D (2012) The digital twin paradigm for future NASA and USair force vehicles: proceedings of the 53rd structures dynamics and materials conference special session on the digital twin. USA: AIAA:1-14

[29] Ghosh A K, Ullah A S, Teti R, et al (2021) Developing sensor signal-based digital twins for intelligent machine tools. Journal of Industrial Information Integration 24(1): 100242

[30] Zhang YZ, Zhang CX, Yan J, et al (2022) Rapid construction method of equipment model for discrete manufacturing digital twin workshop system. Robotics and Computer Integrated Manufacturing 75: 102309

[31] Luo W, Hu T, Ye Y, et al (2020) A hybrid predictive maintenance approach for CNC machine tool driven by digital twin. Robotics and Computer Integrated Manufacturing 65(1): 101974

[32] Sun K, Zhou C, Li J, et al (2020) Three-dimensional visual monitoring system of workshop based on digital twin. http://kns.cnki.net/kcms/detail/11.5946.TP.20200817.0917.008.html

[33] Zhou F R (2020) Development and application of CNC virtual machine tool. Manufacture & Upgrading Today 1(10) :84-87

[34] Tian X K (2021) Research and implementation of virtual simulation monitoring system for machine tool machining process based on digital twin. Chengdu: University of Electronic Science and Technology

[35] Wang T (2019) Virtual simulation of workshop production system based on UNITY3D. Jinan: Shandong University

[36] Ma C (2015) Research and Development of Virtual Reality Numerical Control Machining Simulation System. Xian: Shanxi University of Science and Technology

[37] Ericson C (2004) Real-time collision detection. Amsterdam: CRC Press

[38] Chen CJ, Pan Y, Li DT, et al (2020) A virtual physical collision detection interface for AR-base interactive teaching of robot. Robotics and Computer Integrated Manufacturing 64101948

[39] Han D, Nie H, Chen JC, et al (2018) Dynamic obstacle avoidance for manipulators using distance calculation and discrete detection. Robotics and Computer Integrated Manufacturing 4998-104

[40] Chen LL, Wei LH, Zhu PC (2012) Research and improvement of collision detection algorithm based on simplex. Computer Knowledge and Technology 8(35): 8542-8545

[41] Liu JP (2018) Research on Collision Detection Algorithm of Moving Objects. Wuhan: Wuhan University of Science and Technology

[42] Liu Y, Hu X, Zhang W (2019) Remaining useful life prediction based on health index similarity. Reliability Engineering & System Safety 185(1) :502-510

[43] PHM Society (2010) PHM society conference data challenge. https://www.phmsociety.org/competition/phm/10 2010

[44] Huang S, Li X, Gan O P (2010) Tool wear estimation using support vector machines in ball-nose end milling. Proceedings of the 2010 Annual Conference of the Prognostics and Health Management Society. Portland. Oregon, USA

[45] Tao Y D, Ceng G S, Li N (2017) Tool wear evaluation based on decision tree regression and adaboost algorithm. Computer Systems & Applications 26(12): 212-219