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A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin

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ABSTRACT

As a typical manufacturing equipment, CNC machine tool (CNCMT) is the mother machine of industry. Fault of CNCMT might cause the loss of precision and affect the production if troubleshooting is not timely. Therefore, the reliability of CNCMT has a big significance. Predictive maintenance is an effective method to avoid faults and casualties. Due to less consideration of the status variety and consistency of CNCMT in its life cycle, current methods cannot achieve accurate, timely and intelligent results. To realize reliable predictive maintenance of CNCMT, a hybrid approach driven by Digital Twin (DT) is studied. This approach is DT model-based and DT data-driven hybrid. With the proposed framework, a hybrid predictive maintenance algorithm based on DT model and DT data is researched. At last, a case study on cutting tool life prediction is conducted. The result shows that the proposed method is feasible and more accurate than single approach.

1. Introduction

CNC machine tool (CNCMT), as the mother machine of industry, is one type of important manufacturing equipment [1]. The performance and reliability of CNCMT determines the quality of products it has processed. However, CNCMT may incur faults unpredictably, which will cause low precision, production stagnation or even serious loss and casualties if troubleshooting is not timely. Therefore, predictive maintenance is necessary to avoid faults and improve the reliability of CNCMT.

Nowadays, predictive maintenance becomes a new trend of Prognostic and Health Management (PHM) for complex equipment [2]. In order to realize accurate and reliable predictive maintenance result of CNCMT, it is necessary to consider the characteristics of CNCMT, which are listed as follows.

(1) **Complex.** CNCMT is a kind of complex electro-mechanical and hydraulic integrated system that consists of various parts and components, which are interdependent and interacting with each other. Different kinds of faults may occur at different parts or subsystems concurrently. Moreover, the performance degradation of CNCMT is a non-linear process with noise, resulting in the difficulty of prediction.
(2) **Time varying.** The environment and working conditions of CNCMT are time-varying during its operation which is reflected in the collected sensing data. Meanwhile, the performance of CNCMT components and parts has an implicit degradation process, which means it is a time-varying process too.
(3) **Coupled.** CNCMT processing involves the conversion of material, energy and information simultaneously. Different disciplines are coupled in a complex way, forming a kind of electromechanical system with complex structure and functions. The residual life and reliability of CNCMT is not simply the superposition of the residual life of one single component. Therefore, analysis of CNCMT should be conducted from system level interaction rather than the component or part level.

Traditionally, reliability statistics method [3] is widely used to make prediction based on the statistical characteristics of historical fault data. However, reliability statistics method requires a lot of tests and historical data, which is difficult to implement for complex and expensive large-scale device such as aircraft, machine tools, nuclear power plants, etc. Another is physical model-based method [4], which conducts fault predictions through establishing the system digital

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model, physical failure model and fatigue life model. Establishing an accurate mathematical model for complex electromechanical systems depends heavily on experts' experience and knowledge. These two kinds of methods do not consider the status variety and consistency of equipment during its life cycle, resulting in the inaccurate, untimely and unintelligent prediction results.

With the development of new generation technology such as sensing, monitoring, simulation, big data and artificial intelligence (AI), many intelligent methods [5-7] have been applied to industry, which provide an effective way for predictive maintenance that driven by the manufacturing data [8]. Based on the historical conditions monitoring data of equipment, features that reflect the health status of equipment can be extracted to construct the data-driven model for prediction and diagnosis of equipment. For data-driven method, performance of different algorithms varies according to the characteristics of target system and its data [9], and inaccuracy exists due to the lacking understanding of equipment's physical characteristics, noise and uncertainty.

To overcome the defects of above mentioned methods, many scholars proposed the hybrid predictive maintenance approach [10, 11]. By constructing a fusion method, advantages of each method are complemented. However, to realize the hybrid predictive maintenance approach, it is necessary to construct accurate mathematical and physical models, acquire reliable real-time running data, and make useful data mining.

Digital Twin (DT) concept provides an effective solution for the implementation of hybrid predictive maintenance approach. DT is an enabling method of cyber-physical systems (CPS) [12-14], which contains physical model, real-time sensing data and historical running data. DT contains a high fidelity digital model of physical equipment based on physical laws, which acquires real-time sensing data during the operation of equipment and stores the historical running data for further utilization. Meanwhile, DT can provide reliable data through intelligent context aware and data mining, at the same time achieve high fidelity and dynamic model through multi-domain modeling along with model consistency maintenance strategy. Therefore, DT provides the possibility for hybrid predictive maintenance approach. To realize the reliable and accurate predictive maintenance of CNCMT, a hybrid approach of physical model and data-driven based on DT is studied in this paper.

The rest of this paper is organized as follows. In Section 2, relevant predictive maintenance researches and DT concept are introduced. Section 3 presents an application scenario of DT for hybrid predictive maintenance approach of CNCMT and the implementation methods. Section 4 presents a case study: DT based life prediction of cutting tool of CNCMT. Section 5 concludes this study and points out the future works.

2. Related works

2.1. Current predictive maintenance methods

At present, three methods [15] are mainly used for the predictive maintenance of complex equipment, namely reliability statistics method, physical model-based method and data-driven method as shown in Fig. 1. Each method has its own characteristics and applicable fields.

(1) **Reliability statistics method**

In reliability statistics method, statistical characteristics of historical fault data are used for fault prediction as shown in Fig. 1(a), which requires less detailed information and no specific data nor mathematical model [16, 17]. The information needed for prediction is contained in a series of different probability density functions. Fault prediction methods based on reliability statistics include Weibull distribution, Bayesian method, and fuzzy logic, etc.

These methods are mostly used for commercial products in large batches. It is not suitable for complex and expensive equipment or systems such as spacecraft, aircraft and CNCMT, which contains millions of parts and components. What's more, this method does not take into account of the complex operating environment, the performance degradation of equipment and so on, which will result in low prediction accuracy and confidence level.

(2) **Physical model-based method**

In physical model-based method [16-18], physical mathematical model that reflects the performance degradation of system is established according to the internal working mechanism of target system as shown in Fig. 1(b) [18-20]. The essence of physical object can be described clearly through mathematical model, through which the degradation trend of object can be predicted to obtain the accurate fault prediction results.

Though the physical model-based method can reveal the fault logic of system without collecting a lot of data, it needs the support of experts to design and establish the model. Most of the equipment is usually complex mechanical and electrical systems, whose corresponding degradation models are difficult to be established accurately because of the ignorance of degradation mechanism.

(3) **Data-driven method**

In data-driven predictive maintenance method, data can be gathered from running devices, and precise fault evolution model or performance degradation process is not needed [21-24]. Autoregressive model, artificial neural network [25], support vector machine, correlation vector machine and Gauss regression process etc. are commonly utilized for the analysis of big data. As shown in Fig. 1(c), features are extracted from historical data and then transformed to the knowledge of system. Through data processing and analysis, health status and degradation information of system that hidden in data can be mined.

In order to obtain the operation status and information of equipment, many sensors are usually installed to collect data, but some key parts cannot install sensors, which brings difficulties for data acquisition and further data analysis [26, 27]. What's more, different algorithms have discrepant performances in different system. Therefore, heavy work for the algorithm experiments is needed to find the most suitable algorithm and corresponding parameters.

In summary, current predictive maintenance method based on single strategy has various defects and cannot meet the requirements of higher accuracy and reliability for fault prediction. With the development of new technology, hybrid method as shown in Fig. 1(d), has become the research hotspots [28-30]. With a hybrid method, the advantages of each method can be adopted, the limitations of each single method can be effectively avoided.

2.2. DT concept

With development of simulation, internet of things (IoT), big data [31], and machine learning, DT becomes a new idea about CPS of physical assets [32]. DT is a simulation process [33] that integrates multi-disciplinary, multi-physical variables, multi-scale and multi-probability by making full use of physical model, sensor updating, and historical operation data. DT is the carrier of model and data, which can realize physical mapping in virtual space, then bridge the physical world and digital world.

Many scholars and companies have studied the application and theory of DT. NASA first proposed the health maintenance of aerospace aircraft by DT [34, 35]. Fei Tao did a series of studies on DT such as Digital Twin driven PHM [36], Digital Twin workshop [37, 38], smart manufacturing [39, 40] and its application [41]. Wang Jinjiang proposed a Digital Twin reference model for rotating machinery fault

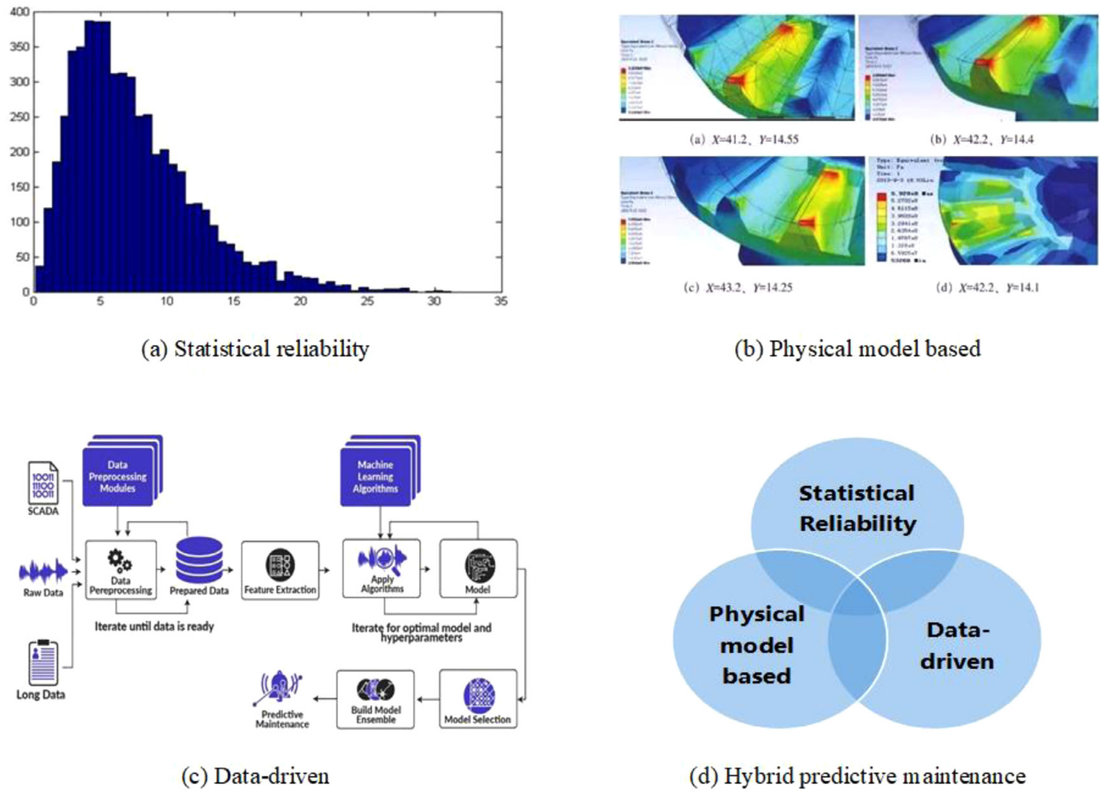


Fig. 1. Current predictive maintenance methods.

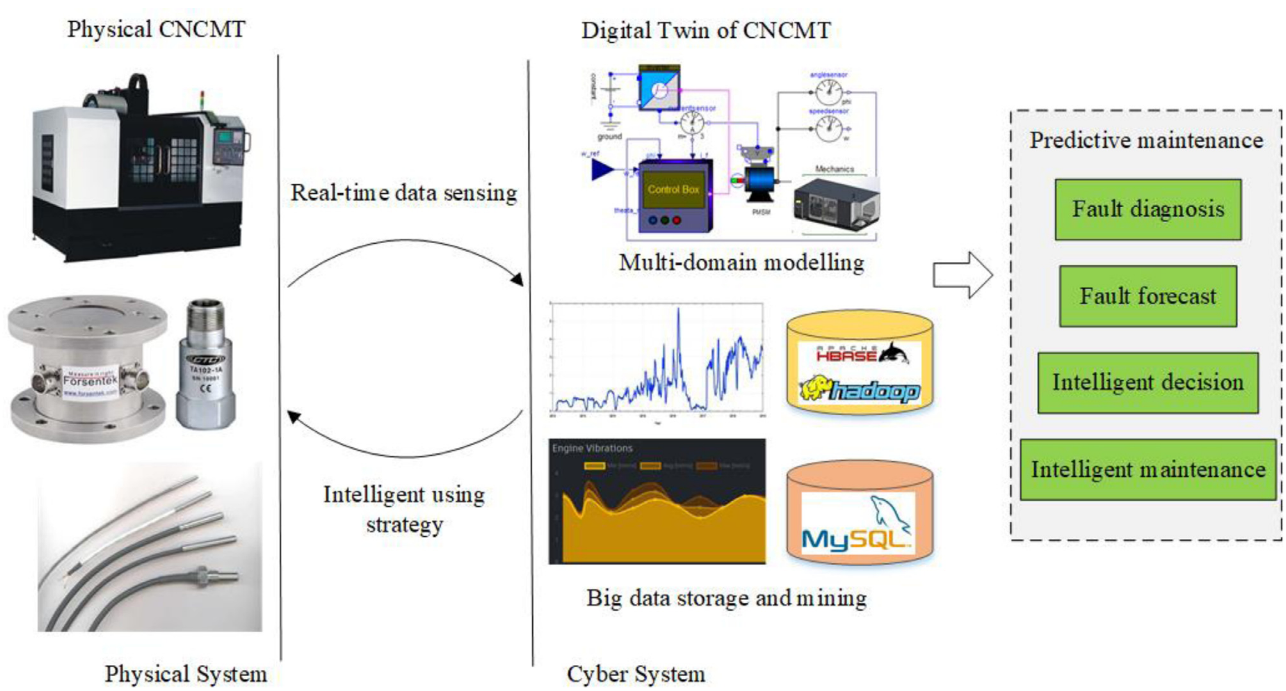


Fig. 2. Building DT and apply it to the CNCMT.

diagnosis and discussed the requirements for constructing the Digital Twin model as well as a model updating scheme [42]. Qiao Qianzhe proposed a data-driven model for digital twin, together with a hybrid model prediction method based on deep learning [43]. Alam [44] presented a digital twin architecture reference model for the cloud-based CPS, C2PS. Yuqian Lu analyzed the connotation, application scenarios, and research issues of Digital Twin-driven smart manufacturing in the context of Industry 4.0 [45]. Sun Xuemin proposed a digital twin-driven assembly-commissioning approach for high precision products [46]. Jiangfeng Cheng proposed a digital twin enhanced Industrial Internet (DT-II) reference framework towards smart manufacturing [47]. Luo proposed a modelling and using method of DT for CNCMT [48, 49]. Some researchers studied DT application on additive manufacturing [50, 51], punching machine [52], production line

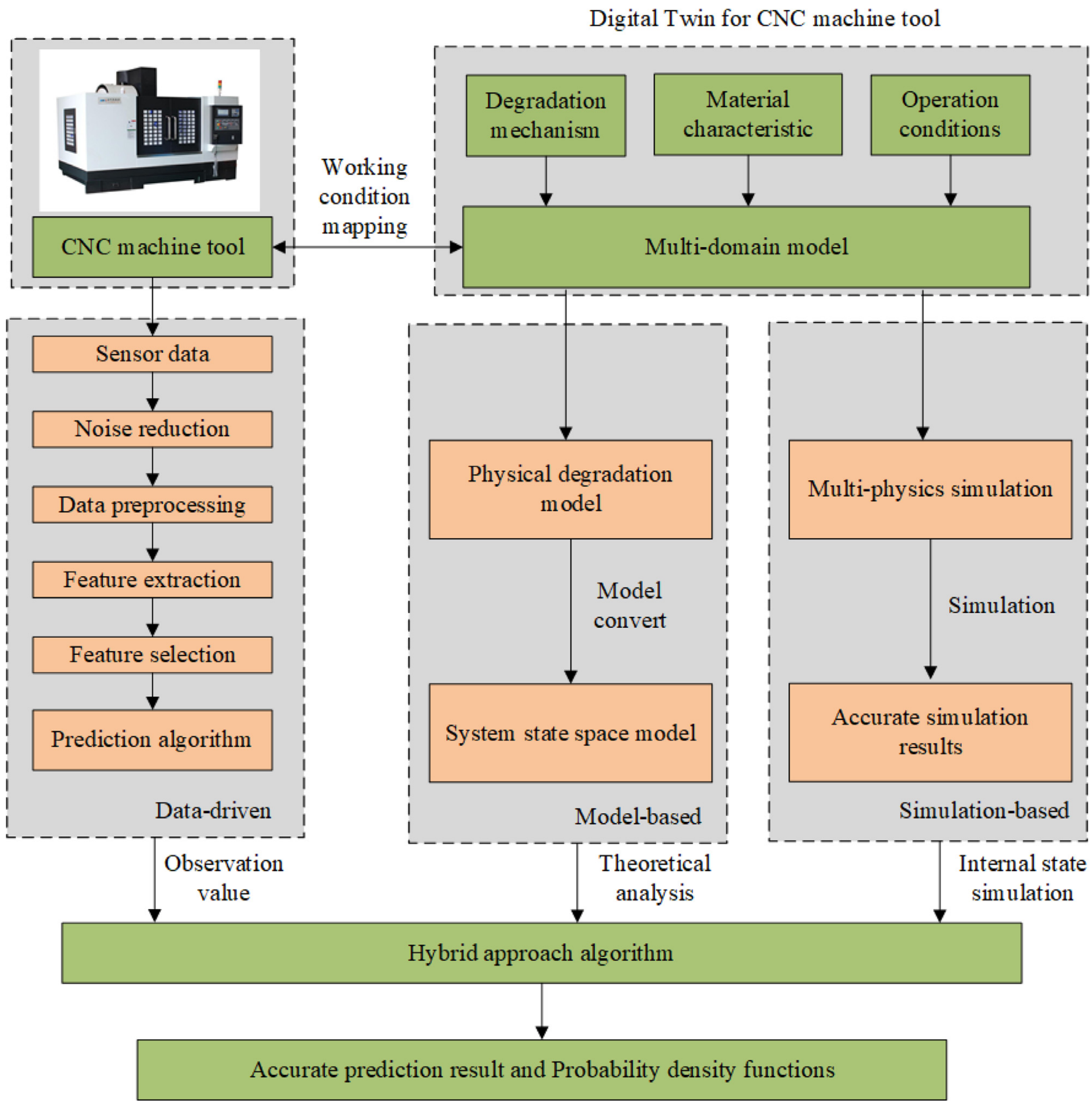


Fig. 3. Hybrid approach predictive maintenance framework based on DT.

[53, 54], machine tool lifecycle [55] and aircraft wing [56]. Many leading companies such as PTC, ANSYS, GE, and Siemens also developed software for building DT.

DT is a one-to-one real-time mapping model of physical devices based on physical degradation. As shown in Fig. 2, after building the multi-physics model of CNCMT, sensing real-time data and conducting big data mining, a DT for CNCMT (DTMT) will come to reality.

Through the simulation of DT, more accurate inner state and data of any part of the system can be obtained from the equipment model without so many sensors installed, which provides a possibility for more accurate and reliable predictive maintenance. This can reduce the number and type of physical sensors installed. In addition, DT is a complete virtual model in computer, which can do a lot of physical damage simulation, and can realize all kinds of harsh and extreme experiment conditions, thus it will provide more possibility and feasibility than physical prototype experiment.

In summary, DTMT provides a more dynamic consistent model and big running data, which can be used for hybrid predictive maintenance method. DTMT will be used for intelligent predictive maintenance such as fault diagnosis, fault forecast, intelligent decision and intelligent maintenance. In this paper, a hybrid approach of physical model and data driven based on DT is studied to achieve reliable predictive maintenance of CNCMT.

3. Hybrid approach based on DT

The hybrid approach contains multi-domain model building, data-driven model building, and hybrid algorithm developing to realize the fusion of model and data. The framework of this hybrid approach and the implementation methods are presented in this section.

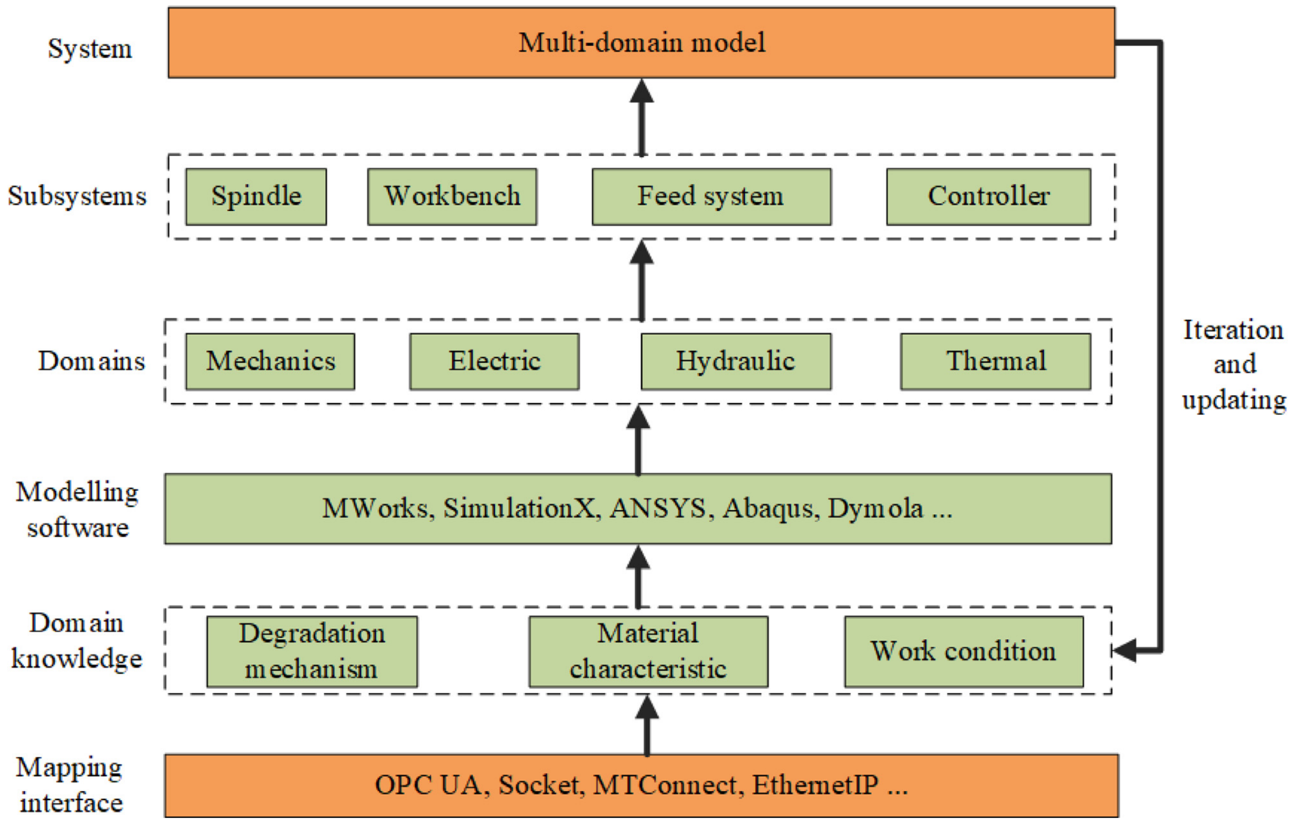


Fig. 4. Multi-domain model implementation.

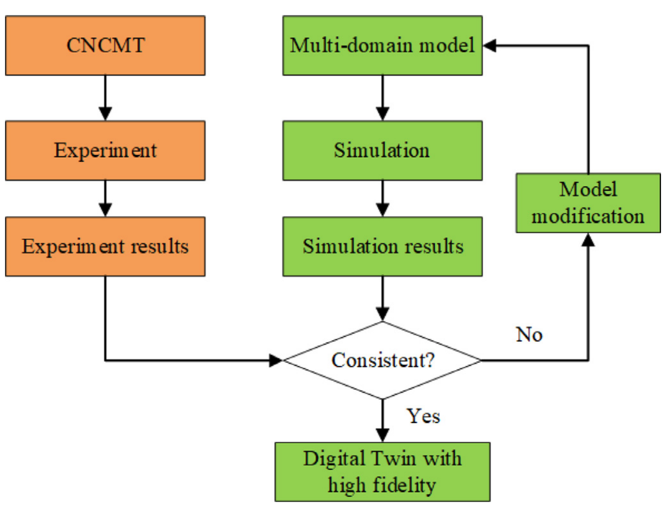


Fig. 5. Method to verify DT accuracy.

3.1. Framework

The hybrid approach framework proposed in this paper is shown in Fig. 3. In this framework, data-driven and model-based method are combined to get a more accurate prediction result and probability density functions (PDFs). A multi-domain model of CNCMT is built based on the degradation mechanism, acting according to the material characteristics and operation conditions. Through multi-physics simulation with the boundary condition mapping from the physical CNCMT, system internal states wherever we care are computed, which is like virtual sensing. System state space model is converted from the DT physical degradation model and utilized for the computation of system states through theoretical analysis with the system internal values from simulation. Specific types of sensors are installed on the physical CNCMT and then provide data support for the data-driven method to predict the remaining useful life (RUL) of parts.

In data-driven method, historical sensing data should go through several steps including noise reduction, data preprocessing, feature extraction, state recognition and finally become applicable for prediction. The RUL predicted by data-driven method is used as the system observation values of CNCMT.

System observation value, system state space model and simulated system inner values are combined through hybrid approach algorithm. The system state space model and simulated system inner values are used to predict the states of CNCMT through prior knowledge. Then the system observation values are used to revise the values of predicted states.

3.2. Implementation

(1) **Multi-domain model implementation**

DT model is a digital presentation of physical CNCMT and plays important role in the data-driven algorithm model. As shown in Fig. 4, multi-domain physics such as mechanics, electric, hydraulic, thermodynamic, etc. should be considered simultaneously during model building. Software supporting multi-domain modeling contains MWorks, SimulationX, ANSYS, Abaqus and Dymola. Therefore, object models from subsystem level like spindle, feed system and workbench can be built and integrated to a unified multi-domain system model by these software.

The high fidelity of the DT is an important basis for the accurate predictive maintenance. In order to improve the accuracy of DT, it is necessary to conduct actual experiment to obtain the practical running results (experimental results). Meanwhile, simulated running results (simulation results) will also be achieved from the simulation based on the multi-domain model that was built according to physical CNCMT.

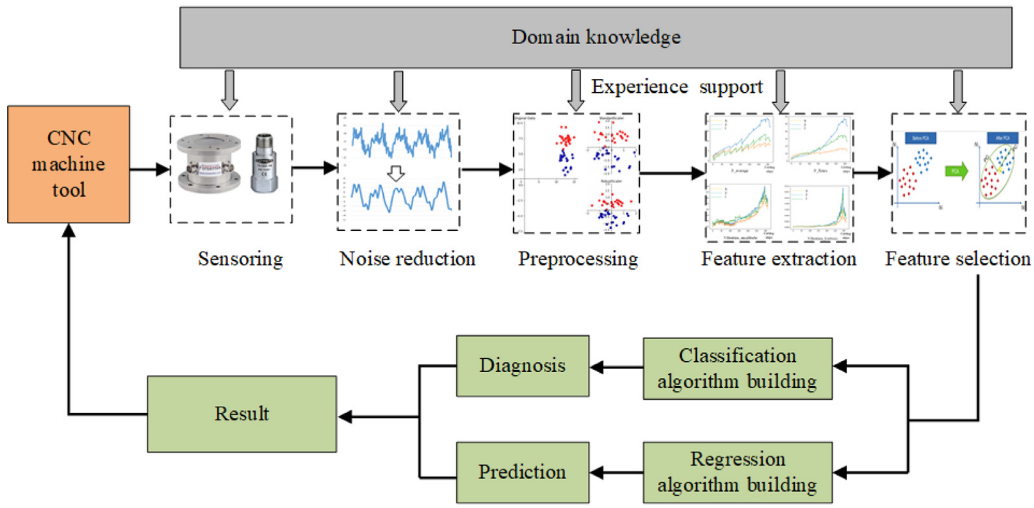


Fig. 6. Data-driven model building.

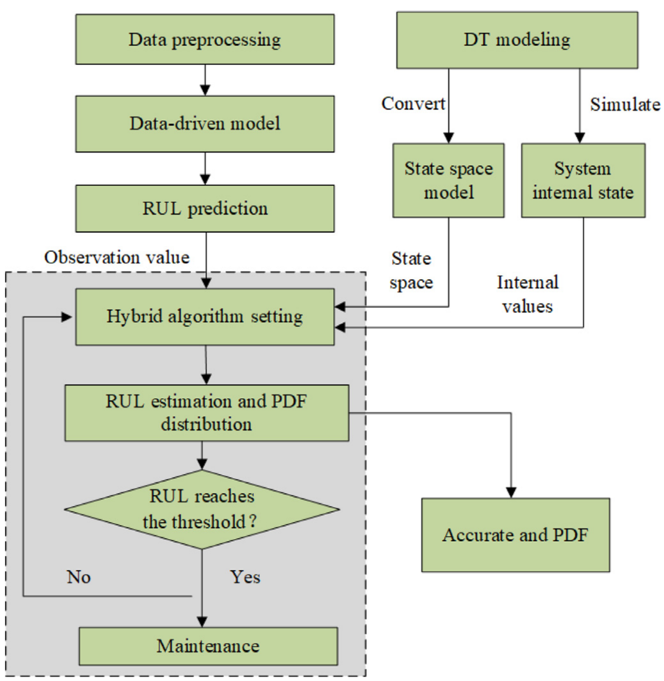


Fig. 7. Hybrid approach steps based on DT.

All the parameters in the model (e.g. material properties, working conditions) should be set same as the practical ones. Then, experimental results and simulation results are compared to determine the consistency of DT, which is an iterative process as shown in Fig. 5. The multi-domain model will be modified and simulated iteratively until the error between the simulation results and the experiment results is small enough. The multi-domain model with small error with experiment can be regarded as a high fidelity DT.

What's more, the mapping interface should also be built to keep the DT model updating in real-time. Domain knowledge and working conditions are mapping through the interface, which is the basis of modelling. Domain knowledge mostly comes from expert experience, mechanical manual, sensor data and controller parameters. Fault diagnosis and prediction of equipment will be realized based on some prior knowledge and experience.

It should be noted that it is unrealistic to establish a completely detailed DT model of the complex equipment nowadays, which will bring enormous energy and time consumption during simulation and operation but make little benefits. Therefore, aiming at the purpose and effect of the research, the physical equipment should be simplified to achieve the goal-oriented hierarchical model.

(2) **Data-driven model implementation**

In data-driven model building, a variety of sensors monitoring conditions of the CNCMT collect big data during the operation. Then, diagnosis and prediction algorithms for the equipment are designed and trained based on collected historical data. To establish the data-driven model, a serious of data processing methods such as noise reduction, preprocess, feature extraction and feature selection as shown in Fig. 6 are necessary, which need the experts' domain knowledge as the basis.

By setting up sensors on CNCMT, the conditions of it can be sensed and monitored, which mainly includes the states and surrounding environment information of CNCMT. The data collected in the workshop usually contains a lot of noise due to the harsh environment. It is necessary to reduce the noise and remove the trend items in data. Then feature recognition is carried out to identify the health-related features from the collected data. At feature selection stage, only features that have strong relationship with equipment health are chosen, which improve the speed of model training and improve the prediction accuracy. At algorithmic model building stage, relevant fault diagnosis and fault prediction algorithms are constructed according to the features after recognition and extraction, so as to achieve data-driven predictive maintenance of CNCMT.

(3) **DT model-based and data-driven hybrid implementation**

Through hybrid approach, the RUL prediction by data-driven method will be used as the observation values of system to revise the result by theoretical empirical deduction. Well-known hybrid algorithms are Karman filter, Particle Filter, ensemble learning and etc.

The steps of the hybrid approach are shown in Fig. 7: (1) Building data-driven model and predicting the RUL result as observation value, (2) Converting DT model to state space model used for hybrid algorithm setting and computing system internal values based on multi-physics simulation, (3) Using hybrid algorithm to estimate more accurate RUL and compute the PDFs, (4) Deciding whether the RUL reaches the threshold, then making suitable maintenance or go back to step (2) for iteration according to the judgment result.

Take particle filtering algorithm for example, the state equation of the system is expressed as Eqs. (1).

$$x_k = f_k(x_{k-1}, v_{k-1}) \tag{1}$$

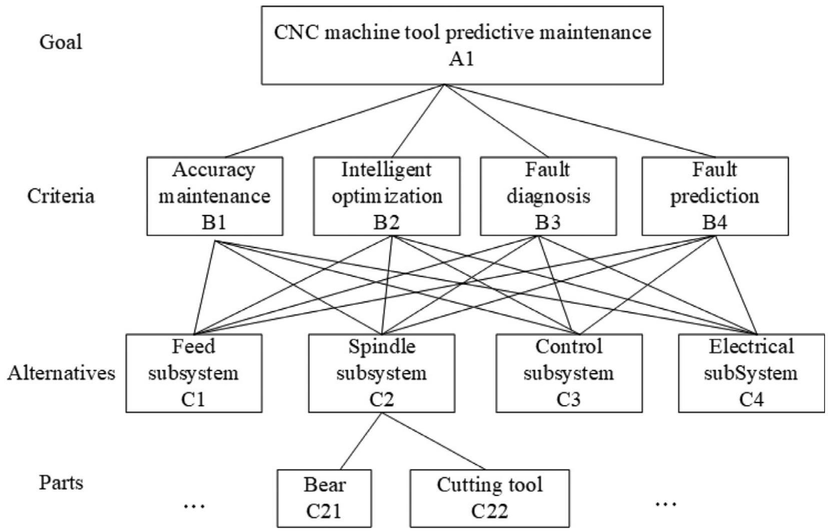


Fig. 8. System level analysis of CNCMT predictive maintenance.

Fig. 9. Cutting tool wear will cause poor accuracy and worsen quality of part.

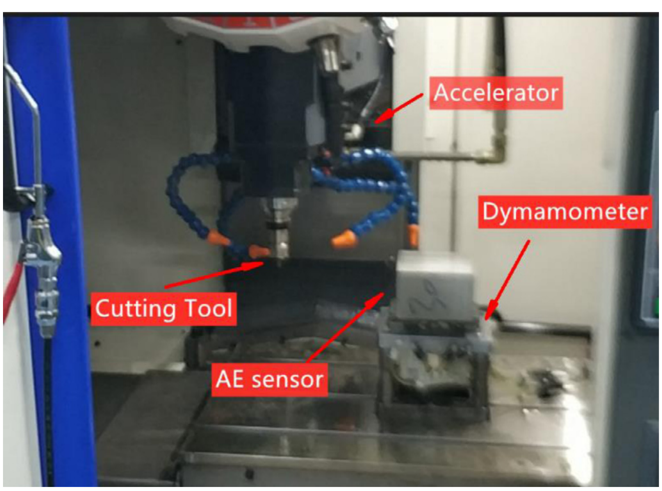


Fig. 10. Sensors installation on milling machine tool.

In Eqs. (1), x is the system state, f is the system state transition function, and v is the system noise. The measurement equation of the system is shown as Eqs. (2), in which y is the measured system state, h is the measurement function and n is the measurement noise.

$$y_k = h_k(x_k, n_k) \tag{2}$$

Particle filter algorithm includes two processes: prediction and updating. In the prediction process, Bayesian calculation as Eqs. (3)-(5) is used to estimate the next state according to the prior probability density of the system (it is often assumed that the next state of the system is only related to the last state), and the updating process uses the measured data to modify the prediction results.

$$p(x_k|y_{1:k}) = \frac{p(y_{1:k}|x_k)p(x_k|y_{1:k-1})}{p(y_{1:k})} \tag{3}$$

$$p(x_k|y_{1:k-1}) = \int p(x_k, x_{k-1}|y_{1:k-1})dx_{k-1}$$
$$p(x_k|y_{1:k-1}) = \int p(x_k, x_{k-1})p(x_{k-1}|y_{1:k-1})dx_{k-1} \tag{4}$$

$$p(y_{1:k}) = \int p(y_k|x_k)p(x_k|y_{1:k-1})dx_k \tag{5}$$

The integration as Eqs. (5) in Bayesian calculation is replaced by Monte Carlo sampling as Eqs. (6) and the average value of the sampled particles is calculated to get the expected value.

$$E[f(x_n)] \approx \frac{1}{N}\sum_{i=1}^{N} f(x^{(i)}{}_n) \tag{6}$$

Particle filter method refers to the process of approximating the probability density function by finding a set of random samples propagating in the state space, and replacing the integral operation with the sample mean to obtain the minimum variance distribution of the state. When the number of particles $N \to \propto$, it can approach any form of probability density distribution. Therefore, the prediction result is more accurate than the theoretical derivation and observation value.

(4) **Whole system predictive maintenance implementation**

The predictive maintenance is mostly conducted on parts and components such as bear, cutting tool, ball screw and so on. CNCMT consists of many parts and components, so the whole system predictive maintenance should be made from system level interaction rather than single component or part. In this research, AHP (Analytical Hierarchy Process) method is used to analyze the problems at system level. The designed hierarchy structure of AHP is shown as Fig. 8. The predictive maintenance for whole system is set as the goal, with several criteria such as accuracy maintenance, intelligent optimization, fault diagnosis and fault prediction. Each criteria contains several subsystem alternatives such as feed, spindle, control and electrical subsystem.

Since different subsystems consist of multi-type parts, in this hierarchy structure, each part is diagnosed, predicted, optimized by the hybrid approach separately and assigned different weights to make up the whole system level predictive maintenance.

4. Case study

Cutting tool is a very important part of CNCMT, because its status directly affects the accuracy and quality of the parts processed. For example, tool wear will not only reduce the dimensional accuracy of parts, but also worsen the surface quality, which leads to the shorting of its service life, as shown in Fig. 9. Traditional cutting tool life prediction

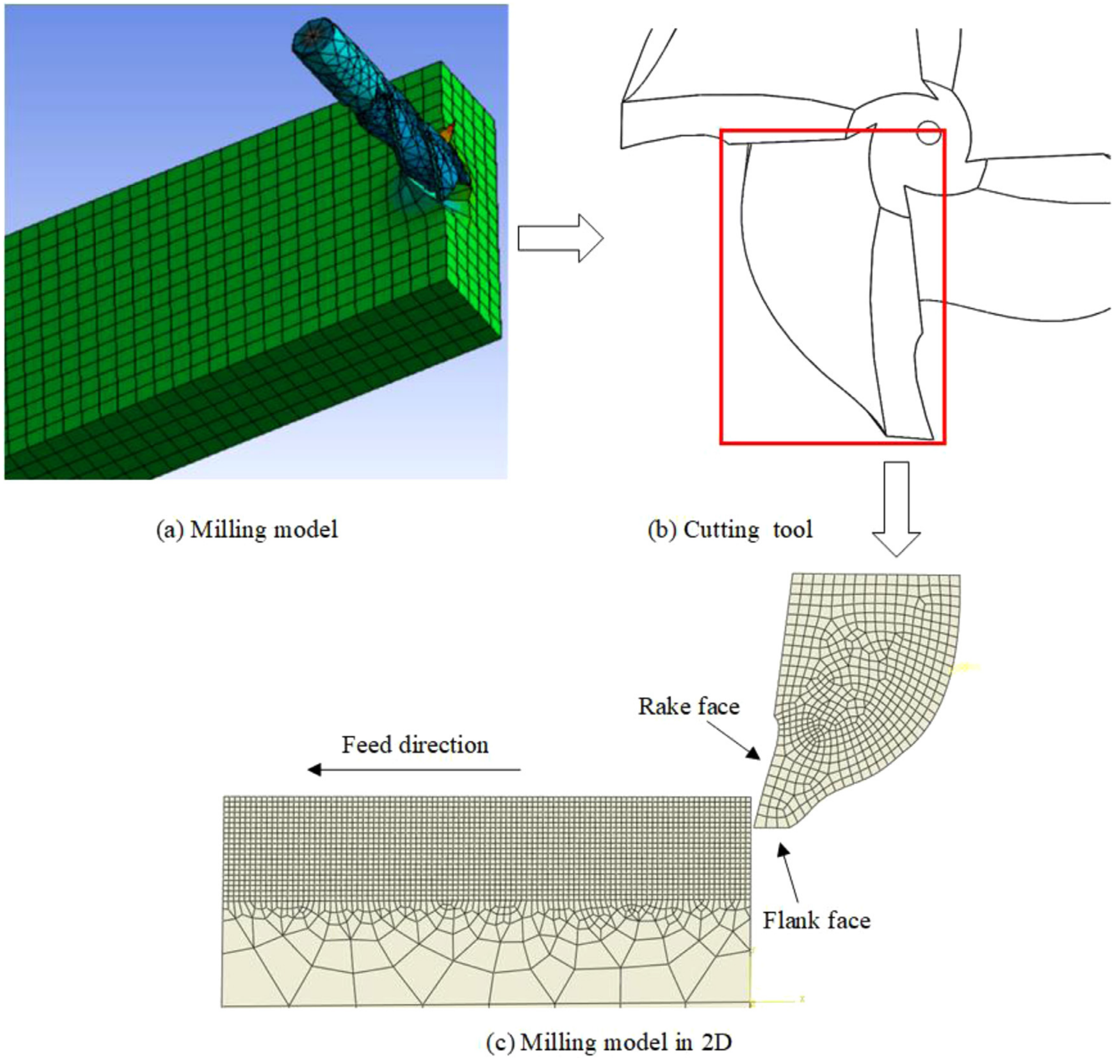


Fig. 11. Milling model of CNCMT cutting tool.

Table 1
Parameters in workpiece Johnson-Cook model.

A(MPa)	B(MPa)	C	n	m	Tm(K)	Tr(K)
265	426	0.015	0.34	1.005	1000	0

Table 3
Failure parameter.

d_1	d_2	d_3	d_4	d_5
0.112	1.243	1.5	0.007	0

is usually based on workers' experience and statistical data. This kind of prediction method will lead to improper maintenance or excessive maintenance. A DT based hybrid application was studied for life prediction of cutting tool.

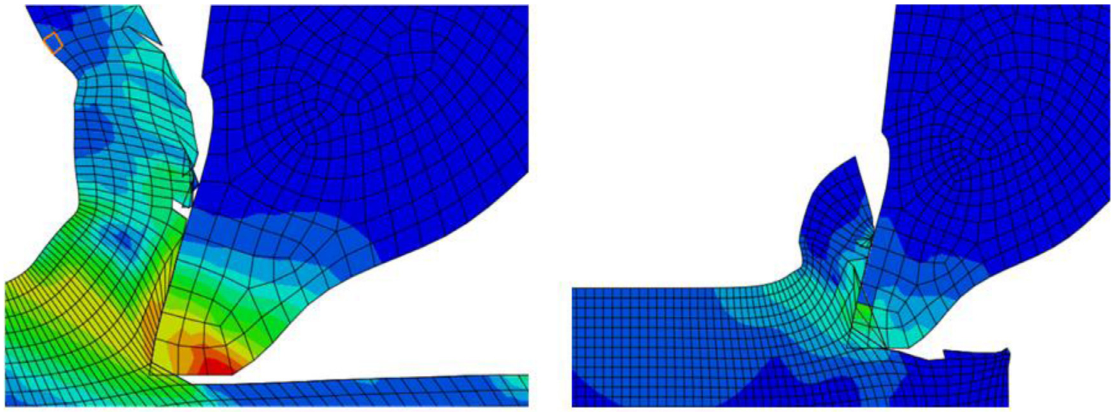
4.1. Experimental platform design

The experiment platform design and sensors installation are shown in Fig. 10. A three-directional accelerometer, a three directions dynamometer and an acoustic emission (AE) sensor were installed in the milling machine tool. The dynamometer was installed between the workbench and the workpiece, while the accelerator was installed on the spindle and AE sensor was installed on the workpiece. For a cutting tool, it was tested by several cutting steps of run-to-failure experiment. The cutting tool had 4 flanks and the wear of each flank was measured after each cutting step. Primary parameters in this experiment were set as follows, spindle speed was 8000RPM(Revolutions Per Minute), diameter of milling tool was 15 mm, feedrate was 1200 mm/min, and sample frequency was 30KHz.

A DT model of cutting tool was built with mapping ability to the actual physical machine tool. Working conditions data like spindle speed, environment temperature, cutting depth and feedrate were

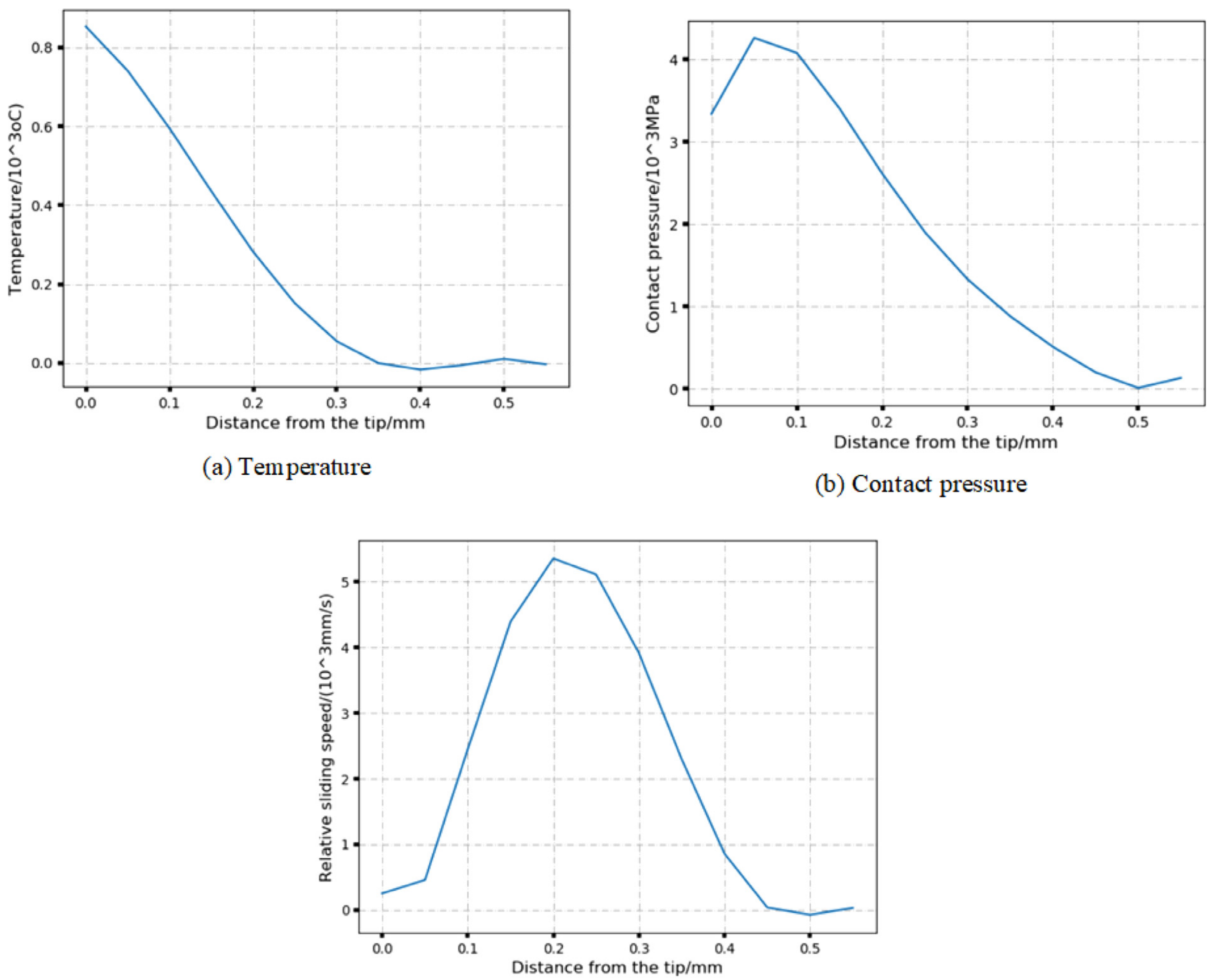
Table 2
Material properties of workpiece and cutting tool.

Property	Density (kg/m^3)	Elastic (GPa)	Poisson's Ratio	Expansion ($10^{-6}/°C$)	Conductivity ($W/(m.°C)$)	Specific Heat
Workpiece	2700	70	0.3	12.3	44.5	502
Cutting tool	12,000	540	0.22	4.7	40	200



(a) Stress (b)Temperature

Fig. 12. Distribution of simulation results.



(a) Temperature (b) Contact pressure (c) Sliding speed

Fig. 13. Inner system values during the simulation.

transferred to DT model through mapping interface, which were used for model updating. Cutting tool wear was calculated by the simulation of updated DT model. The collected data like vibration and cutting force were used to train machine learning models and predict the tool wear in another way. Both the tool wear value by model simulation and data-driven prediction were computed, while neither of them was really accurate because of the noise in result. In order to achieve a more accurate result, a DT based hybrid predictive maintenance approach was applied in this case.

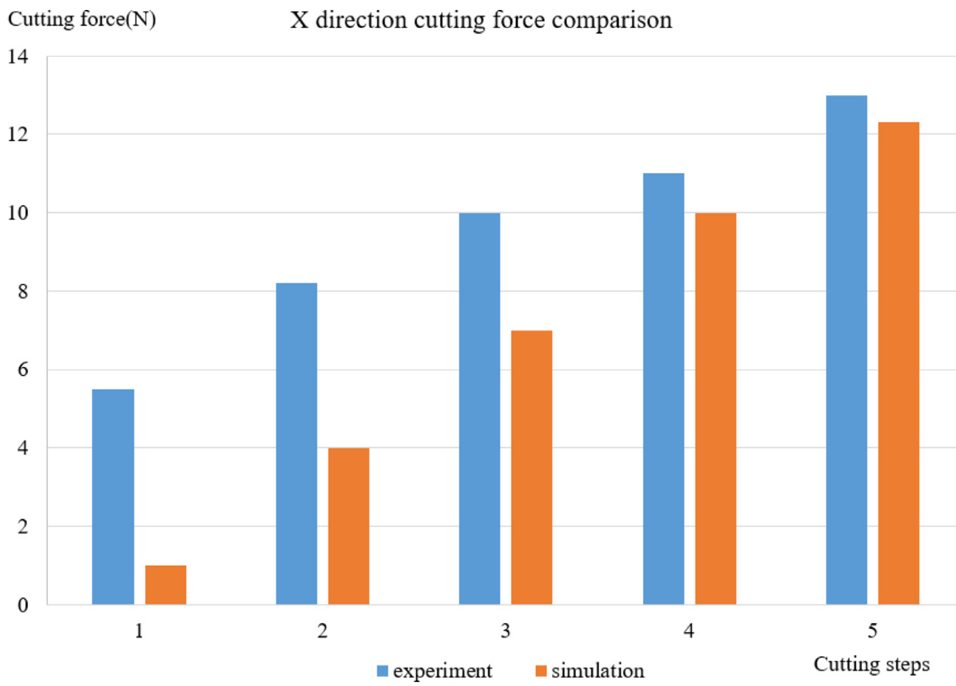


Fig. 14. DT accuracy verification results.

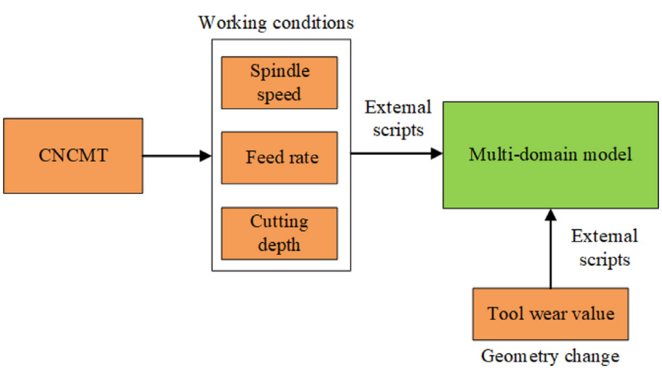


Fig. 15. DT real-time update method.

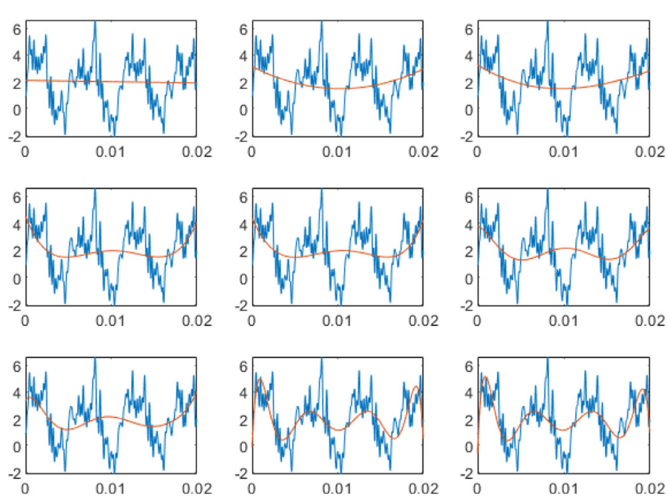


Fig. 16. Trend eliminating with different order polynomials.

4.2. DT based hybrid predictive maintenance approach for cutting tool

(1) **Cutting tool multi-domain model realization**

As mentioned in Section 3.2 (1), it is unrealistic to establish a DT model that completely reflects every details of the whole system at present. Therefore, it is necessary to establish a goal-oriented DT model with simplification purposefully. The main purpose of this study is to accurately predict the RUL of cutting tool. Therefore, the spindle, cutters and workpiece of CNC milling machine are simplified to some extent.

During the milling process, the workpiece will undergo elastic deformation and plastic deformation, and a large amount of heat will be generated at the same time, so the milling process is a thermal-mechanical coupling process. In this study, a multi-domain model of coupled dynamics and thermodynamics was established, and multi-domain simulation was performed to solve the temperature, stress, and relative slip speed during milling. The milling process occurs in three-dimensional space, but the strain in the cutting speed direction of the tool is much larger than that in other directions. Therefore, the milling process is simplified to two-dimensional space in this study, as shown in Fig. 11.

In order to accurately simulate the milling process, a Johnson-Cook constitutive model is used to describe the relationship between stress, strain and temperature during the milling process, as shown in Eqs. (7).

$$\sigma = (A + B\varepsilon_p^n)\left(1 + C\ln\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right)\left[1 - \left(\frac{T - T_0}{T_{melt} - T_0}\right)^m\right] \tag{7}$$

In Eqs.7, A is the initial yield strength, B is the hardening coefficient, ε_p is the equivalent plastic strain, n is the hardening index, C is the strain rate strengthening parameter, $\dot{\varepsilon}$ is the equivalent plastic strain rate, $\dot{\varepsilon}_0$ is the reference strain rate, T_0 is the room temperature coefficient (usually 25°C is used), T_{melt} is the melting point of the material and m is the thermal softening parameter.

Johnson-Cook model parameters for aluminum alloy workpiece can be obtained through experiments or manuals, as shown in Table 1.

The material properties of the workpiece and cutting tool are as Table 2:

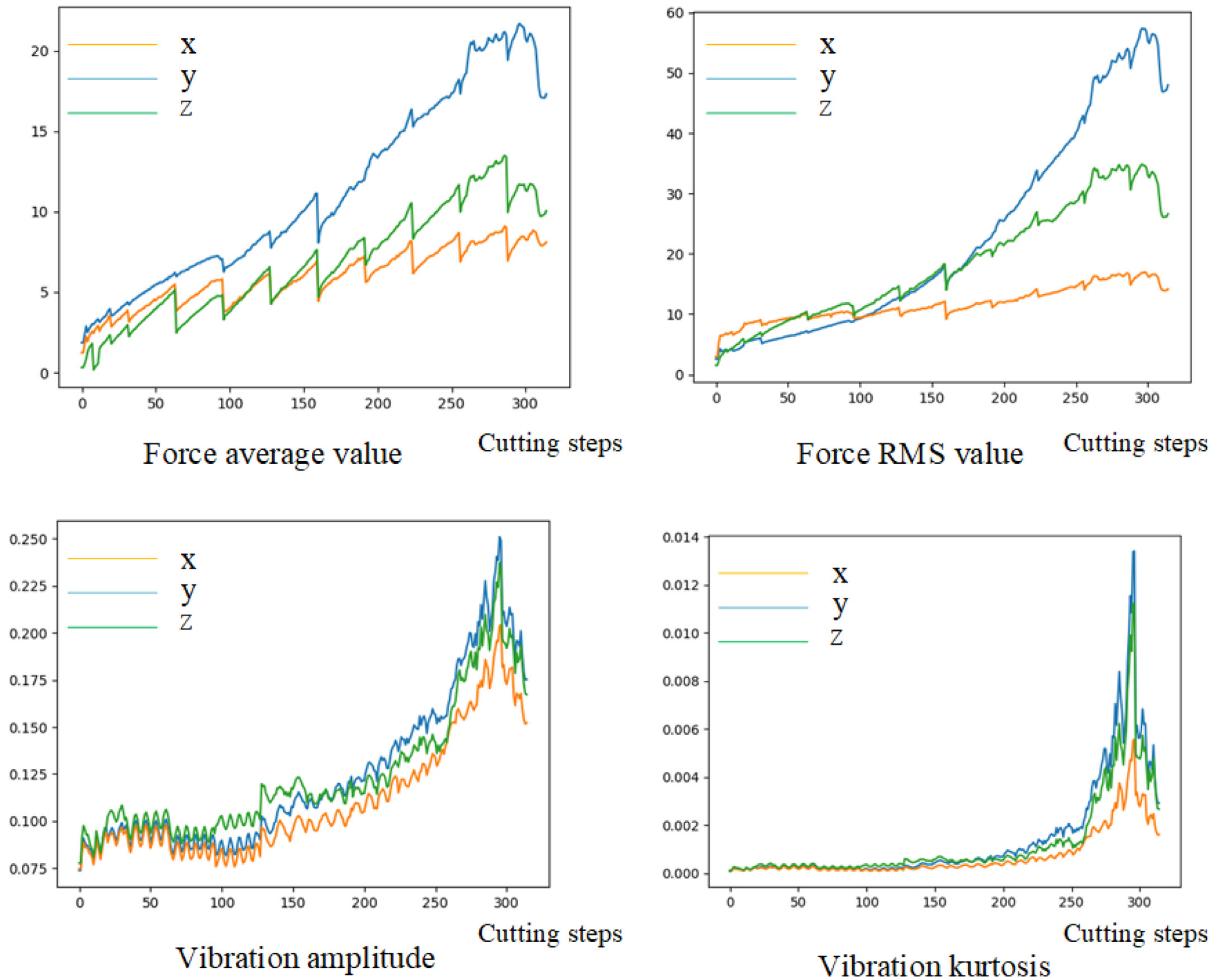


Fig. 17. Several time domain features extracted.

For the failure model during milling process, a shear failure model as shown in Eqs. (8) is used.

$$\varepsilon_f = \left[d_1 + d_2 \exp(d_3 \frac{p}{q})\right](1 + d_4 \ln \frac{\dot{\varepsilon}}{\dot{\varepsilon}_0})(1 + d_5 \theta) \tag{8}$$

$d_1 \sim d_5$ is the failure parameter in Eqs.8, and its value is set as Table 3.

The geometry type of the tool and the workpiece is set to a two-dimensional planar solid element, the mesh element shape is set as quad-dominated, and the element is defined as an explicit coupled Temperature-Displacement type. The interaction between workpiece and cutting tool is defined as the penalty contact method. The penalty contact is easier to achieve convergence, which is suitable for coupled Temperature-Displacement simulation. Field output and historical output are recorded during milling simulation. The stress and temperature distribution during milling are shown as Fig. 12.

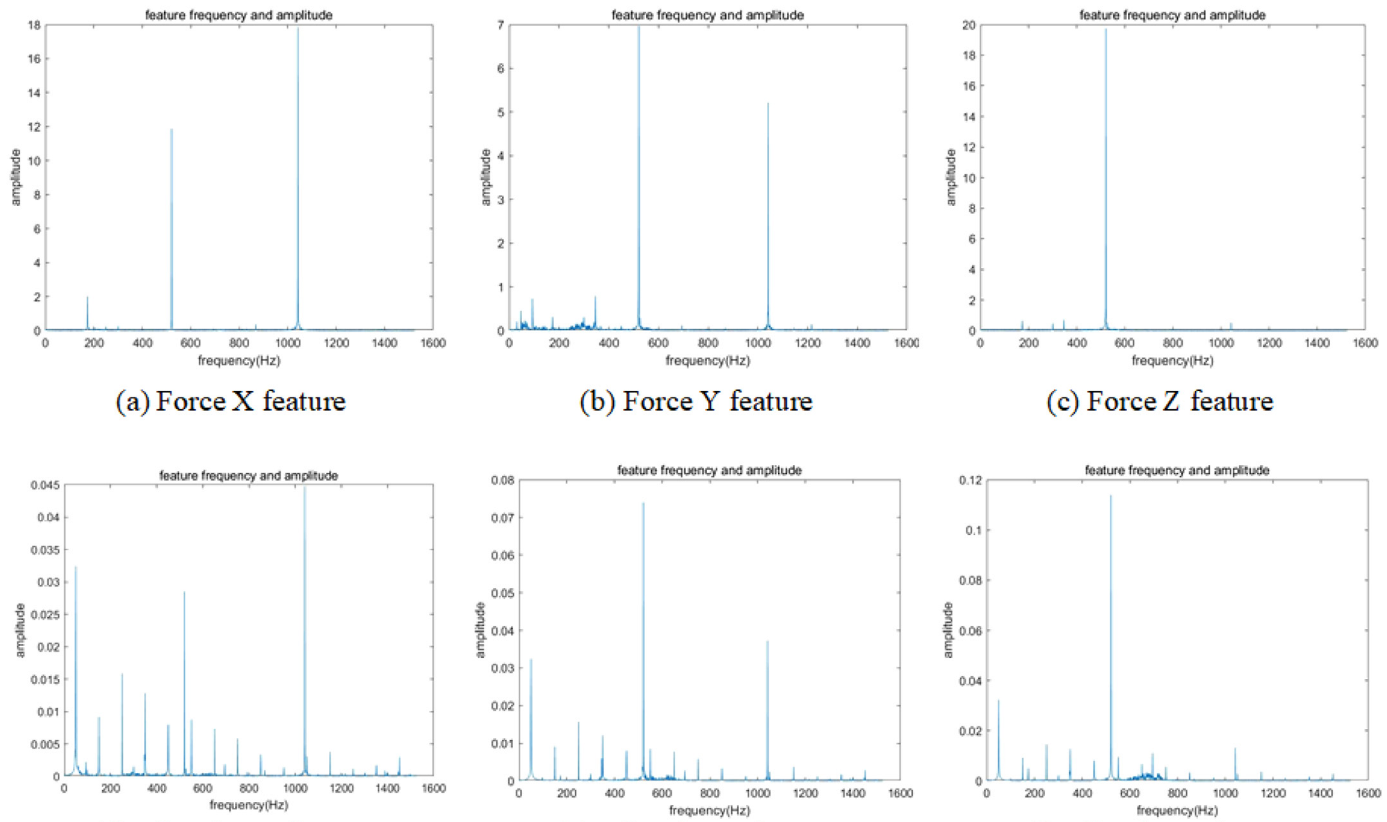
The inner system values such as temperature, stress, and relative slip speed at the end of the simulation are shown in the Fig. 13, which will be used for the calculation of tool wear rate.

For the verification of the model accuracy in the milling process, both the cutting forces obtained from experiment and model simulation in X direction are compared from cutting step 1 to step 5. Through the comparison results as shown in Fig. 14, it can be seen that the error between the simulated cutting force and the experimental cutting force is getting smaller and smaller (reduced from 80% to 9%) after iteratively modifying the model and conducting simulation on it. Because the comparison result is within an acceptable error range, it can be considered that the accuracy of DT model has been verified.

Real-time update of DT is necessary to keep real mapping with the physical machine tool. The changed states of the cutting tool during process can be divided into two types:

(a) Working conditions: refers to the processing parameters such as spindle speed, feed rate, cutting depth, etc. These parameters are read from the CNCMT controller, and have a direct impact on the simulation results of the milling process.
(b) Geometry size: refers to the geometric dimension change caused by tool wear during milling process which also has an impact on the simulation results.

Before running the next step simulation, actual processing parameters and the tool wear value from last milling simulation were input to the DT model by external python scripts to update it, as shown in Fig. 15.



(a) Force X feature (b) Force Y feature (c) Force Z feature

(d) Vibration X feature (e) Vibration Y feature (f) Vibration Z feature

Fig. 18. Features in frequency domain.

Table 4
Features extracted in raw data.

Sensor data	Time domain features	Frequency domain features
Cutting force X direction	RMS, means value, skewness and kurtosis	174 Hz, 521.1 Hz, 1042Hz
Cutting force Y direction	RMS, means value, skewness and kurtosis	347 Hz, 521.1 Hz, 1042Hz
Cutting force Z direction	RMS, means value, skewness and kurtosis	521.1Hz
Vibration X direction	RMS, means value, skewness and kurtosis	50.35 Hz, 521.1 Hz, 1042Hz
Vibration Y direction	RMS, means value, skewness and kurtosis	50.35 Hz, 521.1 Hz, 1042Hz
Vibration Z direction	RMS, means value, skewness and kurtosis	50.35 Hz, 521.1 Hz, 695 Hz, 1042Hz
AE sensor data	RMS	None

Table 5
Correlation between features and cutting tool wear.

Feature	Correlation	Meaning
Tfx1	0.933	Time domain force X RMS
Ffx3	0.926	Frequency domain force X feature at 1042Hz
Ffx2	0.924	Frequency domain force X feature at 521.1Hz
…	…	…
Fvx1	−0.505	Frequency domain vibration X feature at 50.35Hz
Ffy1	−0.630	Frequency domain force Y feature at 347Hz

Table 6
Parameters in data-driven model.

Parameter	Value
bootstrap	False
max_features	4
n_estimators	3

(2) **Cutting tool data-driven model realization**

Within this experiment, the data gathered from sensors are acceleration, cutting force and AE data. Due to sensor drift caused by temperature variation, the raw data contains trend items. What's more, the raw data sampled is often superimposed with noise signal, including power frequency signal, periodic interference signal and random interference signal, which leads to the burrs in the signal waveform. In order to reduce the influence of interference signals and improve the smoothness of the vibration curve, raw data smoothing is conducted too. Elimination of trend terms is conducted by polynomials based on Least Square Method. 4 order polynomials is used in the elimination, because the vibration data is large and the trend curve will be almost the same after 4 order, as shown in Fig. 16.

Five_three smoothing method is used to smooth the raw data. It is a cubic polynomial smoothing method and can effectively remove the high-frequency random noise in the signal.

After data preprocessing, features in time domain are extracted, like root means square value (RMS), means value $\bar{x}$ and skewness α as shown in Eqs. (9)-(11). The AE sensor data has been processed to root mean square value (RMS), so only the average value of AE sensor data

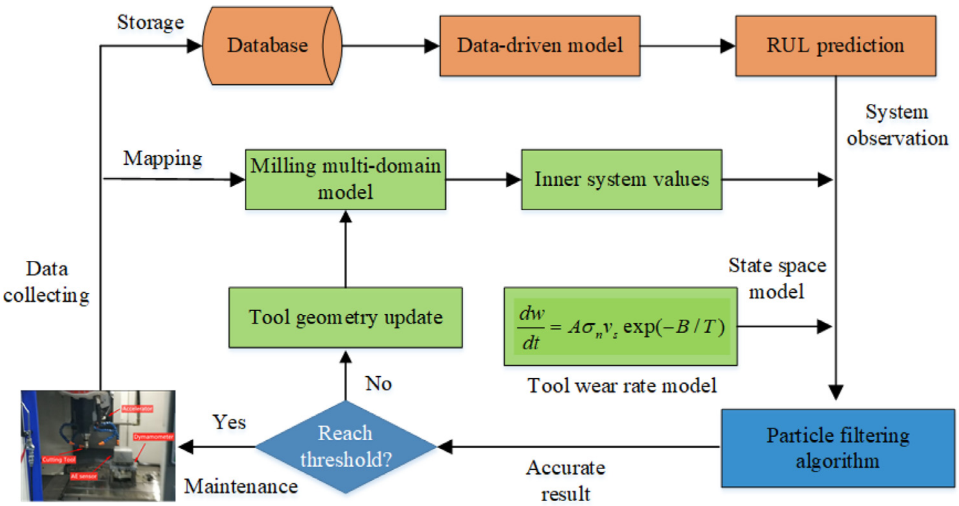


Fig. 19. Hybrid predictive maintenance approach of CNCMT cutting tool.

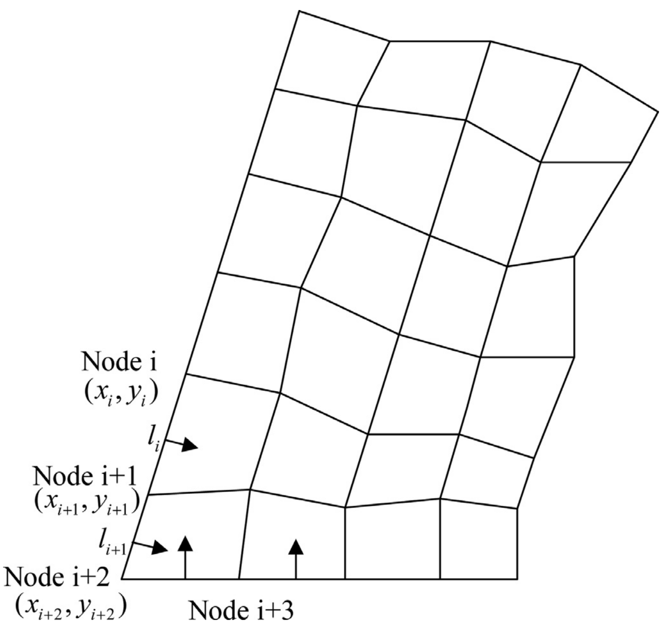


Fig. 20. The cutting tool and its nodes moving direction.

need to be calculated in each cutting step.

$$x_{\text{rms}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{9}$$

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{10}$$

$$\alpha = \frac{1}{N}\sum_{i=1}^{N} x_i^3 \tag{11}$$

Mean value describes the average level of the signal and RMS describes the average energy of signal. Skewness index describes the asymmetry of signal and will increase with the increase of asymmetry. The primary features extracted are shown in Fig. 17. It can be seen that the cutting force and vibration signals have a gradually increasing trend in the cutting steps, while AE sensor data changes sharply at the end stage.

In frequency domain, the main frequency and harmonics of the signals are extracted by the fast Fourier transformation (FFT) algorithm. The amplitude of the feature describes the energy of vibration at a specific frequency. Features are extracted from the three-directional cutting force and three-directional vibration. Through analysis of FFT result, frequencies are different of these sensor data features, as shown in Fig. 18. The total extracted features of time domain and frequency domain are shown as Table 4.

The features as listed in Table 4 are extracted from original signal, while it may contain some redundant and irrelevant features. If feature selection is not carried out, the complexity of the model will be increased and the dimension disaster will appear. Therefore, it is necessary to select features according to the correlation between features and tool wear value. The correlation between each feature and cutting tool wear is computed by *standard correlation coefficient* (also called *Pearson's* r) as shown in Eqs. (12).

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{12}$$

By analyzing features correlation and comparing the r values of each feature, the result shows that the wear of cutting tool is more relative to the RMS of and frequency feature of X-direction cutting force. Meanwhile cutting force signal has larger correlation than vibration and acoustic emission signal. As shown in Table 5, the correlation between RMS of X direction cutting force and tool wear is 0.933. When it is close to 1, it means that there is a strong positive correlation.

This is a typical multi-variables regression problem. So linear regression, decision tree regression, random forest regression, and SVR are built to train the model and then predict the cutting tool wear. Results show RMSE (Root Mean Squared Error) of random forest regression is the best, and grid search is used to search the best hyperparameter values in the model. The final parameter in random forest regression is shown as Table 6. Through best performance of data-driven method has been achieved, a big error from the actual wear value still exists, meaning that data-driven method cannot afford a very accurate result.

(3) **Realization of cutting tool hybrid approach**

The framework of the hybrid predictive maintenance approach of CNCMT cutting tool is shown in Fig. 19.

In this research, theoretical value with simulation and data-driven RUL predicted values are fused in particle filtering algorithm. The RUL prediction from data-driven method is taken as the observation value of particle filtering algorithm to adjust the theoretical value of wear.

At present, tool life model as Eqs. (13) and tool wear rate model as

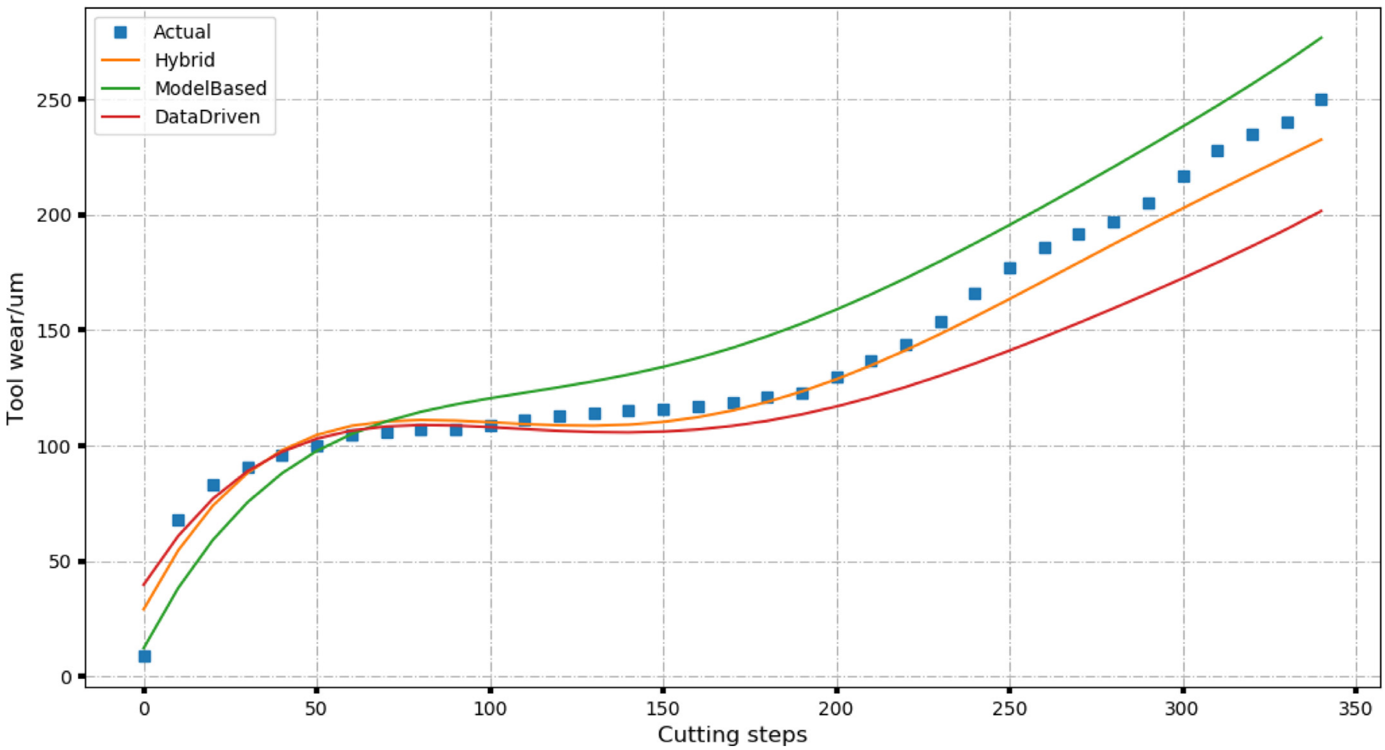


Fig. 21. RUL prediction of cutting tool by different methods.

Table 7
Prediction error ratio of different methods with actual value.

	Initial stage	Medial stage	End stage
Data-driven	9.51%	8.21%	19.59%
Model-based	21.36%	14.91%	10%
Hybrid approach	3.17%	3.56%	6.21%

Eqs. (14) are the commonly used mathematical models for tool wear prediction. The tool life model can only calculate the tool life based on the cutting speed, so its accuracy is not very high.

$$v_c T^n = C_T \tag{13}$$

$$\frac{dw}{dt} = A\sigma_n v_s \exp(-\frac{B}{T}) \tag{14}$$

Eqs. (14) includes three variables besides constant: relative slip velocity between tool and chip v_s, temperature of tool surface T and stress σ_n. The tool wear rate model originates from the tool wear mechanism, and describes the volume loss rate per unit contact area at per unit time. With DT, these variables can be obtained by multi-domain simulation of cutting process, as presented above, so the tool wear rate model is used in this research.

Tool wear usually refers to the wear value measured on the flank. As shown in Fig. 20, the moving direction of the flank node is perpendicular to the workpiece machined surface, which is consistent with the positive direction of the Y axis, as shown in Eqs. (15).

$$\vec{n} = (0, 1) \tag{15}$$

According to Eqs. (14), the theoretical derivation of the tool wear w_t at time t will be as Eqs. (16). At the same time, the tool wear observed value from data-driven method will be as Eqs. (17)

$$w_t = w_{t-1} + A\sigma_n v_s \exp(-\frac{B}{T})dt + v_t \tag{16}$$

$$RUL_t = Data - drivenModel(features) + n_t \tag{17}$$

Eqs. (16) and Eqs. (17) were set as the state equations and observation equations in the particle filter algorithm. The number of particles was set to 200. The pseudo code of the fusion algorithm was shown as below.

(1) Initialize the variables and particles with Gaussian distribution;
for n = 1:cutting steps
(2)$w_t = w_{t-1} + A\sigma_n v_s \exp(-\frac{B}{T})dt + v_t$;
(3) $RUL_t = Data - drivenModel(features) + n_t$;
for i = 1:200
(4) Sampling from the known distribution as (2);
(5) Calculating the prediction value RUL_{ti} of particles by (3);
(6) Calculating the weightω_i of each particle based on the Gaussian distribution;
End;
(7) Normalizing the particle weights as $\tilde{\omega}_i = \frac{\omega_i}{\sum \omega_i}$;
(8) Resampling based on the normalized particle weights;
(9) Calculating the mean value of particles prediction values RUL_{est} as the estimation of cutting tool life;
End;

The RUL_{est} value is the final tool wear predicted by the hybrid approach. Cutting tool maintenance is conducted if RUL_{est} has reached the threshold, otherwise cutting tool geometric size is updated, and the cutting tool wear is predicted by hybrid approach again.

4.3. Experiment and result analysis

The RUL result calculated by the hybrid approach is shown as Fig. 21. When using the single-strategy approach (e.g. data-driven and model-based), the predicted value has a big error from the actual value. When adopting the hybrid approach, the predicted value is closer to the actual value with smaller error. As shown in Table 7, prediction error ratio of data-driven method is large (9.51% at initial stage, 8.21% at medial stage and 19.59% at end stage), and the performance of model-based method is also not good. Driven by DT, the prediction error ratio of hybrid approach becomes smaller (3.17% at initial stage, 3.56% at medial stage and 6.27% at end stage).

Hybrid predictive maintenance approach can output a more accurate predicted RUL with less error which is superior to the single-strategy approach at any stage. The hybrid approach based on DT overcomes the incorrectness of physical model-based and poor adaptability of data-driven method, and thus improves the prediction results greatly.

5. Conclusion and future works

In this paper, a hybrid predictive maintenance method for CNCMT driven by DT is proposed. This method is fused by particle filtering algorithm based on DT model and driven by DT data. With this method, DT model is built in multi-domain and reflects the actual working conditions; and DT data is gathered by different type of sensors and used for the data-driven RUL prediction model. Then the system observation value and theoretical derivation value are fused by the particle filtering algorithm. This method enables the DT model and data to be better integrated and applied, thus can give out a more accurate result than single-strategy method. The validity and accuracy of the proposed approach are verified by a case study of the CNCMT cutting tool life prediction.

In the future, DT model implementations based on cloud and edge as well as model migration learning based on DT will be further studied.

CRediT authorship contribution statement

Weichao Luo: Conceptualization, Methodology, Writing - original draft, Software. **Tianliang Hu:** Conceptualization, Project administration, Writing - review & editing. **Yingxin Ye:** Writing - review & editing. **Chengrui Zhang:** Conceptualization, Supervision. **Yongli Wei:** Investigation.

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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