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Tool wear condition monitoring method of five-axis machining center based on PSO-CNN

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Abstract:
The effective monitoring of tool wear status in the milling process of a five-axis machining center is important for improving product quality and efficiency, so this paper proposes a CNN convolutional neural network model based on the optimization of PSO algorithm to monitor the tool wear status. Firstly, the cutting vibration signals and spindle current signals during the milling process of the five-axis machining center are collected using sensor technology, and the features related to the tool wear status are extracted in the time domain, frequency domain and time-frequency domain to form a feature sample matrix; secondly, the tool wear values corresponding to the above features are measured using an electron microscope and classified into three types: slight wear, normal wear and sharp wear to construct a target Finally, the tool wear sample data set is constructed by using multi-source information fusion technology and input to PSO-CNN model to complete the prediction of tool wear status. The results show that the proposed method can effectively predict the tool wear state with an accuracy of 98.27%; and compared with BP model, CNN model and SVM model, the accuracy indexes are improved by 9.48%, 3.44% and 1.72% respectively, which indicates that the PSO-CNN model proposed in this paper has obvious advantages in the field of tool wear state identification.
Keywords: *five-axis machining center; tool wear; PSO-CNN; intelligent monitoring*

1 Introduction

Five-axis machining center is a set of high-tech, high precision, high efficiency in one of the high precision end equipment, specifically for processing complex curved parts, its key technology to improve the level of equipment manufacturing industry is of great significance. And five-axis machining center. Due to its flexibility, versatility and high throughput, the machining environment is more complex and tool wear is more severe. Tool wear beyond a given threshold can greatly affect the machining accuracy of the workpiece, resulting in poor quality of the machined product [1]. On the other hand, in order to ensure the machining accuracy, if the tool has a long remaining life, it will affect the economy of its use and increase the production cost, especially in the process of batch processing will also cause interruptions in the production beat, lower production efficiency and other problems. For complex curved parts with high precision machining requirements, how to make the tool wear before the critical threshold for intelligent tool change will be an important research direction for the future high-end manufacturing industry.

Tool Condition Monitoring (TCM) has been recognized as an important method for preventing excessive tool wear and maintaining part tolerances and surface quality during the milling process [2]. Its essence is the real-time acquisition of signals related to tool wear using sensor technology, as well as the capture of correlated features of tool wear using data-driven techniques to construct a reference model for feature monitoring. In the process of tool condition monitoring, it is usually necessary to pre-process the acquired raw signal, extract the effective features from the signal and construct a sample feature matrix as the input to the prediction model. The most commonly used feature extraction methods are: Empirical Mode Decomposition (EMD) [3], Fourier Transform [4] and Wavelet Packet Analysis [5] etc. Empirical mode decomposition (EMD) can effectively extract tool wear state features from the time and frequency domain, but it requires a high level of signal frequency processing and may suffer from severe endpoint effects and mode confounding in the process [6] . The Fourier transform is independently adaptive, allowing time domain features to be better revealed in the frequency domain, and is therefore widely used to extract frequency domain features of sample signals [7]. Wavelet packet

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analysis is used to decompose the time domain features into different frequency bands by using different types of filters to refine the signal, so it is mostly used to extract the time-frequency domain features of the sample signal [8].

In the automated production process, a high-precision tool wear state prediction model can effectively predict the future tool wear degree, which is of great significance to improve the productivity and surface machining quality. Early scholars have made some achievements in constructing a tool wear state prediction model using mechanical learning techniques. Han Chengwen et al. identified two valuable features related to tool wear based on discrete wavelet transform (DWT) of thrust signal and artificial neural network (ANN), and then extracted them using DWT.This method can accurately estimate the CFRP drilling process tool wear[9]. Soufiane Laddada et al. used continuous wavelet transform for feature extraction and proposed an improved extreme learning machine (IELM) to map the input data by a nonlinear function in order to generate a degradation model to obtain health indicators to complete the prediction of the remaining tool life[10] . Liang Yu et al. used a combination of time domain, frequency domain and wavelet analysis to extract the force and vibration signals and constructed the IHDGWO-SVM model for tool wear prediction. The experimental results showed that the prediction accuracy of the model was 92 %, which was significantly higher than other models [11]. However, the machine learning method does not deeply mine the implicit information of the data, and its prediction accuracy and precision are not high.

In recent years, deep learning theory has been widely used in the field of tool condition monitoring, and Convolutional Neural Network (CNN) is a typical representative of deep learning. Convolutional neural networks (CNNs) have powerful feature extraction capabilities, and their convolution and pooling operations can adaptively mine the deep features of the input data, which can better approximate the objective function through a large number of nonlinear mappings and improved feature representations [12]. Therefore, a large number of researchers have started to use CNN network models for tool wear state recognition, such as Xin Cheng et al. conducted milling experiments on S45C steel under different machining parameters and used convolutional neural networks to mine potential features of multi-scale 2D signals to construct a wear state recognition model, and the results showed that the method can effectively recognize tool wear state [13]. Although CNN networks have achieved some achievements in tool wear status monitoring, how to avoid the overfitting phenomenon caused by gradient dispersion is an urgent problem to be solved.

To solve the above problem, the hyperparameters in the convolutional neural network (CNN) tool condition monitoring model need to be optimized, such as batch size and Epoch count and other key parameters. Currently, the more common hyperparameter optimization methods include random optimization [14], gradient-based optimization [15], genetic algorithm optimization [16], particle swarm algorithm optimization [17], etc. Particle swarm algorithm (PSO) has powerful search performance and individual optimization capability, and can choose adaptive weights according to the number of iterations, thus avoiding the phenomenon of global optimal solution omission due to too fast convergence, so it has been widely used and studied by scholars in recent years [18].

Therefore, this paper proposes a dynamic monitoring method for tool wear status based on machine vision, feature extraction, deep learning, and information fusion. The CNN convolutional neural network is used to mine the tool wear features, and the classifier is constructed in the output layer after a series of operations such as convolutional layer and pooling layer to output the tool wear status information; meanwhile, the particle swarm optimization algorithm (PSO) is used to optimize the hyperparameters in the CNN convolutional neural network to improve the accuracy and precision of the prediction model. It is verified that the PSO-CNN model proposed in this paper can accurately and efficiently predict the tool wear status, effectively ensure the machining quality of the part, improve the efficiency of tool use, and reduce the machining cost, which is an important step to realize the intelligence of CNC machining.

2 Tool wear condition monitoring method

2.1 PSO-CNN tool wear condition monitoring model

Convolutional Neural Network (CNN)[19] is a typical representative of deep learning, which is a locally connected and weight-sharing neural network structure consisting of input layer, convolutional layer, pooling layer, fully connected layer and output layer, and has obvious advantages for deep mining of data features. However, improper selection of hyperparameters in CNN networks can lead to slow convergence of the model and overfitting phenomenon. Therefore, this paper proposes a CNN convolutional neural network model based on the optimization of the PSO algorithm to classify and predict the tool wear state. The model firstly mines the features in the sample dataset deeply through a series of operations such as convolutional and pooling layers in the CNN network, The principle is as follows:

The sample feature matrix after batch normalization and dimensionality reduction is input to the CNN convolutional neural network for convolutional operation. The sample information is indirectly characterized by the local features of the sample through the weight value of each layer derived from the convolutional operation, and the higher the layer is, the more detailed the local features are extracted, and also the spatial continuity of the sample is maintained, and its convolutional operation is shown in equation (1):

$$X_i^k = \sum_{j=1}^{n} W_i^{kj} \otimes X_{i-1}^j + b_i^k \tag{1}$$

Where X_i^k denotes the feature matrix of the kth neuron at the output of the ith layer, and W_i^{kj} denotes the weight value of the kth neuron in the ith layer, and $\otimes$ denotes the convolution operator, and X_{i-1}^j denotes the feature matrix of the jth neuron at the output of layer i-1, and b_i^k is the bias coefficient of the kth neuron in layer i.

Each tool wear feature data is input to the pooling layer after convolution operation, and the pooling type is selected as maximum pooling, which can retain the original features and reduce the parameters of network training, and improve the robustness of the extracted features. The maximum pooling is shown in equation (2):

$$C_i^k(s,t) = \underset{\substack{1+(s-1)Q\le d\le sQ \\ 1+(t-1)P\le h\le tP}}{\mathrm{Max}} \{V_i^k(d,h)\} \qquad (2)$$

Where $V_i^k(d,h)$ is the eigenvalue of column h of row d of the ith feature matrix input to the pooling layer, and$C_i^k(s,t)$ is the eigenvalue of the sth row t column of the ith feature matrix obtained after pooling, and P and Q are the length and width of the pooled region, respectively.

For another, the PSO algorithm is introduced to optimize the hyperparameters of batch size and Epoch count in the CNN model, so as to Finally, a Softmax classifier is constructed in the output layer to predict the tool wear status and output the tool wear type, thus completing the prediction of the tool wear status of the 5-axis machining center. The 5-axis machining center will take different processing solutions according to different prediction results, such as the system will have a warning prompt when the tool enters into a sharp wear stage, and complete intelligent tool change and other operations, and its PSO-CNN tool wear state monitoring model is shown in Figure 1.

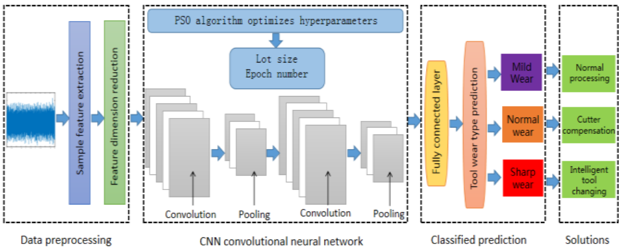


Figure 1 PSO-CNN tool condition monitoring model

2.2 Prediction process of PSO-CNN monitoring model

The tool condition monitoring process based on CNN convolutional neural network optimized by PSO algorithm proposed in this paper contains four main stages.

(1) The original signal is pre-processed to eliminate the noise effect, and then the feature quantities related to the tool wear state are extracted in the time domain, frequency domain, and time-frequency domain to construct the sample data set M.

(2) The sample data set M is randomly divided, and the first 200 samples are used as the training set and the remaining samples are used as the test set. The training set is input to the CNN network for model training, and the training process mainly includes two stages of forward propagation and backward propagation. Forward propagation is a series of operations such as convolution, pooling and full connection to obtain the output of the network, i.e., the probability distribution of the category of tool wear. Back propagation is to calculate the error between the probability value of the output of the CNN network and the standard answer, and then back propagate the calculated error to obtain the error of each layer, and finally fine-tune the whole network parameters by using gradient descent method to improve the whole CNN model.

(3)The PSO algorithm is introduced to optimize the two hyperparameters of batch size and Epoch count to derive the best combination of parameters, and the best parameters are used for forward propagation of the CNN network, and iterative operations are performed on the network connection weight matrix until the errors converge and then the operations are terminated to complete the optimal training of the final model.

(4)The test set is fed into the trained CNN model, and the three types of tool wear are output using the fully connected layer to complete the prediction of the type of tool wear state on a 5-axis machining center.

3 Construction of tool wear sample data set

3.1 Acquisition of cutting vibration signals and spindle current signals

This paper uses sensors to collect cutting vibration signals and spindle current signals during the milling process of a 5-axis machining center in real time, and uses an electron microscope to measure the corresponding tool wear values to provide data support for the realization of tool remaining life prediction, the Measuring system models is shown in Figure 2.

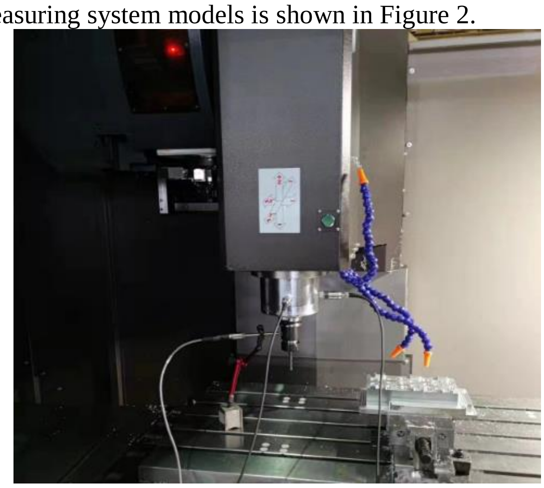


Figure 2 Measuring system models

3.1.1 Vibration signal acquisition scheme

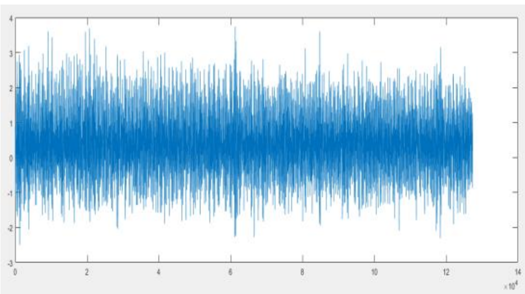
The vibration signal is caused by the periodic vibration of the cutting system composed of machine workpiece or tool, and the strength of the vibration between systems is closely related to the tool wear state. Acquisition of vibration signals generally choose acceleration sensors, according to the different measurement principles are broadly divided into three ways: piezo-resistive sensors, piezoelectric sensors and capacitive sensors, this paper uses BVM-YD-139 piezoelectric acceleration sensors to collect vibration signals, in the installation, you can use magnetic adsorption on the surface of the parts to be processed for detection, but the results of measuring the tool vibration signal by the location of the installation However, the result of measuring the tool vibration signal is affected by the location of the installation, and the strength of the machine tool system vibration and the interference of external environmental factors will also have an impact on the vibration signal acquisition, so the vibration signal collected needs to be processed for noise reduction.

3.1.2 Spindle current signal acquisition scheme

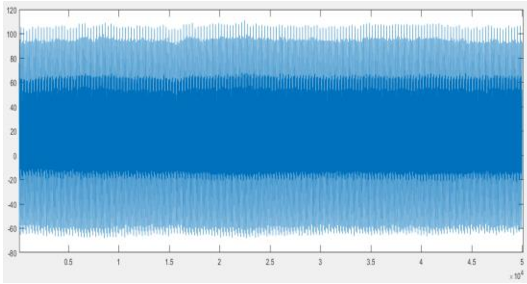
The spindle current during milling is the operating current generated by the spindle during the machining of the part. According to the relevant data, the more serious the tool wear, the higher the machine tool spindle current, which is almost linearly proportional, so the machine tool spindle current signal can indirectly reflect the tool wear status. This paper uses HC33C3 current sensor to acquire spindle current signal, which is characterized by simple installation, not restricted by machining environment and relatively wide application range. At the same time, the machine tool spindle current signal is easy to obtain and can be collected directly from the machine tool, but the spindle motor interferes with the collected data at the moment of starting and braking, so the collected current signal also needs to be processed for noise reduction.

3.1.3 Noise reduction processing of the original signal

In this paper, taking the cutting vibration signal as an example, the original vibration signal is collected every Δt, and its data volume is about 200000 or more, so the data labeled 50001～100000 in each collected signal is extracted for study to avoid the interference of the noise signal, and the comparison results of the original signal and the signal after noise reduction are shown in Figure 3. Then the signal data after noise reduction are extracted in the time domain, frequency domain and time-frequency domain respectively to extract the feature quantities related to the tool wear state in order to form the sample data set available for model training.



(a)



(b)

Figure 3 Comparison results between the original signal and the noise reduction signal

(a) Raw signal data (b) Signal data after noise reduction

3.2 Extraction of tool wear characteristics

3.2.1 Time domain feature extraction scheme

The time domain characteristics of the signal are for a certain time period of the milling process without limits of expansion, and discovering and analyzing the pattern of variables of interest as they change over time. Although the acquired signal possesses a continuously changing waveform, it is difficult to extract the features related to tool wear directly from the original signal due to the high sampling frequency and the limitations imposed by frequent noise interference, so time domain analysis is required. Time domain analysis is to process the original signal with relevant parameters calculation and data analysis, so that the extracted time domain features are more representative. In this paper, in order to realize the intelligent prediction and health management of tool wear, the time domain features of the original signal are mainly divided into dimensional and dimensionless features. The dimensional time domain features can directly reflect the various changes of the milling tool machining process, mainly including five kinds of time domain features, which are absolute mean, variance, rms, peak and peak-to-peak; the dimensionless parameters are obtained by dividing the same dimension, which can avoid the interference of signal The dimensionless parameters are obtained by dividing by the same magnitude, which can avoid the interference of signal amplitude and other factors, and also can reflect other information of tool wear. The dimensionless features mainly include five time-domain features, which are skewness indicator, cliffness indicator, peak factor, coefficient of variation, and waveform factor.

3.2.2 Frequency domain feature extraction scheme

The frequency domain characteristics of a signal describe the pattern between the variables associated with the observed signal in terms of frequency, which is more profound and convenient than the time domain analysis. Fourier Transform is the most commonly used method for frequency domain analysis, which essentially converts the signal in the time domain to the frequency domain and performs tool life prediction by extracting the spectral features of the sample signal. When the wear level of the tool changes during the milling process, the frequency components of the signal spectrum will change, so by analyzing the frequency domain features, we can accurately characterize the signal spectrum information and learn whether the tool is in a healthy state or not. The frequency domain features extracted in this project mainly include four frequency domain features: frequency mean square, frequency center of gravity, frequency variance, and peak frequency.

3.2.3 Time-frequency domain feature extraction scheme

Due to the change of geometric features or process parameters of the machined part, the signal collected by the sensor during the tool wear signal monitoring process can change instantaneously and abruptly, so the signal on the time-frequency domain needs to be analyzed. In this paper, we use wavelet packet analysis to sample the high frequency signal and low frequency signal respectively during the layer-by-layer decomposition process. After the decomposition of high and low frequency signals, so that the low and high frequency parts have the same resolution , the signal is subdivided into different frequency bands, and the frequency band structure of the monitoring signal will change with the change of tool wear state, resulting in the change of energy parameters in different frequency bands, so the energy magnitude of each frequency band is The energy level of each frequency band can accurately characterize the degree of tool wear[20] , and the energy value of the frequency band is calculated as shown in equation (3):

$$\mathrm{E_n}\,(\mathrm{x(t)}) = \frac{1}{2^{-\mathrm{k}}\mathrm{N}-1}\sum_{\mathrm{m}-0}^{2^{\mathrm{k}}-1}(\mathrm{x}^{\mathrm{k,m}}(\mathrm{i}))^2 \qquad (3)$$

The time domain signal is decomposed into wavelet packets according to the above principle, and the number of decomposed layers is set to 3, all done by the db5 wavelet basis, and then the decomposed signal of each layer is reconstructed by wavelet coefficients for more accurate analysis. Because of the orthogonality of the wavelet packet basis, the energy of the frequency bands can be characterized by the wavelet packet coefficients of each frequency band. After 3 layers of decomposition, the frequency domain is divided into 8 frequency bands, and thus 8 time-frequency domain features are extracted.

3.3 Construction of the sample feature matrix

In this paper, the time domain, frequency domain and time-frequency domain features are extracted from the noise reduced data, while the noise reduction process is carried out every Δt time for the original data, i.e. the original cutting vibration signal and the original spindle current signal are extracted every Δt time. The above analysis extracts 10 time-domain features, 4 frequency-domain features and 8 time-frequency-domain features, making a total of 22 feature values, thus forming a sample matrix, i.e.: from t to t + Δt time, let the noise reduced cutting vibration data set as A = {A1，A2，⋯, AN} and the spindle current data set as B ={B1，B2，⋯，BN} and assuming that the above 22 features are calculated as Fi , where i = 1, 2, .⋯ , 22; then the extracted features for cutting vibration are Xi = Fi (A); and the features for spindle current are Yi = Fi (B), where i = 1, 2, and ⋯ , 22.

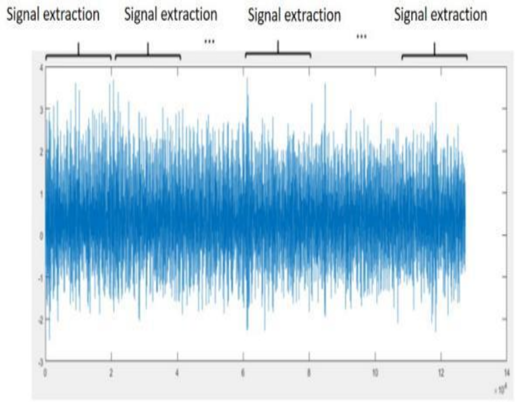


Figure 4 Extraction method of raw signal data

As shown in Figure 4, the above operation is repeated in the next Δt time, i.e. from t + Δt to t + 2Δt time, to calculate each sample feature value X, Y, until all features of all samples are extracted. However, the extraction of features in the time domain, frequency domain and time-frequency domain will have some data that are invalid and require corresponding dimensionality reduction, otherwise it will have a negative impact on the model training. For example, in the actual processing there is a spindle stall, similar to no load, or the spindle motor in the moment of starting and braking have a great impact on the collected data, which is a negative feature and should be identified and deleted. Therefore, for the sample set after feature extraction, the absolute average feature in each sample is thresholded, and if it is no-load data, stalled data or pulse data, the sample is deleted as a whole, and if it is not invalid data, the sample is retained. In this way, after screening all the samples, the remaining samples are the sample set after data processing, and each sample is the sample generated when the tool is cutting effectively. Based on this, a sample feature matrix is constructed for each signal with dimension N x 22 , the number of rows N of the matrix being the number of samples, and the structure of the cutting vibration sample eigenvalue X and the spindle current eigenvalue Y is shown in equations (4) and (5) as follows:

$$X = \begin{bmatrix} X_{1,1} & \cdots & X_{1,22} \\ \vdots & \ddots & \vdots \\ X_{N,1} & \cdots & X_{N,22} \end{bmatrix} \qquad (4)$$

$$Y = \begin{bmatrix} Y_{1,1} & \cdots & Y_{1,22} \\ \vdots & \ddots & \vdots \\ Y_{N,1} & \cdots & Y_{N,22} \end{bmatrix} \qquad (5)$$

3.4 Construction of the sample target matrix

Slight wear, normal wear, severe wear are the three major stages to characterize the degree of tool wear during the milling process[21] .Table 1 gives the range of wear VB values of the back face of the tool in the three stages.

Table 1 Tool wear range at various stages of back tool face

Type	Wear phase	Rear tool face wear V_B values
1	Slight wear and tear	0-0.1mm
2	Normal wear and tear	0.1-0.5 mm
3	Rapid wear and tear	0.5mm or more

The high pressure and temperature between the rear face of the tool and the machined surface during the milling process of the 5-axis machining center causes its rear face to wear faster and reach the dullness standard before the front face, so this paper mainly uses the electron microscope to measure the wear value VB in the rear face area of the tool. The measurement is performed by sampling every Δt time and corresponds to the sample characteristics, and the magnitude of the rear face wear value VB at each moment is the sample target value of tool wear. Each sample target value can correspond to the wear stages in Table 1 to construct the sample target matrix Q. The dimension of the target matrix sample Q is $N \times 1$, which mainly contains three types of minor wear (set as label 1), normal wear (set as label 2) and sharp wear (set as label 3). The time domain, frequency domain, and time-frequency domain features of the cutting vibration signals and spindle current signals of the extracted tool under different wear states are fused with the target sample matrix Q using the multi-source information fusion technique, and finally a sample data set M is obtained, whose data set M is shown in equation (6):

$$M = \begin{bmatrix} X_{1,1} & \cdots & Y_{1,22} & \cdots & Q_1 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{N,1} & \cdots & Y_{N,22} & \cdots & Q_N \end{bmatrix} \tag{6}$$

Since the measured wear value of the back tool face is a few moments, and the tool wear value is a continuous curve, the coordinates of the actual wear value can be interpolated to generate a cubic polynomial fit curve, and the reliability of the sample data set can be verified by comparing it with the tool wear curve. In this paper, a cubic polynomial is used for the interpolation calculation, as shown in equation (7):

$$y(t,\omega) = \sum_{j=0}^{3} \omega_j t^j \tag{7}$$

Where ω_j ist^j the coefficient, y is the interpolated tool wear value, and t is the time. For the tool wear values y_i collected at time x_i, a total of N times were collected, the loss function of the cubic polynomial interpolation curve is shown in equation (8):

$$E_n(\omega) = \frac{1}{2}\sum_{i=0}^{N}[y(t_i,\omega) - y_i]^2 \tag{8}$$

And the difference curve coefficient ω_j can be found by calculation, which is shown in equation (9):

$$min\frac{1}{2}\sum_{i=0}^{N}[y(t_i,\omega) - y_i]^2 \tag{9}$$

The fitted curve of the cubic polynomial derived from the above calculation is shown in Figure 5. The fitted curves show that the tool wear is faster at the early stage, smoother when it enters the middle stage, and faster at the later stage, which is consistent with the curve situation of tool wear. The results show that this sample data set M can effectively characterize the tool wear state at each moment, and can be used as the input to the PSO-CNN model.

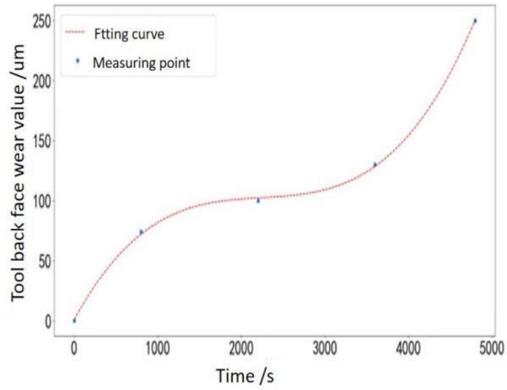


Figure 5 Cubic polynomial interpolation of tool wear curves

4 Experimental verification and analysis of tool wear

4.1 Structural parameters of CNN network model

In this experimental model, two hyperparameters, batch size and Epoch number , are selected as the object of the optimization process. To avoid the influence of external factors, the number of particle swarm individuals in the PSO algorithm is set to 10 and the maximum number of iterations is set to 50, as shown in Table 2. The optimized CNN model batch size parameter is set between 300 and 500, and the Epoch number is set between 5 and 15. The optimization was performed according to the parameter settings in Table 2, resulting in the best combination of hyperparameters with a batch size of 330 and an Epoch number of 10 iterations.

Table 2 Initial parameter settings for the PSO algorithm

PSO algorithm parameters	Parameter values
Number of individuals in the particle population	10
Maximum number of iterations	50
Cognitive factors c1, c2	2, 2
Inertia factor	0.5
Particle vector dimension	2

The optimized parameters of the PSO algorithm were input to the CNN model for tool wear prediction, and the specific parameters of the CNN network model were set as shown in Table 3. Table 3 shows that the CNN network structure contains two convolutional layers, two pooling layers and one fully connected layer. In order to improve the prediction performance of the model, the training process uses the RELU function for nonlinear activation, which has good non-saturation characteristics and can avoid the gradient disappearance phenomenon, and the activation function is shown in equation (10):

$$V_i^k = Relu(X_i^k) = \begin{cases} 0, x_i^k < 0 \\ x_i^k, x_i^k > 0 \end{cases} \tag{10}$$

where x_i^k is the X_i^k each eigenvalue in the feature matrix.

Table 3 CNN network structure parameters

Structural section	Network structure Name	Parameter settings
1	Convolutional layer 1 Batch standardisation layer 1 Pooling layer 1	Activation function: RELU Convolution kernel: 3*3 Maximum pooling
2	Convolutional layer 2 Batch standardisation layer 2 Pooling layer 2	Activation function: RELU Convolution kernel: 3*3 Maximum pooling
3	Dropout layer	25% discard
4	Output layer	Activation function: Softmax

In order to quantify the results of tool wear status monitoring, the precision, accuracy, recall, and F1-score values are selected as evaluation indexes in this paper, and the precision (Precision), accuracy (Accuracy), recall (Recall), and F1 values (F1-score) are calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

$$F1 - score = \frac{2TP}{2TP + FP + FN} \tag{14}$$

In the above equation, the values of TP, TN, FP, and FN can be found in the confusion matrix, and the confusion matrix is shown in Table 4 for the dichotomy example.

Table 4 Confusion Matrix

		True Value	
		1	0
Predicted value	1	TP	FP
	0	FN	TN

4.2 Prediction results of PSO-CNN model

In this paper, we use the convolutional neural network architecture based on particle swarm optimization for tool state recognition training, and it can be seen from the accuracy and loss function of the model in Figure 6: the accuracy of the model shows an increasing trend during the first 50 iterations, and then the accuracy gradually increases.

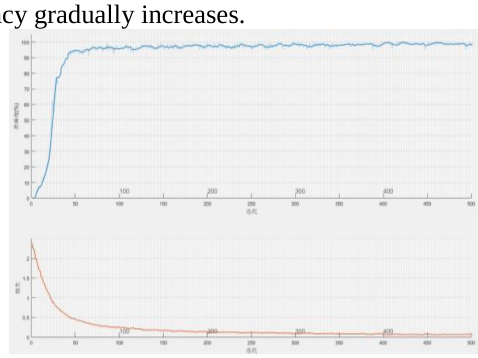


Figure 6 Accuracy and loss function graph

The sample data set M is randomly divided, and the first 200 samples are used as training sets to train the constructed PSO-CNN model. The predicted results of the training set are shown in Figure 7. which shows that only 2 out of 200 training samples were incorrectly identified, with an accuracy of 99.13%. The remaining samples are used as a test set to test the model, and the predicted results of the test set are shown in Figure 8. It can be found that only 2 out of 116 test samples were identified incorrectly, and the accuracy of the test set reached 98.28%; the results show that the PSO-CNN model constructed in this paper can effectively identify the tool wear status and achieve better results.

The confusion matrix of the PSO-CNN tool condition monitoring model test set is shown in Figure 9, which shows that the test set contains 42 samples of slight wear (label 1), 31 samples of normal wear (label 2) and 43 samples of sharp wear (label 3). The model proposed in this paper identifies all the slight wear samples correctly when testing them, and the test accuracy reaches 100%; when testing the normal wear samples, one sample is incorrectly identified as slight wear, and the accuracy is 96.8%; when testing the sharp wear samples, one sample is incorrectly identified as normal wear, and the accuracy is 97.7%.

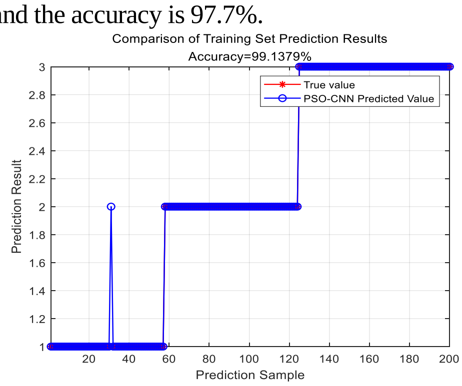


Figure 7 Training set prediction results

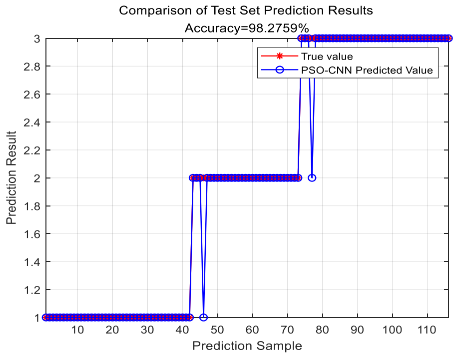


Figure 8 Test set prediction results

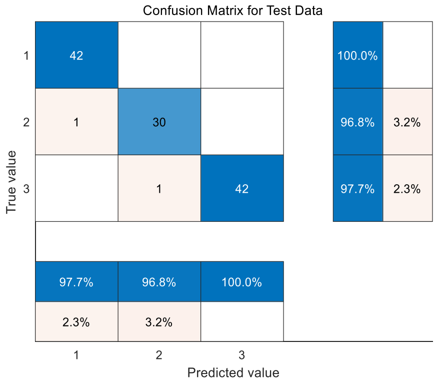


Figure 9 Confusion matrix

The evaluation indexes of tool condition monitoring can be calculated through the confusion matrix, and the results of the evaluation indexes of its three condition labels are shown in Table 5. For the accuracy rate index, it can be seen that the slight wear has the highest accuracy rate, and its performance is ranked as slight wear ＞ sharp wear ＞ normal wear; for the correct rate index, it can be seen that the accuracy rate of all three wear states is 98%, which is consistent with the previous analysis; for the recall rate index, it can be seen that the recall rate of slight wear and normal wear does not reach 100%, which indicates that there are other wear states incorrectly identified These four results further verify the effectiveness of the PSO-CNN tool state recognition model.

Table 5 Results of three tool condition evaluation indexes

Label classification	Accuracy rate	Accuracy	Recall Rate	F1 value	Test samples	Sample error
Slight wear and tear	1	0.98	0.98	0.99	42	0
Normal wear and tear	0.97	0.98	0.97	0.97	31	1
Rapid wear and tear	0.98	0.98	1	0.99	43	1

In order to further verify the recognition performance of PSO-CNN model tool wear status, a comparative analysis was performed with other traditional recognition models in the past, such as BP neural network, CNN convolutional neural network, and SVM support vector machine, and the prediction results of these three traditional tool wear status recognition models are shown in Figure 10. From Fig. 8 and Fig. 10, it can be seen that the prediction effects of the four tool wear state recognition models are ranked as PSO-CNN model ＞ CNN model ＞ SVM model ＞ BP model. It can be seen that the CNN model optimized based on the PSO algorithm proposed in this paper has obvious advantages in tool wear state recognition because the CNN network in the PSO-CNN model can perform deep mining of the hidden layer features using convolution and pooling operations, and the PSO algorithm is able to match the two hyperparameters of batch size and Epoch count in the CNN network for seeking the best, thus avoiding the blindness of setting parameters, thus improving the accuracy of the prediction model.

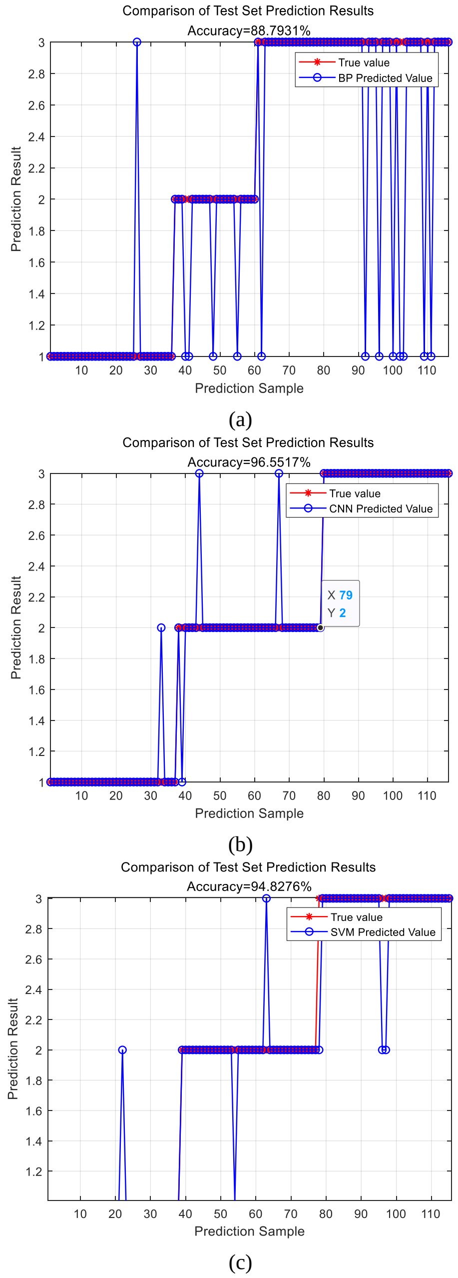


Figure 10 Prediction results of the three traditional models

BP model. (b) CNN model.(c) SVM mode

Table 6 shows the performance comparison results of the four tool wear state recognition models. The number of error samples identified by the BP model, SVM model and CNN model are 13, 6 and 4, respectively, and their accuracy rates are 88.79%, 94.83% and 96.55%, respectively. In contrast, the PSO-CNN model proposed in this paper identifies only 2 incorrect samples, and the accuracy rate is as high as 98.27%, which is 9.48%, 3.44%, and 1.72% higher than the above three traditional models respectively. This shows that the prediction accuracy of the tool wear status of the CNN model optimized based on the PSO algorithm is significantly higher than other models under the conditions of the same number of samples, and its generalization ability is stronger and the network fitting speed is faster, which indicates that the prediction of the tool wear status using the PSO-CNN model is more accurate and can more effectively realize the tool status monitoring and intelligent tool change during the milling process of the 5-axis machining center. This shows that using PSO-CNN model to predict the tool wear status will be more accurate and can more effectively realize the tool condition monitoring and intelligent tool change in the five-axis machining center.

Table 6 Performance comparison results of four prediction models

Network Model	Number of misidentified samples: Minor Wear and tear	Normal wear and tear	Rapid Wear and tear	Accuracy
BP Neural Networks	1	4	8	88.79%
SVM Support vector machines	1	2	3	94.83%
CNN Convolutional Neural Networks	1	3	0	96.55%
PSO-CNN Hybrid model	0	1	1	98.27%

5 Conclusion

In this paper, firstly, cutting vibration signals and spindle current signals are collected, and data features characterizing tool wear are extracted in the time domain, frequency domain and time-frequency domain; secondly, the tool wear values corresponding to the above features are measured by electron microscopy, and they are divided into three categories according to wear values: slight wear, normal wear and sharp wear, and the construction of sample data sets is completed; finally, the PSO-CNN model proposed in this paper is used to complete classification and prediction of tool wear status and compare and analyze with other models, the results show that:

(1) Parameter search optimization of CNN convolutional neural network by PSO algorithm yields the best combination of hyperparameters with a batch size of 330 and an Epoch count of 10. The blindness of setting parameters is avoided, thus improving the model prediction accuracy and precision.

(2) The prediction accuracy of the PSO-CNN model constructed in this paper reaches 98.27%, which can meet the requirements of monitoring the tool wear status and can realize the predictive maintenance of CNC machining tools, that is, intelligent tool change before the tool wear is in sharp wear .

(3) Comparing the prediction performance of the PSO-CNN model constructed in this paper with BP neural network, CNN convolutional neural network and SVM support vector machine, the results show that the PSO-CNN prediction model constructed in this paper has obvious advantages in the field of tool wear condition identification, and its accuracy indexes are improved by 9.48%, 3.44% and 1.72% respectively compared with other models.

In the future, this PSO-CNN tool wear state prediction model can be widely used in the fields of tool life prediction and intelligent operation and maintenance of CNC machine tools in various factories. By monitoring the cutting vibration signal and spindle current signal of the tool system in real time, the prediction of different tool wear states can be realized, and based on the prediction results the machine tool can make intelligent judgments and make corresponding processing, so as to improve the product machining quality and reduce the scrap rate, which has certain practical significance.

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